Technische Universität Dortmund
Fakultät für Erziehungswissenschaft, Psychologie und Bildungsforschung

Short-Term Developmental Processes of Students' Expectancies and Task Values in Math-Intensive Study Programs and Links to Academic Success and Dropout Tendencies

Kumulative Dissertation zur Erlangung des akademischen Grades
Doktorin der Philosophie (Dr. phil.)

vorgelegt von
Daria Katharina Benden

Erstgutachterin: Prof. Fani Lauermann, Ph.D.
Zweitgutachterin: Prof. Dr. Nele McElvany

Dortmund, August 2022

Dissertation in der Fakultät für Erziehungswissenschaft, Psychologie und Bildungsforschung
an der Technischen Universität Dortmund

Acknowledgements

I would like to acknowledge and thank Fani Lauermann for being the most supportive and encouraging mentor I could have asked for. Thank you for your guidance and feedback throughout my dissertation project, for providing so many learning opportunities, for encouraging me to pursue ambitious goals, and for being my cheerleader at times! I am incredibly grateful for everything you have done for me as an advisor and mentor.

Furthermore, I would like to thank Nele McElvany and Hanna Gaspard for their time and effort invested in reading my dissertation and for agreeing to serve on my dissertation committee.

Thank you to all my current and former colleagues at the Center for Research on Education and School Development (IFS) at TU Dortmund University. I am thankful for the time I spent at the IFS, with its supportive and collaborative culture and the many opportunities to develop my skills and receive feedback on my work. I am especially grateful to my officemate and friend, Inga ten Hagen. Thank you for your never-ending support, for our inspiring discussions about research and life, for our walks, and for celebrating our accomplishments with sushi.

I would also like to thank everyone involved in the BONNS study: the participating instructors and students, as well as everyone who helped with the data collection. A special thank you to Michael Evers, not only for your support of the BONNS study but also for the great time we spent together at the University of Bonn.

Furthermore, I want to thank my friends and my handball team at TV Wattenscheid for your support and understanding, for taking my mind off work, and for lifting me up when I needed it.

Finally, to my family: thank you for believing in me, for supporting me, and for providing me with the opportunity to follow my interests and goals!

Abstract

Students' math-related expectancies of success and subjective task values are important predictors of their educational and career choices (Eccles et al., 1983; Eccles & Wigfield, 2020). These choices include, for instance, the decision to persist in or drop out of math-intensive study programs in the fields of science, technology, engineering, and mathematics (STEM), which are characterized by high dropout rates. Furthermore, the first year after the transition to postsecondary education is a critical time in students' educational careers because dropout from math-intensive STEM programs is particularly high during this time. Introductory math courses are frequently seen as a gatekeeper to further engagement and success in STEM fields because they play an important role in students' decisions to persist in or drop out of math-intensive STEM programs. However, little is known about how students' expectancies of success and subjective task values change in math gatekeeper courses shortly after the transition to postsecondary education, and to what extent potential declines in these motivational beliefs may contribute to high dropout rates during this critical time period. Building on Eccles and colleagues' situated expectancy-value theory (Eccles et al., 1983; Eccles & Wigfield, 2020), the present dissertation thus examined (a) how students' expectancies of success and task values changed in the first semester of math-intensive study programs, (b) whether the developmental processes of students' expectancies and task values across the semester differed as a function of students' personal characteristics (e.g., gender, prior achievement, socioeconomic status), and (c) whether potential motivational declines predicted later academic struggles (i.e., low academic achievement, dissatisfaction with the study program, and dropout tendencies).

The empirical studies in this dissertation used data from the BONNS project (*Bonner Studienverlaufsstudie*). The BONNS study followed six cohorts of students enrolled in physics, math, or math teacher education programs across their first semester at a German university (N = 1,004; two cohorts in each study program). In all cohorts, students reported their expectancies of success and subjective task values towards their math course at the beginning (Week 2), midpoint (Week 8), and end of the semester (Week 15). Additional surveys in Weeks 3 through 5 were administered in five of the six cohorts and asked students to reflect on their weekly experiences with mandatory math worksheets in their math course.

Study 1 consisted of two studies (*Study 1a* and *Study 1b*) focusing on motivational changes across the entire semester (Study 1a; beginning, midpoint, and end-of-term data collections; N = 1,004) as well as across the first weeks of the semester (Study 1b; Weeks 2

to 5; $N = 773$). Both studies examined changes in students' expectancies and task values over the respective time periods, whether motivational trajectories are predicted by student characteristics (i.e., gender, prior achievement, socioeconomic status), and whether motivational changes are predictive of students' end-of-term exam performance, study satisfaction, and course dropout. Latent change score analyses in Study 1a showed that students' expectancies and task values declined from the beginning towards the midpoint of the semester and remained relatively stable towards the end of the semester. Analogous analyses in Study 1b revealed that students experienced a "motivational shock" between Week 2 and Week 3 of the semester, which was characterized by a rapid decline in students' intrinsic and utility values and a sharp increase in their perceived psychological and effort costs. This motivational shock coincided with the students' first feedback on mandatory weekly math worksheets. Across both studies, female students and students with comparatively lower achievement in high school experienced greater motivational declines. Importantly, the motivational shock predicted students' end-of-term exam performance, study satisfaction, and course dropout, suggesting that motivational declines at the beginning of the semester serve as early warning signs of later academic struggles and dropout tendencies in math-intensive fields.

Study 2 further examined potential gender differences in students' expectancies and task values beyond the mean-level differences identified in Study 1. Using data from the beginning, midpoint, and end-of-semester time points ($N = 927$), Study 2 examined the variability of students' expectancies of success, task values, and self-assessed performance over time and the variability of these motivational beliefs within each time point (i.e., their consistency with each other in a given situation). Multilevel analyses revealed significant gender differences in the variability of students' expected success and self-assessed performance across the semester, whereas no significant gender differences were found in the variability of students' subjective task values over time. Furthermore, the variability between students' expectancy, task values, and performance was greater for female than male students at two of the three time points across the semester. These results suggest that female compared to male students may be more likely to experience fluctuations in their expectancy and self-assessed performance over time and that females' motivational beliefs may be less closely aligned within a given situation.

As part of the overall discussion of this dissertation, central findings of the two studies are discussed in light of the broader research context. To this end, further analyses (*Study 3*) are presented that extend the findings of the two contributions of this dissertation. These analyses investigated within-person processes that likely contribute to the observed short-term motivational declines in Study 1. Using data from five of the six cohorts of the BONNS study (*N* = 773), Study 3 examined changes in the within-person associations of students' expectancies and task values over time as well as within-person reciprocal links among expectancies and task values. Similar to Study 1, analogous analyses were conducted for the assessments of students' expectancies and task values at the beginning, midpoint, and end of the semester (course-specific assessments) as well as the weekly assessments across three weeks at the beginning of the semester (Weeks 3 to 5; situated assessments). Random intercept cross-lagged panel analyses revealed an increasing alignment of students' expectancies and intrinsic and utility values across the semester (i.e., these motivational beliefs became increasingly correlated across the semester), whereas the associations of the weekly expectancy-value beliefs referencing the current math worksheet remained relatively stable. Similarly, "motivational spillover effects" (i.e., significant cross-lagged effects) were limited to students' course-specific expectancies and task values and unidirectional. Students' expectancy of success emerged as a driving force of within-person changes in their intrinsic and utility values. In contrast, no significant motivational spillover effects emerged for students' situated assessments that referenced weekly mandatory math worksheets, which suggests that these situational experiences were relatively self-contained within a given week.

The present dissertation highlights the role of short-term developmental processes of students' expectancies and task values shortly after the transition to postsecondary education in math-intensive study programs. Motivational declines in the very early stages of postsecondary education serve as a warning sign of low academic achievement and dropout tendencies at the end of the first semester in math-intensive STEM fields. Results suggest that interventions to support students' motivation in math-intensive study programs are needed in the early stages of students' postsecondary education. Intervention approaches that target both students' expectancies of success and subjective valuing of the learning material across multiple weeks at the beginning of the semester may be most fruitful in preventing motivational declines and increasing retention in STEM majors. Further implications for future research and educational practice are discussed.

Zusammenfassung

Die Erfolgserwartungen und subjektiven Wertüberzeugungen von Studierenden, beispielsweise in Bezug auf die Domäne der Mathematik, sind wichtige Prädiktoren für ihre Bildungs- und Berufsentscheidungen (Eccles et al., 1983; Eccles & Wigfield, 2020). Zu diesen Entscheidungen gehört beispielsweise die Entscheidung, einen mathematikintensiven Studiengang aus den Bereichen Mathematik, Informatik, Naturwissenschaften, oder Technik (MINT) fortzusetzen oder abzubrechen. Bisherige Forschung im Bereich von Studienabbruch in MINT-Studiengängen zeigt, dass das erste Studienjahr eine besonders kritische Zeit nach dem Übergang in die Hochschulbildung ist, da die meisten Studierenden, die sich für einen Studienabbruch entscheiden, ihr Studium in diesem Zeitraum ohne Abschluss beenden. Eine zentrale Rolle bei der Entscheidung für einen Studienabbruch spielen dabei oft verpflichtende Mathematikveranstaltungen in der Studieneingangsphase, die für viele Studierende eine Hürde für weiteres Engagement und Erfolg in mathematikintensiven Studienfächern darstellen. Dennoch gibt es vergleichsweise wenig Forschung zu Veränderungen in den Erwartungs- und Wertüberzeugungen von Studierenden in verpflichtenden Mathematikveranstaltungen in der Studieneingangsphase und inwieweit mögliche Abnahmen in diesen motivationalen Überzeugungen zu Studienabbruchtendenzen in dieser kritischen Zeitspanne nach dem Übergang in die Hochschulbildung beitragen könnten. Aufbauend auf der Erwartungs-Wert-Theorie von Eccles und Kolleg*innen (*situated expectancy-value theory*; Eccles et al., 1983; Eccles & Wigfield, 2020) wurde in der vorliegenden Dissertation daher untersucht, (a) wie sich die Erfolgserwartungen und subjektiven Wertüberzeugungen von Studierenden im ersten Semester in mathematikintensiven Studiengängen verändern, (b) ob sich die Entwicklungsprozesse der Erwartungs- und Wertüberzeugungen der Studierenden unterscheiden abhängig von persönlichen Merkmalen der Studierenden (z. B. Geschlecht, schulische Vorleistungen, sozioökonomischer Status) und (c) ob mögliche Abnahmen in den Erwartungs- und Wertüberzeugungen der Studierenden spätere Schwierigkeiten im Studium vorhersagen (d. h. schlechte Studienleistungen, Unzufriedenheit mit dem Studium und Studienabbruchtendenzen).

Die empirischen Studien dieser Dissertation nutzten Daten aus dem BONNS-Projekt (*Bonner Studienverlaufsstudie*). Die BONNS-Studie begleitete sechs Kohorten von Studierenden aus den Fächern Physik, Mathematik und Mathematik auf Lehramt über ein gesamtes Semester in verpflichtenden Mathematikveranstaltungen des jeweiligen Studienfachs (N = 1.004; je zwei Kohorten pro Studienfach). In allen Kohorten bewerteten die Studierenden

ihre Erwartungs- und Wertüberzeugungen bezüglich ihrer Mathematikveranstaltung jeweils zu Beginn (Woche 2), zur Mitte (Woche 8) und zum Ende des Semesters (Woche 15). In fünf der sechs Kohorten wurden zudem wöchentliche Erhebungen in den Wochen drei bis fünf des Semesters durchgeführt, in denen die Studierenden ihre Erfolgserwartungen und subjektiven Werte bezüglich verpflichtender Übungsblätter bewerteten.

Studie 1 bestand aus zwei Teilstudien (*Studie 1a* und *Studie 1b*) und fokussierte motivationale Veränderungen im Verlauf des gesamten Semesters (Studie 1a, Datenerhebungen zu Beginn, in der Mitte und am Ende des Semesters; N = 1.004) sowie innerhalb der ersten Wochen des Semesters (Studie 1b; Wochen 2 bis 5; N = 773). In beiden Teilstudien wurde untersucht, ob sich Erfolgserwartungen und Wertüberzeugungen in den jeweiligen Zeiträumen verändern, ob die Motivationsverläufe durch Merkmale der Studierenden (d. h. Geschlecht, schulische Leistungen, sozioökonomischer Status) vorhergesagt werden können und ob mögliche motivationale Veränderungen mit der Studienzufriedenheit der Studierenden am Ende des ersten Semesters, ihren Prüfungsleistungen und einem möglichen Abbruch des Kurses zum Semesterende zusammenhängen. Latente Veränderungsmodelle in Studie 1a zeigten, dass die Erfolgserwartung und subjektiven Wertüberzeugungen der Studierenden von Beginn bis zur Mitte des Semesters abnahmen und innerhalb der zweiten Hälfte des Semesters vergleichsweise stabil blieben. Analoge Analysen in Studie 1b zeigten weiterhin, dass die Studierenden zwischen Woche 2 und Woche 3 des Semesters einen „Motivationsschock" erlebten, der durch eine rapide Abnahme des intrinsischen Wertes und der wahrgenommenen Nützlichkeit der Lerninhalte sowie einen signifikanten Anstieg in den wahrgenommenen psychologischen und Anstrengungskosten gekennzeichnet war. Der Motivationsschock fiel dabei mit dem ersten Leistungsfeedback zusammen, das die Studierenden zu ihren verpflichtenden, wöchentlichen Übungsblättern erhielten. In beiden Studien erlebten weibliche im Vergleich zu männlichen Studierenden und Studierende mit vergleichsweise schlechteren Abiturnoten einen stärkeren Motivationsabfall. Sowohl der Motivationsabfall in Studie 1a als auch der Motivationsschock am Anfang des Semesters in Studie 1b waren signifikante Prädiktoren der Studienzufriedenheit und der Klausurleistungen der Studierenden am Ende des ersten Semesters sowie eines Kursabbruchs innerhalb des Semesters.

Studie 2 untersuchte darüber hinaus mögliche Geschlechtsunterschiede in der Erfolgserwartung und den subjektiven Werten der Studierenden, die über die in Studie 1 identifizierten Mittelwertunterschiede hinausgehen. Anhand der Daten der drei Messzeitpunkte zu Beginn, zur Mitte und zum Ende des Semesters wurde in Studie 2 die Variabilität der

Erfolgserwartungen, subjektiven Werte und der selbsteingeschätzten Leistung im Laufe des Semesters sowie die Variabilität dieser motivationalen und leistungsbezogenen Einstellungen innerhalb jedes Zeitpunkts (d. h. ihre Konsistenz untereinander) untersucht (N = 927). Mehrebenenanalysen identifizierten dabei signifikante Geschlechtsunterschiede in der Variabilität der Erfolgserwartung und der selbsteingeschätzten Leistung der Studierenden im Laufe des Semesters, während keine signifikanten Unterschiede in der Variabilität der subjektiven Werte im Laufe des Semesters gefunden wurden. Darüber hinaus zeigten sich signifikante Geschlechtsunterschiede in der Variabilität zwischen den motivationalen und leistungsbezogenen Überzeugungen an zwei der drei Messzeitpunkten, wobei die Variabilität bei weiblichen im Vergleich zu männlichen Studierenden größer war. Die Ergebnisse deuten darauf hin, dass weibliche Studierende verglichen mit männlichen Studierenden anfälliger für Fluktuationen in ihren Erfolgserwartungen und Leistungseinschätzungen sein könnten sowie dass ihre motivationalen Überzeugungen innerhalb einer Situation weniger eng verzahnt sein könnten.

Im Rahmen der Gesamtdiskussion der vorliegenden Dissertation werden zentrale Befunde der beiden Beiträge studienübergreifend diskutiert und in den Forschungskontext eingeordnet. Dazu werden zunächst vertiefende Analysen (*Studie 3*) vorgestellt, die die Befunde aus den beiden Beiträgen der Dissertation erweitern. Diese Analysen fokussierten auf intraindividuelle Prozesse, die zu den in Studie 1 beobachten Motivationsveränderungen innerhalb der ersten Wochen bzw. im Laufe des gesamten Semesters beitragen könnten. Unter Verwendung der Daten aus fünf der sechs Kohorten der BONNS-Studie (N = 773) wurden in Studie 3 Veränderungen in den intraindividuellen Zusammenhängen zwischen Erfolgserwartungen und subjektiven Werten der Studierenden (d. h. im Grad der Übereinstimmung) sowie intraindividuelle, reziproke Zusammenhänge zwischen Erfolgserwartungen und Wertüberzeugungen untersucht. Vergleichbar mit dem Vorgehen in Studie 1 wurden analoge Analysen für die kursspezifischen Assessments der Erwartungs- und Wertüberzeugungen zu Beginn, Mitte und Ende des Semesters sowie für die situativen Assessments in den Wochen drei bis fünf des Semesters durchgeführt. Random-intercept-cross-lagged-panel-Analysen zeigten einen zunehmenden Grad der Übereinstimmung zwischen den kursspezifischen Erfolgserwartungen und intrinsischem Wert bzw. wahrgenommener Nützlichkeit im Verlauf des Semesters (d. h. die Korrelationen zwischen diesen motivationalen Überzeugungen nahmen im Laufe des Semesters zu), wohingegen die Zusammenhänge zwischen den situativen Erwartungen und Werten, die sich auf das aktuelle Übungsblatt bezogen, relativ stabil blieben. Analog dazu fanden sich „motivationale Überlaufeffekte“ (d. h. signifikante kreuzverzögerte

Effekte) nur für die kursspezifischen Erwartungen und Werte im Verlauf des ganzen Semesters. Diese Effekte waren unidirektional: Die Erfolgserwartungen der Studierenden zeigten sich als signifikanter Prädiktor von intraindividuellen Veränderungen in intrinsischem Wert und der wahrgenommenen Nützlichkeit der Lerninhalte. Im Gegensatz dazu wurden keine signifikanten kreuzverzögerten Effekte für die situativen Bewertungen der Erwartungs- und Wertüberzeugungen der Studierenden bezüglich der wöchentlichen Übungsblätter gefunden, was darauf hindeutet, dass die situativen Einschätzungen der Studierenden bezüglich des aktuellen Übungsblätter relativ unabhängig voneinander waren.

Die vorliegende Dissertation unterstreicht die Bedeutsamkeit von Veränderungsprozessen in den Erfolgserwartungen und subjektiven Werten von Studierenden kurz nach dem Übergang in mathematikintensive Studiengänge im Hochschulkontext. Motivationseinbrüche innerhalb der sehr frühen Phase des Studiums können Warnzeichen für geringe Studienleistungen und Studienabbruchtendenzen am Ende des ersten Semesters im MINT-Bereich darstellen. Die Ergebnisse deuten darauf hin, dass Interventionsmaßnahmen zur Förderung der Motivation von Studierenden in mathematikintensiven Studiengängen bereits in der Anfangsphase des Studiums notwendig sind. Interventionsansätze, die wiederholt sowohl auf die Erfolgserwartungen der Studierenden als auch auf die subjektive Bedeutsamkeit der Lerninhalte fokussieren, könnten dabei besonders geeignet sein, einen Motivationsschock in der Anfangsphase des Studiums abzuschwächen und Studienabbruchquoten im MINT-Bereich zu reduzieren. Weitere Implikationen für zukünftige Forschung und Bildungspraxis werden diskutiert.

Table of Contents

Acknowledgements ... iii

Abstract ... iv

Zusammenfassung ... vii

1 Introduction and Theoretical Framework ... 13

1.1 Situated Expectancy-Value Theory of Achievement-Related Choice ... 16

1.1.1 Conceptualization and Assessment of Students' Expectancies and Subjective Task Values ... 19

1.1.2 Developmental Processes of Students' Expectancies and Task Values ... 22

1.1.3 Students' Personal Characteristics as Predictors of Their Expectancies and Task Values and Academic Success in STEM Fields ... 28

1.1.4 Students' Expectancies and Task Values as Predictors of Academic Success in STEM Fields ... 33

1.2 Research Questions of the Present Dissertation ... 37

References I ... 41

2 Contributions of the Cumulative Dissertation ... 54

2.1 Study 1a and Study 1b: Students' Motivational Trajectories and Academic Success in Math-Intensive Study Programs: Why Short-Term Motivational Assessments Matter ... 54

2.2 Study 2: Geschlechtsunterschiede in der Variabilität situationsspezifischer Erwartungs- und Wertüberzeugungen und selbsteingeschätzter Leistung in mathematikintensiven Studienfächern: Eine Mehrebenenanalyse von motivationalen Schwankungen ... 128

3 General Discussion ... 159

3.1 Further Analyses (Study 3): Searching for Short-Term Motivational Spillover Effects: A Random Intercept Cross-Lagged Panel Analysis of Students' Expectancies and Task Values in Math-Intensive Study Programs ... 160

3.2 Summary of the Main Results of the Three Empirical Studies ... 221

3.3 Discussion of the Main Results ... 223

3.3.1 Short-Term Developmental Processes of Students' Math-Related Expectancies and Task Values ... 223

3.3.2 Interindividual Differences in Students' Situated Expectancies and Task Values as a Function of Students' Personal Characteristics ... 228

3.3.3 Students' Situated Expectancy-Value Beliefs as Predictors of Their Academic Success in STEM Majors ... 232

3.4 Strengths and Limitations of the Present Dissertation ... 234

3.5 Implications for Future Research and Educational Practice ... 236

3.5.1 Implications for Future Research 237
3.5.2 Implications for Educational Practice 240
3.6 Conclusion 243
References II 244
4 Appendix 251
4.1 Übersicht der Einzelarbeiten 251
4.2 Eigenanteile der Doktorandin bei den Einzelarbeiten 252
4.2.1 Veröffentlichte Beiträge der kumulativen Dissertation 252
4.2.2 Beiträge zu weiteren Analysen 253
4.3 Eidesstattliche Erklärung 254

1 Introduction and Theoretical Framework

Increasing the graduation rates in the fields of science, technology, engineering, and mathematics (STEM) in postsecondary education is an important societal goal to meet the demand for highly skilled individuals in the (inter)national labor markets, diversify the workforce in STEM fields, and spur economic growth (Anger et al., 2022; OECD, 2020). Yet, a substantial number of students enrolled in postsecondary STEM programs leave their program without obtaining a degree (43% in math/science in Germany, Heublein et al., 2020; 48% in the US, Chen, 2013). Dropout rates are particularly high in the most math-intensive STEM fields, reaching up to 49% in physics and 58% in mathematics in Germany (Heublein et al., 2020). Furthermore, female students, who are traditionally underrepresented in math-intensive STEM programs, are even more at risk of dropping out of math-intensive STEM fields compared to their male peers (Isphording & Qendrai, 2019; Meyer & Strauß, 2019; Shaw & Barbuti, 2010). Importantly, the first year after the transition to higher education is a particularly critical time in students' postsecondary educational careers: Students need to adapt to a new learning environment, to the high demands and workload of their math-intensive study programs, and to a new academic context with many high-achieving peers (Credé & Niehorster, 2012; Heublein et al., 2017; Seymour & Hewitt, 1997). Indeed, most students in Germany drop out of their math-intensive study programs during the first year of higher education (47%; Heublein et al., 2017). Accordingly, it is important to better understand which factors contribute to students' dropout tendencies in the early stages of their math-intensive study programs in STEM fields.

Eccles and colleagues' situated expectancy-value theory (SEVT; Eccles et al., 1983; Eccles & Wigfield, 2020) is one of the most prominent theoretical frameworks to explain students' educational and occupational choices, including students' decision to persist in or drop out of math-intensive STEM fields. According to SEVT, students' expected success (Can I do this?) and valuing (Do I want to do this?) of academic tasks and domains are the most proximal psychological predictors of their achievement-related choices and behaviors (Eccles et al., 1983; Eccles & Wigfield, 2020). SEVT has informed much research over the last four decades and a substantial number of studies have supported its core theoretical assumptions (for a review, see Wigfield & Cambria, 2010a). For instance, students' expectancies and subjective task values have emerged as powerful predictors of their math- or science-related career aspirations (Lauermann et al., 2017; Nagengast et al., 2011; Wang, 2012), university entry and major selection in STEM fields (Gaspard et al., 2019; Guo, Parker, et al., 2015; Parker et al., 2012), and academic achievement and retention in math-intensive study programs in STEM fields (Perez et al., 2014; Robinson et al., 2019).

Most of the existing research grounded in SEVT has focused on the developmental processes of students' expectancies of success and subjective task values across the elementary and secondary school years and their role in influencing students' long-term educational and career choices (Wigfield & Eccles, 2020). This research has identified long-term declines in students' domain-specific expectancy-value beliefs across the elementary and secondary school years and has linked these declines to students' educational and occupational choices (e.g., Gaspard et al., 2020; Jacobs et al., 2002). It has also examined how the relation between students' expectancy of success and their subjective task values develops over time (e.g., Denissen et al., 2007; Wigfield et al., 1997) as well as whether these motivational beliefs influence each other over time (e.g., Arens et al., 2019; Marsh et al., 2005).

In contrast, relatively little is known about the developmental processes of students' expectancy-value beliefs over shorter periods of time (e.g., one semester), particularly in postsecondary education. This is an important gap in the literature because declines in students' expectancy-value beliefs may be most likely at important time points in students' educational careers such as the transition to postsecondary education and such motivational declines may be a warning sign of later academic difficulties and dropout tendencies (Eccles & Wigfield, 2020; see also Rosenzweig et al., 2022). Furthermore, students' situational experiences, for instance, in a given course, accumulate over time and may shape their more global motivational beliefs regarding their study program in general, thus likely contributing to students' long-term educational and occupational choices. As emphasized by Eccles and Wigfield (2020) by renaming their theory *situated* expectancy-value theory, students' expectancies of success and task values are assumed to be tied to the specific situation and form a complex system of interrelated motivational beliefs. A better understanding of the short-term developmental processes, including the timing and extent of potential motivational declines after the transition to higher education, and how different situation-specific motivational beliefs influence each other over such short periods of time, is thus necessary to design and implement motivational interventions at critical time points before students' motivations start to decline (Rosenzweig & Wigfield, 2016; Rosenzweig et al., 2022).

However, only a few studies to date have examined the development of students' expectancies and task values across relatively short time periods in postsecondary educational settings and these studies are limited in several important ways. Specifically, prior studies have rarely included more than two measurement points, have only included selected components from the expectancy-value framework, or have used relatively global assessments of students' expectancy-value beliefs that do not take into account that students' experiences can vary across different situations within a given course depending on context-specific factors (e.g., available feedback). More research is therefore needed that focuses on short-term developmental processes of students' expectancy-value beliefs using not only domain-specific but also situation-specific assessments of students' motivational beliefs that are sensitive to capture motivational fluctuations.

Thus, the aim of the present dissertation was to examine the development of students' expectancies and subjective task values across their first semester in math-intensive study programs. The present research focused on demanding mandatory math courses in the first semester of students' study programs that often serve as a gatekeeper to further engagement and success in STEM fields (Chen, 2013; Gasiewski et al., 2012; Seymour & Hewitt, 1997). Across three empirical studies, this dissertation examined motivational changes across students' first semester in math-intensive STEM programs, whether students' expectancy-value beliefs were related to each other both within a given situation and over time, and whether potential motivational declines served as warning signs of end-of-term academic struggles and dropout tendencies in STEM fields. Additionally, interindividual differences in the developmental processes of students' motivational beliefs were examined to identify groups of students who were comparatively more at risk of negative motivational trajectories and low academic achievement and dropout tendencies towards the end of their first semester in STEM fields.

The present dissertation is structured as follows: The introduction presents the theoretical framework of the three empirical studies, namely, Eccles and colleagues' situated expectancy-value theory (SEVT; Eccles et al., 1983; Eccles & Wigfield, 2020). After a brief overview of SEVT, I will describe important theoretical underpinnings and corresponding findings from prior research on the development of students' expectancies and task values. Next, I will discuss important predictors and outcomes of students' expectancy-value beliefs. The introduction closes with an overview of the guiding questions of the dissertation. In the following chapters, the two empirical studies (Studies 1a and 1b and Study 2) of the present dissertation will be presented. The concluding chapter of the dissertation will present further analyses (Study 3), summarize and discuss key findings of the three empirical studies, and outline directions for future research and implications for educational practice.

1.1 Situated Expectancy-Value Theory of Achievement-Related Choice

Expectancy-value models are widely used in motivation research with the goal of explaining human behavior (for an overview, see Feather, 1959, 1982/2021; Heckhausen, 1977). The basic premise of expectancy-value models is that an individual's motivation to perform a given task is determined by two key factors: their expectancy to be successful at the task and their valuing of the task or its successful completion (Atkinson, 1957; Eccles et al., 1983; Feather, 1959). The first elaborated expectancy-value theory of achievement motivation by Atkinson (1957, 1964) focused mainly on explaining individuals' immediate achievement-related choices and behaviors in lab experiments (e.g., task choice, persistence in the face of failure, or task performance; for an overview, see Maehr & Sjogren, 1971). In Atkinson's model, an individual's expectancy of success refers to their subjective probability of succeeding at a given task, whereas the incentive value refers to the relative attractiveness of being successful at the task (Atkinson, 1957). Furthermore, incentive value is defined as the inverse of expectancy of success, which effectively removes the value construct from the mathematical formulation of Atkinson's model and was thus often neglected in lab experiments on individuals' achievement motivation (Parsons & Goff, 1980; Wigfield & Eccles, 1992). Lastly, expectancy and incentive value are assumed to have a multiplicative association such that the strength of the motivation is a multiplicative function of the individual's expectancy and incentive value (Atkinson, 1957).

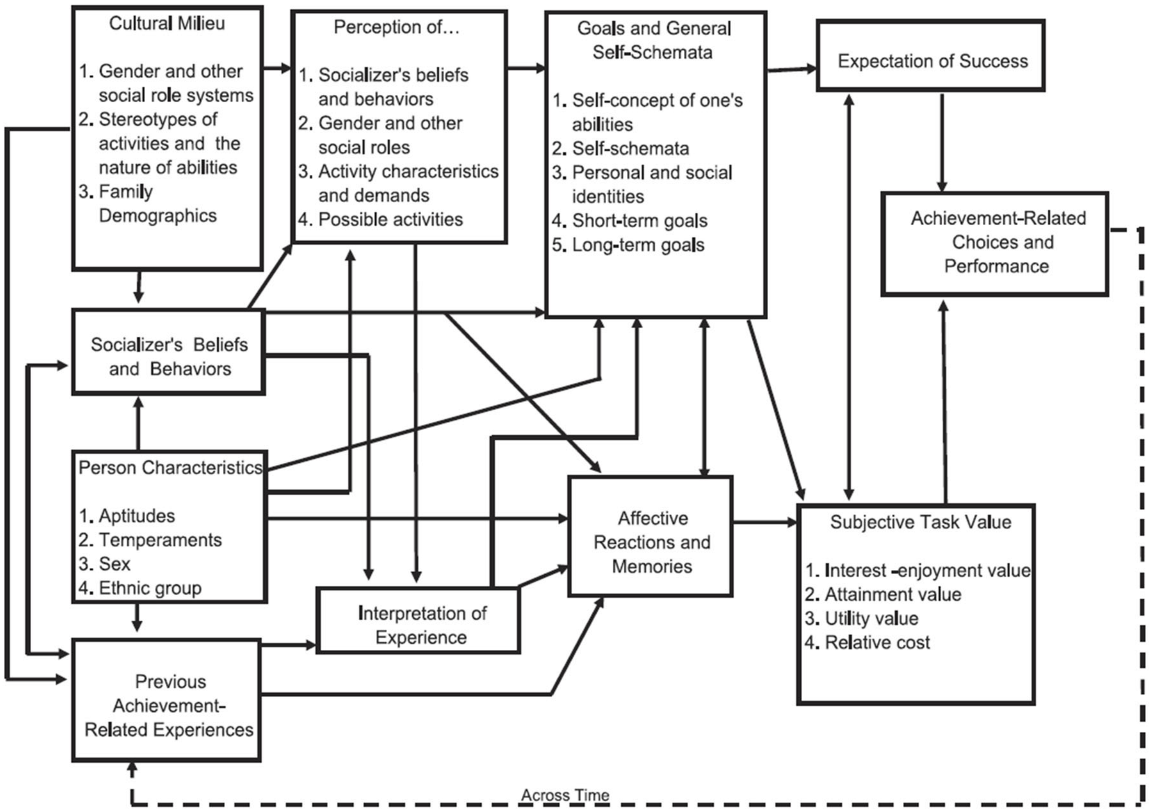
Eccles and colleagues extended Atkinson's model in several ways to explain important achievement-related choices in authentic contexts, such as students' course-taking in high school or major selection in college. A particular aim of the work of Eccles and her colleagues was to explain gender differences in students' educational and career choices in math-intensive domains (Eccles, 1984; Eccles et al., 1983; Parsons & Goff, 1980). First, building on work from other social cognitive theories of achievement motivation (Bandura, 1977; Weiner, 1979) and achievement values (E. S. Battle, 1965, 1966; Rokeach, 1979/2008), Eccles and colleagues further expanded the task value component of the model by defining task value as a multi-faceted construct in contrast to the comparatively narrow incentive value in Atkinson's model (Eccles, 2005b; Eccles et al., 1983; Wigfield & Eccles, 1992). Second, Eccles and colleagues included a broad range of sociocultural factors as determinants of students' expectancy-value beliefs and thus built a comprehensive expectancy-value model of students' achievement-related choices (Eccles, 2005b; Eccles et al., 1983; Wigfield & Eccles, 1992). Lastly, in contrast to Atkinson's model, Eccles and colleagues assumed that students' expectancy of success and subjective task values are positively related to each other in authentic achievement contexts; that is, individuals value the tasks and activities at which they expect to do well and vice versa (Eccles & Wigfield, 1995; Wigfield & Eccles, 1992).

The most recent formulation of Eccles and colleagues' expectancy-value theory is shown in Figure 1 (SEVT; Eccles & Wigfield, 2020). As mentioned before, students' expectancy of success and their subjective task values, which are shown at the right-hand side of the model, are key components of SEVT. These motivational beliefs are posited to be the most proximal psychological predictors of students' achievement-related choices and performance. In turn, students' expectancies and task values are influenced by various self-beliefs (e.g., self-concepts of ability, identity-related beliefs), goals, and affective memories of previous achievement situations. These beliefs, goals, and affective memories are themselves influenced by a broad range of social and cultural factors (e.g., gender roles and stereotypes, socializers' beliefs), personal characteristics (e.g., gender, individual aptitudes and talents), and students' previous achievement-related experiences. A key assumption of the model is that students' goals, self-schemata, and motivational beliefs are influenced by students' perceptions of their social-cultural environment, including important socializer's beliefs and attitudes (e.g., teachers, parents, peers), and their interpretation of past achievement-related experiences. Finally, the model is hypothesized to be iterative over time: students' current achievement-related choices and performances become past achievement-related experiences and thus affect their expectancy-value beliefs in a subsequent achievement-related situation.

Furthermore, expectancy-value theory was recently renamed *situated* expectancy-value theory (SEVT) by Eccles and Wigfield (2020) to emphasize the importance of situational factors affecting students' expectancies and task values and their educational and occupational choices. According to Eccles and Wigfield, students' expectancies and subjective task values are shaped not only by developmental processes but also by the particular situation and educational context in which they find themselves. For instance, situation- and context-specific factors such as situation-specific demands and available resources are assumed to influence students' expectancy-value beliefs for a given achievement-related choice as well as the different choices and behaviors a student considers in that situation. The authors point out that these situational and contextual influences were always part of the model, as has been highlighted in prior work (e.g., Eccles, 2005b; Wigfield & Cambria, 2010a). Thus, in their most recent version of SEVT, the authors highlight the importance of studying not only developmental processes over many years but also more short-term and situational processes to better understand students' decision-making regarding their educational and career paths. These processes will be covered in more detail in the sections that follow.

Figure 1

Eccles and Colleagues' Situated Expectancy-Value Theory (SEVT)



Note. From "*From Expectancy-Value Theory to Situated Expectancy-Value Theory: A Developmental, Social Cognitive, and Sociocultural Perspective on Motivation*" by J. S. Eccles and A. Wigfield, 2020, *Contemporary Educational Psychology, 61*, Article 101859 (https://doi.org/10.1016/j.cedpsych.2020.101859). Copyright 2020 by Elsevier. Reprinted with permission.

The present dissertation primarily focuses on the right-hand side of the model shown in Figure 1 by examining students' situated expectancy of success and subjective task values and their links to academic success shortly after the transition to postsecondary education in math-intensive STEM fields. Additionally, determinants of students' expectancy-value beliefs from the most left column are of importance for the present dissertation, namely, personal and family characteristics and prior achievement-related experiences that can lead to interindividual differences in students' motivational trajectories after the transition to STEM fields. Specifically, the empirical studies of this dissertation examine how students' expectancies and task values change after the transition to postsecondary education, how these beliefs are related to each other (both within a given situation and across time), and whether potential declines in students' expectancy-value beliefs correspond to academic difficulties shortly after the transition to postsecondary education in math-intensive STEM fields. Thus, the next sections will focus on the conceptualization and assessment of students' expectancies and task values, how these motivational beliefs are related to each other, and how students' expectancies and task values change over time. The review of SEVT will close with an overview of important research findings on students' personal characteristics as predictors of their expectancy-value beliefs and academic success in STEM fields and on links between students' expectancies and subjective task values and academic success in STEM fields.

1.1.1 Conceptualization and Assessment of Students' Expectancies and Subjective Task Values

As mentioned above, according to SEVT, students' expectancy of success and subjective task values are the two key motivational constructs that shape their educational and career choices (Eccles et al., 1983). Whereas expectancies of success refer to the question "Can I do this?", subjective task values deal with the question of "Do I want to do this?". An individual's expectancy of success is defined as their belief about how well they will do on an upcoming task (e.g., an upcoming exam or course assignment; Eccles et al., 1983; Eccles & Wigfield, 2020). Expectancy of success is conceptually related to other constructs referencing individuals' beliefs about their ability, which play a prominent role in theories of achievement motivation (e.g., self-efficacy, Bandura, 1997; academic self-concept, Marsh, 1990; for an overview, see Wigfield & Cambria, 2010b; Wigfield et al., 2015). In their SEVT, Eccles and Wigfield (2020) distinguished students' expectancy of success from their self-concept of ability in a given domain. In contrast to task- and time-specific expectancies of success, students' domain-specific ability self-concept reflects more global and relatively stable beliefs about their ability in a particular domain (e.g., the math domain). Along with students' perceptions of the difficulty of a given task, their self-concepts of ability are posited to be key determinants of these task- and time-specific expectancies of success (Eccles & Wigfield, 2020; Wigfield & Eccles, 1992).

However, due to the conceptual overlap of expectancy beliefs and ability self-concepts, these beliefs are typically highly correlated and cannot always be empirically separated (Eccles & Wigfield, 1995, 2020). Thus, despite the theoretical distinction between these two constructs, researchers have often combined items measuring students' expectancies and self-concepts of ability or have labeled them interchangeably (Eccles & Wigfield, 2020; see also Marsh et al., 2019). The level of specificity of the items assessing students' expectancy beliefs or self-concept of ability might play a role in the ability to distinguish these two constructs (e.g., focusing on a specific task as a math problem or the math domain in general). I will return to the importance of the level of specificity of items assessing students' expectancy-value beliefs below. In the following sections I will, however, also review work on the developmental processes of students' expectancy-value beliefs that has operationalized students' expectancy of success by using other types of competence-related beliefs (e.g., domain-specific ability self-concept, self-efficacy).

Turning to students' valuing of academic tasks, Eccles and colleagues have expanded Atkinson's model by differentiating four major components of subjective task value in their SEVT: intrinsic value, attainment value, utility value, and relative cost (Eccles et al., 1983; Eccles & Wigfield, 2020). Individuals can value a given task or domain because of their interest in or enjoyment of the task or domain (*intrinsic value*, sometimes also referred to as interest or enjoyment value, see Figure 1), because of its perceived importance for their identity (*attainment value)*, because of the usefulness of the task or domain for personal short- or long-term goals (*utility value*), or because there are no or only few perceived drawbacks of engaging with the task or domain (*relative cost*). Furthermore, Eccles and colleagues (Eccles et al., 1983; Wigfield & Eccles, 2020) described different subfacets of perceived costs while engaging in a given task, referring to the amount of effort required to be successful (*effort cost*), the reduced time for other valued tasks (*opportunity cost*), and the anticipated or experienced stress and negative emotions linked to potential failure (*psychological cost*). Compared with the three positively valenced task value facets (intrinsic value, attainment value, and utility value), perceived costs have initially received less attention in empirical work focusing on students' expectancy-value beliefs and their role in predicting students' educational choices and performance (Wigfield & Eccles, 2020). Research on students' cost perceptions has, however, increased over the last 15 years (e.g., A. Battle & Wigfield, 2003; Flake et al., 2015; Gaspard et al., 2015; Perez et al., 2014), but there remain ongoing debates about the specific subdimensions of perceived costs (Wigfield & Eccles, 2020; Wigfield et al., 2017).

Students' expectancy-value beliefs have most often been measured at the domain-specific level in the work of Eccles and colleagues (Wigfield & Cambria, 2010a; Wigfield & Eccles, 2000). Research grounded in SEVT in the school context has mostly focused on assessing students' domain-specific expectancy-value beliefs by referencing different school subjects (e.g., math or English; Eccles et al., 1993; Wigfield & Cambria, 2010a; Wigfield &

Eccles, 2000). Similarly, research in postsecondary education settings has often used measures referencing students' study programs or majors (e.g., Dresel & Grassinger, 2013; Perez et al., 2014) or specific courses that students were enrolled in (e.g., Kosovich et al., 2017; Perez, Dai, et al., 2019). Despite this focus on domain-specific expectancies and subjective task values, Wigfield and Cambria (2010a) state that more situation-specific measures could be developed, referencing, for instance, a specific activity within a given domain. The authors state that more specific measures are needed to better understand situational and contextual factors that shape students' expectancies and task values, which was a key argument in renaming expectancy-value theory *situated* expectancy-value theory (Eccles & Wigfield, 2020). Examining students' situation-specific expectancy-value beliefs is important to understand to what extent students' situational experiences are shaped by and contained within that situation (e.g., beliefs about a math task) or how these situation-specific motivational beliefs influence students' more global motivational beliefs and long-term educational choices (e.g., beliefs about the math domain; Eccles, 2022; Eccles & Wigfield, 2020). In addition, changes in students' expectancy-value beliefs across different situations (e.g., different time points within a class) may be more or less "random" fluctuations or these changes could describe important developmental processes such as students' adaptation to a new educational context (e.g. motivational declines similar to the long-term declines in students' expectancy-value beliefs observed in prior research from the school context).

Indeed, researchers have recently used more time-intensive observation methods (e.g., experience sampling methods) and have begun examining students' situation-specific expectancy-value beliefs referencing specific tasks (e.g., "I like these contents."; Dietrich et al., 2017; see also Nuutila et al., 2018; Salmela-Aro et al., 2021) or a specific lesson (e.g., "Today's class was interesting."; Tanaka & Murayama, 2014; see also Beymer & Robinson, 2022; Parrisius et al., 2022). In line with the assumptions of SEVT that students' expectancy-value beliefs are shaped by the particular achievement situation, several studies have revealed substantial variability of students' expectancies and task values as a function of the specific lesson or topic covered in class (Dietrich et al., 2017; Parrisius et al., 2022) and point to the relevance of these situation-specific experiences in shaping students' domain-specific motivational beliefs (Dietrich et al., 2019).

However, as argued by Eccles (2005a), the chosen level of specificity of the measures should match the substantive research questions and theoretical assumptions regarding the underlying developmental processes (e.g., long-term development vs. short-term fluctuations). This match between measures and hypothesized developmental processes has important implications for interpreting prior findings on the development of students' expectancies of success and subjective task values over comparatively short periods of time (e.g., one semester in college settings), which will be described in the following chapter.

1.1.2 Developmental Processes of Students' Expectancies and Task Values

Research on the developmental processes of students' expectancies and task values has mainly focused on three central questions, namely, (a) when does the positive association of students' expectancy of success and task values emerge (and how does this association develop over time)?, (b) do expectancies of success and task values influence each other over time?, and (c) how do students' expectancy beliefs and task values develop over time? Because the main focus of Eccles and colleagues' work is on elementary and secondary school students, much of the theoretical explanations and prior research on these developmental processes focused on primary and secondary education. I will therefore describe the assumptions underlying these developmental processes and corresponding empirical evidence not only based on research in postsecondary education settings but also in K-12 school settings, and I will discuss the relevance and implications of this research for postsecondary contexts.

Positive Associations of Students' Expectancies and Task Values: Motivational Alignment and Its Development

As stated above, a key assumption of SEVT is that students' expectancies of success and subjective task values are positively related to each other; that is, students tend to value tasks or domains in which they expect to do well and vice versa (Eccles et al., 1983; Eccles & Wigfield, 1995, 2020). Empirical evidence across various domains and contexts, including postsecondary education in STEM fields, corroborates this positive association between students' expectancies and positively valenced task values (i.e., intrinsic, utility, and attainment values) and a negative association between students' expectancies and perceived costs (e.g., Gaspard et al., 2015; Gaspard et al., 2017; Perez et al., 2014; Robinson et al., 2019; Steinmayr & Spinath, 2010; Wigfield et al., 1997). Eccles and colleagues proposed that the emergence of this positive association between students' expectancies and task values is an important developmental process (Eccles, 2009; Wigfield, 1994; Wigfield & Eccles, 1992). Specifically, Eccles and colleagues stressed the importance of a high alignment of students' expectancy-value beliefs at a high level (also termed "synchrony" of motivational beliefs), and argued that well-aligned motivational beliefs at a high level should lead to positive learning experiences, long-term engagement, and well-being in school settings (Eccles, 2009; Wigfield & Eccles, 1992; see also Harter, 1990).

Eccles and her colleagues proposed that the positive relation between students' competence beliefs and task values becomes established during the elementary school years (Wigfield, 1994; Wigfield & Cambria, 2010a; Wigfield & Eccles, 1992). Indeed, research from the school context has shown that students can differentiate between their expectancies of success (or other competence-related beliefs) and task values for a given domain beginning in elementary school (Arens, 2021; Eccles et al., 1993; Wigfield et al., 1997). Yet, the association of these beliefs is relatively low to moderate at the beginning of elementary school and increases over time as students gain more experience in school (Fredricks & Eccles, 2002; Wigfield et al., 1997). Several explanations for this increasing alignment of students' expectancies and task values have been offered in the literature. First, most students tend to be quite optimistic about their academic competencies across different domains at the beginning of elementary school (Helmke, 1999; Stipek & Mac Iver, 1989; Wigfield et al., 2015). As students receive feedback and engage in social comparisons with their peers in school, they are likely to develop a more accurate view of their ability self-concepts across different domains (Eccles & Wigfield, 1995; Wigfield, 1994; Wigfield & Cambria, 2010a). As a consequence of positive learning experiences, students then come to value the tasks and domains on which they have done well in the past, which results in an increasingly positive association of their expectancies and task values (Eccles & Wigfield, 1995; Wigfield, 1994). Second, across high school, processes of identity formation start and prompt students to reflect on their abilities and interests across different domains and to think about potential long-term educational and career options (Eccles, 2009). Thus, students increasingly engage in dimensional comparisons (i.e., they compare their abilities across different domains, for instance, math vs. verbal domain; Wan et al., 2021; Wigfield et al., 2020) and develop an intraindividual "hierarchy" of different domains (Eccles, 2009). Denissen et al. (2007) found that the within-person association of students' self-concept of ability and their interest (e.g., in the math domain) increases across the secondary school years. The authors have interpreted this increased within-person alignment as a specialization process, in which students—through dimensional comparisons across domains (e.g., math vs. verbal domain)—come to value those domains for which they have the highest self-concept of ability and in which they have been most successful in the past.

These theoretical assumptions and explanations regarding the development of the association of students' expectancies and task values are important for the present dissertation because a similar process might occur after the transition to higher education. Prior research has shown that students often start their postsecondary education with unrealistic expectations (Hasenberg & Schmidt-Atzert, 2013; Heublein et al., 2017), particularly in math-intensive domains, where the gap between high-school and university-level mathematics is relatively large (Gueudet, 2008). In addition, due to self-selection, most students who decide to enroll in math-intensive study programs likely had comparatively high math grades in high school compared to their peers. Accordingly, students' expectancy of success may not yet be well calibrated to the demands of their math-intensive study program, triggering a (re)alignment process as students gain experience in this new educational context similar to the process at the beginning of elementary school.

Reciprocal Links Among Students' Math- and Science-Related Expectancies and Task Values Over Time

The above-mentioned explanations of an increasing alignment of students' expectancies of success and subjective task values imply that students' expectancy-value beliefs influence each other over time. Even though Eccles and colleagues do not specify a causal direction between expectancies and task values in their SEVT (Eccles, 2009; Wigfield & Eccles, 1992), the authors argue that individuals likely come to value the tasks and domains for which they have a high expectancy of success or at which they have done well in the past (Eccles, 2009, Eccles et al., 1995; Wigfield, 1994). This reasoning is in line with Bandura's assumptions in his social cognitive theory, which states that individuals' interests emerge from their self-efficacy (i.e., beliefs about their capability to produce a designated outcome, Bandura, 1997). However, the empirical evidence on reciprocal links among students' math-related expectancy of success (or other competence-related beliefs) and their valuing of academic tasks or domains is mixed. A handful of studies have observed reciprocal links among students' competence-related beliefs and task values (Clem et al., 2021; Marsh et al., 2005), several studies have identified significant cross-lagged effects only from students' competence-related beliefs on their task values (Du et al., 2021; Lauermann et al., 2017; Lent et al., 2008; Sewasew et al., 2018; Viljaranta et al., 2014) or vice versa (Grigg et al., 2018; Lee & Seo, 2021; Pinxten et al., 2014), and some studies have found no significant or inconsistent cross-lagged effects over time (Ganley & Lubienski, 2016; Moeller et al., in press; Perez, Dai, et al., 2019; Skaalvik & Valås, 1999; Spinath & Spinath, 2005; Spinath & Steinmayr, 2008; Yoon, 1996). Several factors might contribute to these mixed results.

First, the available studies examined reciprocal links in different settings from elementary school to postsecondary education and used vastly different time lags between the assessments, ranging from half an hour to three years. Accordingly, the available studies may capture different developmental processes (e.g., short-term fluctuations vs. long-term changes in students' expectancy-value beliefs; Eccles, 2005a). Depending on the context, time lags may have been either too short or too long for reciprocal links between students' expectancies and task values to emerge (Dormann & Griffin, 2015). Time lags may be too short if no (within-person) changes in students' expectancy-value beliefs occurred during the repeated assessments. On the other hand, time lags over many years may not show significant reciprocal links because context-specific factors might shape students' expectancy-value beliefs in between the measurement points (e.g., educational transitions, new teachers/instructors, new class compositions).

Relatedly, second, the available evidence relies on various types of assessments for studying the developmental processes of students' expectancies and subjective task values. As mentioned before, measures of students' motivational beliefs can range from situation-specific items, referencing a given task or situation (e.g., Moeller et al., 2022; Nuutila et al., 2018), to course- or domain-specific items, referring to a given class or domain (e.g., Eccles et al., 1995; Perez et al., 2019; Spinath & Steinmayr, 2008). Analyses of developmental processes and reciprocal links require measures at the appropriate level of specificity as well as appropriate time lags between measurement points (Eccles, 2005; Dormann & Griffin, 2015). For instance, Spinath and Steinmayr (2008) examined reciprocal links among elementary students' competence beliefs and interest in math at four time points across one school year (i.e., with a time lag of three months). The authors used domain-specific measures to assess students' competence beliefs and interest in math (e.g., "How good are you at math?"). These domain-specific measures may have been to stable to reveal changes across such a short time period.

Third, several studies included additional variables in their cross-lagged panel model, such as students' academic achievement, which may mask reciprocal links from students' math-related expectancies or competence-related beliefs on later task values. Since students' competence-related beliefs and their achievement are typically highly correlated (e.g., Marsh et al., 2022), including achievement as a (time-varying) covariate in the model might explain parts of the variance in students' task values that would otherwise be explained by students' expectancies. Indeed, the three studies that have found evidence of significant cross-lagged effects from students' valuing of academic tasks or domains on their ability self-concepts or self-efficacies (but not vice versa) have all included students' achievement as a (time-varying) covariate in the cross-lagged panel models (Grigg et al., 2018; Lee & Seo, 2021; Pinxten et al., 2014).

To sum up, empirical studies examining reciprocal links among students' expectancy (or other competence-related beliefs) and their task values have revealed mixed results, which might stem from different contexts, age groups, but also different methodological approaches, including the level of specificity of the measures, time lags between data collections, and analytical approaches. Only a handful of studies have examined reciprocal links among students' expectancies and task values in postsecondary settings, with similarly inconsistent results. Thus, more research is needed to examine potential reciprocal links among students' expectancies and task values in postsecondary education, particularly in the critical time shortly after the transition to postsecondary education. Motivational declines may be most likely to happen shortly after the transition to higher education and may be in part driven by reciprocal links among expectancies and task values (e.g., students' expectancy contributing to declines in their intrinsic value; Eccles & Midgley, 1989; Rosenzweig et al., 2022). In the next section, I will thus describe important findings on motivational declines across students' primary, secondary, and postsecondary education.

Mean-Level Changes in Students' Math- or Science-Related Expectancies and Task Values Over Time

Research focusing on the development of students' expectancies and subjective task values has mostly focused on long-term developmental trajectories of these motivational beliefs. This research typically revealed average declines in students' expectancy-value beliefs over time (Chouinard & Roy, 2008; Jacobs et al., 2002; Robinson et al., 2019; Watt, 2004; for a review, see Scherrer & Preckel, 2019). Most of these studies have been conducted in school contexts and show a consistent pattern of average declines in students' expectancy-value beliefs in different countries (e.g., United States/Canada, Germany, or Australia) and educational contexts (elementary school, e.g., Helmke, 1999; Spinath & Spinath, 2005; Wigfield et al., 1997; secondary school, e.g., Chouinard & Roy, 2008; Frenzel et al., 2010; Jacobs et al., 2002; Watt, 2004). Three key explanations for this average decline can be found in the literature. Two of those explanations were described in the section on the alignment processes of students' expectancy-value beliefs, namely that students' competence beliefs become increasingly realistic over time and that students increasingly specialize in certain domains (via dimensional comparisons), which results in average declines of students' competence-related beliefs and task values. Furthermore, third, several researchers argue that context-specific factors affect the development of students' expectancy-value beliefs, for instance, at educational transitions (Eccles & Midgley, 1989; Watt, 2004; Wigfield, 1994). Specifically, motivational declines after the transition to middle or junior high school have been attributed to a stronger emphasis on academic achievement and social comparisons and less close relationships with teachers compared to elementary school.

The transition to postsecondary education may be accompanied by similar contextual changes, especially in math-intensive study programs. Students need to adapt to the high demands of their study program and to a new learning environment, which is typically less structured compared to school. However, compared to research in elementary and postsecondary school contexts, less is known about the development of students' expectancy-value beliefs in postsecondary settings. In line with evidence from the school context, some studies have found declines in students' motivational beliefs in postsecondary education settings (Dresel & Grassinger, 2013; Kosovich et al., 2017; Perez et al., 2014; Robinson et al., 2019; Sonnert et al., 2015; Sutter et al., 2022; Totonchi et al., 2021; Zuhso et al., 2003), whereas others have found little average changes (Hardin & Longhurst, 2016; Henning & Shulruf, 2011; Moschner, 2000; Rösler et al., 2013; Rosman et al., 2018) or even increases in students' motivations over time (Finney & Schraw, 2003). Similar to the discussion of reciprocal links among expectancies and task values, several factors might contribute to these mixed results. First, most studies used relatively global assessments of students' motivations (e.g., referencing students' domain-specific motivational beliefs), which may have been too stable to reveal motivational declines. Second, in contrast to studies from the school context, most studies in postsecondary education relied on only two measurement time points, thus likely overlooking motivational declines if the time lag was too long and students have already had time to recover. Lastly, the available studies rely on different samples for examining motivational declines (e.g., single courses vs. mixed samples across diverse study programs), which may mask motivational declines due to context-specific effects (see for example, Mac Iver et al., 1991, for subject-specific motivational declines in high school). Thus, more research is needed assessing students' expectancy-value beliefs across multiple time points during a semester and relying on measures that are suitable to detect motivational declines across the critical time period shortly after the transition to postsecondary education (Heublein et al., 2017; Seymour & Hewitt, 1997).

However, prior research has also found variability in students' motivational trajectories, that is, not all students experience declines in their math- or science-related motivational beliefs to the same extent in school or postsecondary settings (e.g., Musu-Gillette et al., 2015; Zusho et al., 2003). Students' personal characteristics and prior learning experiences have been shown to contribute to interindividual differences in motivational trajectories (e.g., Gaspard et al., 2020; Robinson et al., 2019). In addition, personal characteristics and past experiences also play a role in students' adaptation to and success in math-related STEM programs so that the next session will present evidence on the role of students' personal characteristics for their expectancy-value beliefs, academic success, and dropout tendencies in STEM fields.

1.1.3 Students' Personal Characteristics as Predictors of Their Expectancies and Task Values and Academic Success in STEM Fields

As described in the overview of SEVT, a broad range of individual student characteristics and sociocultural factors are assumed to influence students' expectancies of success and subjective task values in SEVT. In the present dissertation, I will focus on key individual and family background characteristics that have been shown to be important predictors not only of students' math- or science-related expectancy-value beliefs but also of students' academic success in STEM fields, namely students' prior achievement, gender, and socioeconomic status (SES; Eccles & Wigfield, 2020). Consistent with the assumptions of SEVT, prior research has found some evidence of interindividual differences in the developmental processes of students' expectancy-value beliefs as a function of students' personal characteristics, but research in postsecondary education settings is still limited, particularly in the first semester after the transition to STEM programs. Underrepresented students in math-intensive STEM fields (e.g., female students, first generation college-going students) and students with comparatively lower prior achievement may experience more maladaptive developmental processes (e.g., greater motivational declines), which may be an early warning sign of disengagement from STEM fields and might thus contribute to higher dropout rates for these groups. A better understanding of these developmental processes for at-risk groups could inform the design of interventions to support these groups, for instance with respect to the timing of interventions or which motivational construct to target.

Students' Prior Achievement as a Predictor of Their Expectancies and Task Values and Academic Success in STEM Fields

Students' prior performance is one of the strongest predictors of their academic achievement and retention in higher education (Richardson et al., 2012; Robbins et al., 2004; Trapmann et al., 2007). Of particular importance in higher education settings is students' high school grade point average (GPA), which is often used as the most important selection criterion for admission into study programs in Germany. Meta-analyses have underscored the importance of students' high school GPA as a key predictor of study success in higher education (Richardson et al., 2012; Robbins et al., 2004; Trapmann et al., 2007). It is often argued that the strong predictive validity of students' high school GPA stems from the fact that a high GPA does not only reflect high academic abilities but also students' motivation and persistence over time. Furthermore, as predicted in SEVT, students' prior academic achievement is an important determinant of students' expectancies of success and subjective task values. Numerous studies across a variety of contexts have shown that students' prior academic performance is one of the strongest predictors of their expectancy-value beliefs (e.g., Guo, Marsh, Morin, et al., 2015; Perez et al., 2014; Robinson et al., 2019; Weidinger et al., 2020) and that students' academic achievement and expectancy-value beliefs predict each other over time (Marsh et al., 2005; Weidinger et al., 2020). Prior research further suggests that students' academic achievement can be a protective factor against motivational declines, although the evidence in higher education contexts is still limited (Perez et al., 2014; Robinson et al., 2019).

Students' Gender as a Predictor of Their Expectancies and Task Values and Academic Success in STEM Fields

In addition, even after controlling for students' prior academic achievement, students' gender remains an important predictor of their decision to enroll and persist in math-intensive study programs. Female students are still less likely than male students to enroll in math-intensive study programs in Germany (26% of all new entrants in STEM majors are women in Germany, OECD-average: 30%; OECD, 2019). Furthermore, even though female students are on average across all domains less likely to drop out of their study programs and to leave the higher education system without earning a degree (Heublein et al., 2017; OECD, 2021), several studies reveal a higher risk of dropping out for female students in math-intensive STEM fields, in which they are typically underrepresented (Brandstätter et al., 2006; Griffith, 2010; Meyer & Strauß, 2019; Shaw & Barbuti, 2010). These results remain consistent even after controlling for students' academic achievement (Griffith, 2010; Meyer & Strauß, 2019).

As mentioned above, a key aim of Eccles and colleagues' work was to explain such gender differences in students' educational choices and behaviors in math-intensive domains. According to SEVT, gender differences in students' expectancies of success and subjective task values are key reasons for gender differences in students' achievement-related choices and behaviors (Eccles, 2009, 2011; Eccles et al., 1983; Eccles & Wigfield, 2020). As shown in Figure 1, female and male students' expectancy-value beliefs are posited to be shaped by a variety of social and cultural factors, including gendered social norms, values, and stereotypes. These gender norms, values, and stereotypes are assumed to influence students' motivational beliefs via feedback from important socializers (e.g., parents or teachers) regarding what activities and occupations are appropriate for them (Eccles, 2009, 2011). To the extent that female students identify with these gender roles and their gender identity, these gender norms and stereotypes can lead to differences in their expectancies and subjective task values compared with their male peers (Eccles, 1984, 2009, 2011). For instance, female students are often seen as less talented in math compared with male students. As a consequence, female students may receive the message from parents or teachers that trying to be successful or aspiring to a career in a math-intensive domain is not worth the effort given their comparatively lower natural ability, thus undermining female students' confidence in their math abilities and the perceived importance of being successful in math.

Numerous studies have shown that gender differences in students' math- or science-related expectancy-value beliefs emerge quite early and persist or even intensify across secondary school and lead to significant gender differences in students' choices of math- or science courses in high school and major selection in STEM fields in postsecondary education (e.g., Arens, 2021; Gaspard et al., 2017; Gaspard et al., 2019; Guo et al., 2016; Simpkins et al., 2006; Wang et al., 2013; Wigfield et al., 1997). The existing literature grounded in SEVT has thus examined potential gender differences in students' expectancy-value beliefs in several ways, including mean-level differences in their expectancies and task values, gender differences in the associations of students' expectancy-value beliefs with educational and career outcomes, and gender differences in the developmental trajectories of students' expectancies and task values. More recently, some studies have also examined gender differences in students' expectancy-value profiles.

First, across secondary and postsecondary settings in Western industrialized countries, female students often report lower math- or science-related expectancies of success (or self-concepts of ability) compared to their male peers (e.g., Gaspard et al., 2015; Guo, Parker, et al., 2015; Watt, 2004; Wigfield et al., 1997). Gender differences in students' math- or science-related subjective task values show a more mixed pattern. Some studies found significant gender differences in students' task values in favor of male students that parallel gender differences in students' competence-related beliefs (e.g., Arens, 2021; Nagy et al., 2006; Steinmayr & Spinath, 2010, in physics), whereas other studies found no or only small gender differences in students' valuing of math or science (e.g., Jacobs et al., 2002; Lauermann et al., 2017; Robinson et al., 2019; Steinmayr & Spinath, 2010, in math). Studies suggest that such motivational differences can be context-specific, construct-specific, and measure-specific. For instance, although the evidence is still limited, gender differences in students' valuing of STEM fields in postsecondary contexts may be somewhat smaller compared to secondary education because students typically self-select into math-intensive STEM fields (Robinson et al., 2019). Furthermore, gender differences may depend on the specific operationalization of the task value component due to gendered social norms (e.g., intrinsic vs. utility value; utility for school vs. utility for future career; Gaspard et al., 2015; Watt, 2004). Lastly, gender differences may depend on the level of specificity with which the items are measured. For instance, Frieze et al. (1978) argued that gender differences in general (e.g., domain-specific) expectancies of success may be larger compared to task- or situation-specific expectancies (see also Eccles et al., 1983), because generalized items also capture more general beliefs and attitudes (e.g., stereotypes that female students are less talented in math than their male peers), whereas individuals should rely more on past experience when answering items that reference a specific task or situation.

Second, researchers have begun examining gender differences in the relations among students' math- or science-related expectancy-value beliefs and important educational outcomes, although these motivational processes are assumed to be identical for female and male students in Eccles and colleagues' SEVT (Wigfield et al., 2015). Indeed, collectively, these studies suggest that the motivational processes linking students' expectancy-value beliefs to educational and career outcomes are similar for female and male students (Guo, Marsh, Parker, et al., 2015; Guo, Parker, et al., 2015; Lauermann et al., 2017; Wang, 2012; but see Nagy et al., 2006; Watt et al., 2012).

Third, a handful of studies grounded in SEVT have also examined gender differences in students' math- or science-related motivational trajectories over time, but the results are inconsistent, likely due to different contexts (e.g., elementary school, high school, postsecondary education), age groups, and different task value facets included in the studies (Chouinard & Roy, 2008; Frenzel et al., 2010; Jacobs et al., 2002; Robinson et al., 2019).

Finally, prior research examining students' expectancy-value motivational profiles has increased in recent years (e.g., Dietrich & Lazarides, 2019; Hong & Bernacki, 2022; Lazarides et al., 2016; Perez, Wormington, et al., 2019; Robinson et al., 2022; Watt et al., 2019). Again, the results regarding gender differences in profile membership are mixed, likely due to different expectancy-value facets included, differences in age groups, or different STEM fields (e.g., math vs. diverse STEM subjects). If significant gender differences emerged, they tend to favor male students, who were less likely to belong to "mixed" profiles compared to their female peers (i.e., profiles consisting of moderate levels of expectancy-value beliefs compared to high levels of expectancies and task values) and more likely to have "positive" profiles (i.e., high levels of expectancies of success and task values; Lazarides et al., 2016; Perez, Wormington, et al., 2019; Watt et al., 2019).

In sum, these results suggest that there are mainly mean-level differences in students' math- or science-related expectancies and task values favoring male over female students, whereas the developmental processes and associations of expectancies and task values with student outcomes are mostly similar across gender. However, as mentioned above, relatively few studies have examined potential gender differences in the developmental processes of students' math-related expectancy-value beliefs in higher education settings in STEM fields. It is unclear if prior findings from the school context should be transferable to the postsecondary context in math-intensive STEM fields. On the one hand, gender differences may be smaller because students self-select into these study programs in the German context. On the other hand, however, gender stereotypes may persist even in postsecondary contexts, in which female students are still underrepresented and potentially face stereotypes about their abilities and academic potential compared to their male peers (e.g., Murphy et al., 2007).

Students' SES as a Predictor of Their Expectancies and Task Values and Academic Success in STEM Fields

Lastly, students' socioeconomic background is another important sociocultural factor within SEVT that is posited to predict students' educational and career choices, mediated through students' expectancy-value beliefs (Eccles et al., 1983; Guo, Marsh, Parker, et al., 2015). Particularly focusing on higher education in Germany, students whose parents did not obtain a postsecondary degree are less likely to enter postsecondary education and are more likely to drop out of their study program without obtaining a degree compared with students whose parents have a postsecondary degree (Isleib, 2019; Watermann et al., 2014). A number of factors contribute to these disparities, including different pathways into postsecondary education (e.g., college admission obtained at non-academic track schools, lower levels of achievement in secondary education, having completed vocational training), lower academic achievement in postsecondary education, financial insecurity, or competing obligations such as employment (Heublein et al., 2017; Isleib, 2019). However, students from comparatively less advantageous socioeconomic backgrounds tend to report similar levels of expectancy of success and subjective task values in math- or science. For instance, prior research grounded in SEVT across secondary and postsecondary education has found either no or only small mean-level differences in students' math- or science-related expectancy-value beliefs for students with lower compared to higher SES (Guo, Marsh, Parker, et al., 2015; Guo, Parker, et al., 2015; Harackiewicz et al., 2016; Robinson et al., 2019). Yet, little is known about potential interindividual differences as a function of students' SES in the developmental trajectories of their expectancy-value beliefs, which might contribute to higher dropout rates for students with comparatively lower SES. Compared to low-SES students, high-SES students may be more likely to successfully handle the transition to math-intensive study programs because they often have more knowledge of the postsecondary education system and the necessary financial resources to focus on their studies.

To sum up, compared to prior research in primary or secondary education, less is known about interindividual differences in the developmental processes of students' expectancy-value beliefs as a function of their prior achievement, gender, and SES in postsecondary contexts, particularly within the first semester of math-intensive study programs in STEM fields. Thus, the present dissertation aimed to examine group differences in the developmental processes of students' expectancies and task values in their first semester in math-intensive STEM programs more closely by examining potential interindividual differences in the motivational trajectories and motivational alignment processes across the semester and by testing whether potential mean-level differences in students' expectancies and task values are constant over time (i.e., "trait-like").

1.1.4 Students' Expectancies and Task Values as Predictors of Academic Success in STEM Fields

As described before, students' expectancies of success and subjective task values are important predictors of their educational and occupational choices, even after controlling for important student characteristics such as prior achievement and gender (for an overview, see Wigfield & Cambria, 2010a). Numerous studies across a variety of educational contexts and domains have shown that students' expectancy-value beliefs predict their academic achievement, effort investment, enrollment in high school courses or college majors, and career aspirations in STEM fields (e.g., Gaspard et al., 2019; Guo, Parker, et al., 2015; Lauermann et al., 2017; Nagengast et al., 2011; Wang, 2012). Compared to the school context, research in postsecondary education is still limited, so that I will also include work from the school context in the following review of important findings with respect to the predictive effects of students' expectancy-value beliefs on student outcomes.

Although students' expectancies of success and subjective task values are posited to be the most proximal psychological predictors of their achievement-related choices and performance (Eccles et al., 1983; Eccles & Wigfield, 2020), empirical studies on the associations of students' expectancy-value beliefs and student outcomes reveal a more nuanced picture. Studies examining separate models for students' expectancy beliefs (or self-concepts of ability) and task values, typically reveal significant predictive effects for both expectancies and task values on students' academic achievement, choices, and behaviors (Durik et al., 2006; Meyer et al., 2019; Robinson et al., 2019; Trautwein et al., 2012; Wang, 2012; Watt et al., 2006). However, when entered into regression models simultaneously, unique predictive effects of students' expectancies and task values emerge, depending on the type of outcome. Collectively, prior research across different contexts suggests that students' expectancy of success appears to be the strongest motivational predictor of their academic achievement, whereas students' subjective task values are more strongly related to their educational and career choices (e.g., Fadda et al., 2020; Guo et al., 2016; Guo, Parker, et al., 2015; Meece et al., 1990; Perez et al., 2014; Robinson et al., 2019; for an overview, see Eccles & Wigfield, 2020; Wigfield & Eccles, 2000). These findings are in line with Eccles' (2009) assumptions that, while having positive success expectancies towards a particular occupation in a given domain is a necessary precondition of entering that domain, students' valuing of that domain is the central predictor of students' occupational choice.

However, this pattern of results is not always found (e.g., Bong, 2001; Kosovich et al., 2017; Simpkins et al., 2006). For instance, Simpkins et al. (2006) found that students' math- or science-related self-concept of ability was a stronger predictor of the number of math or physics courses taken in high school than their intrinsic or importance value (a composite of utility and attainment value). The authors argued that students in their sample likely knew the importance of advanced math or science courses for college admission, which might have reduced the importance of valuing the coursework in predicting their course choices. These results point to potential context- or situation-specific factors that affect the relative importance of different expectancy and task value facets in predicting student outcomes (Eccles & Wigfield, 2020; Wigfield & Cambria, 2010a). Indeed, Eccles and Wigfield (2020) recently emphasized the role of both developmental and situational factors in shaping the relative importance of different expectancy and task value facets for students' achievement-related choices. Specifically, Eccles and Wigfield argued that the hierarchy of different expectancy and task value facets varies developmentally and across situations (Eccles & Wigfield, 2020; Wigfield, 1994; Wigfield & Eccles, 1992). For instance, according to Eccles (2009), the importance of students' attainment value should increase across adolescence, as students begin to think about such important choices as potential major or career options that are linked to their identity.

Yet, no study to date has systematically examined changes in the relative importance of different expectancy and task value facets for their educational and career choices across time. The study by Perez et al. (2014) provides some evidence of changes in the relative importance of different task value facets. The authors found that different cost facets differentially predicted college students' intentions to leave their STEM majors: perceived effort cost emerged as the strongest predictor of students' intentions to leave across two time points during the semester, whereas opportunity cost only predicted dropout intentions at the end of the semester, and psychological cost was unrelated to students' intentions to leave STEM fields (after controlling for students' competence beliefs and values).

Compared to primary and secondary education settings, less research has focused on the importance of different expectancy-value beliefs for students' academic success and retention in STEM fields. Thus, relatively little is known about which motivational facets are most strongly related to key student outcomes, including students' academic achievement, well-being, and retention in STEM fields. Collectively, prior research in postsecondary education suggests that students' expectancies of success (or other competence-related beliefs) and valuing of their study programs significantly predict students' academic achievement (Perez et al., 2014; Perez, Dai, et al., 2019; Robinson et al., 2019; Sutter et al., 2022), study satisfaction (Fleischer et al., 2019; Kryshko et al., 2022), and retention (intentions) in STEM fields (Fleischer et al., 2019; Lee et al., 2022; Perez et al., 2014; Robinson et al., 2019; Schnettler et al., 2020). Whereas results from higher education settings are generally consistent with work from the school context in that students' expected success is the strongest motivational predictor of their academic achievement (Perez et al., 2014; Perez, Dai, et al., 2019; Robinson et al., 2019), results are more mixed with respect to students' study satisfaction and retention or dropout intentions in STEM fields. Yet, the existing studies differ substantially in the specific motivational variables and student outcomes included in the analyses as well as in the analytical approaches, which makes it difficult to generalize and compare findings across studies. For instance, some studies included only selected facets of the expectancy-value framework (e.g., Fleischer et al., 2019; Sutter et al., 2022), used composite scores of task values to examine their predictive effects on student outcomes (e.g., Kryshko et al., 2022; Perez et al., 2014), or tested separate models for different expectancy-value constructs vs. models including multiple motivational beliefs (Robinson et al., 2019). For instance, in the study by Fleischer et al. (2019), students' expectancy of success significantly predicted students' end-of-term dropout intentions across different STEM majors (for similar results in a psychology course, see Kosovich et al., 2017), whereas students' expectancy or competence beliefs were unrelated to (changes in) dropout intentions in STEM majors in Perez et al. (2014) and Schnettler et al. (2020). A better understanding of how different components of the expectancy-value framework are linked to students' academic achievement, well-being, and retention in STEM fields is necessary to design motivational interventions aimed at improving students' study success and retention in STEM fields.

Furthermore, with respect to the role of motivational declines for students' academic success, only a handful of studies in the school or postsecondary education context have specifically examined the links between motivational declines in students' expectancy-value beliefs and students' academic achievement, major choice, and retention (Gaspard et al., 2020; Kosovich et al., 2017; Musu-Gillette et al., 2015; Robinson et al., 2019). In general, these studies suggest that more maladaptive motivational trajectories are linked to lower academic achievement and decisions against a particular career path (e.g., in the math domain). For instance, Robinson et al. (2019) found that declines in students' expectancies and task values across the first two years in engineering majors were linked to lower levels of achievement and lower retention rates at the end of students' second year in college. As mentioned above, however, no study to date has examined students' motivational trajectories and their links to academic success across one semester in introductory math courses that often serve as a gatekeeper to further engagement in STEM fields (for an exception in a psychology course, see Kosovich et al., 2017). Thus, in sum, little is known about the extent to which students' expectancy-value beliefs decline in gateway math courses and which facets of the expectancy-value framework show the greatest change over time. Additionally, it remains unclear whether potential motivational declines are part of students' adaptation to the new educational context and may thus be only temporary, or whether declines in their expectancies, values, and costs are precursors to later academic struggles and (differentially) predict low academic achievement and dropout tendencies in STEM fields.

1.2 Research Questions of the Present Dissertation

The present dissertation investigated short-term developmental processes of students' expectancies of success and subjective task values shortly after the transition to higher education in math-intensive study programs. As posited in SEVT, prior research across different postsecondary contexts has identified students' expectancies of success and subjective task values as key predictors of their decisions to persist in or drop out of math-intensive study programs (Fleischer et al., 2019; Perez et al., 2014; Robinson et al., 2019). Longitudinal studies over several years have identified declines in these motivational beliefs as a precursor to low levels of achievement and drop out of educational and occupational STEM fields (Gaspard et al., 2020; Robinson et al., 2019), but only a handful of studies have examined the developmental processes of students' expectancies and task values over shorter periods of time, shortly after the transition to postsecondary education (e.g., one semester; Kosovich et al., 2017). This is an important gap in the literature because the first year of higher education is a particularly critical time of students' postsecondary education (Heublein et al., 2017; Seymour & Hewitt, 1997). Highly demanding mandatory math courses in the first year of higher education often serve as gatekeepers to further engagement and academic success in STEM fields (Chen, 2013; Gasiewski et al., 2012; Seymour & Hewitt, 1997). These courses are often particularly challenging for traditionally underrepresented students in math-intensive STEM fields (e.g., female students, first generation college-going students; Ellis et al., 2016; Griffith, 2010; Sanabria & Penner, 2017). Thus, the following three main research questions guided the present dissertation:

(1) How do students' expectancies of success and subjective task values develop in the first semester of math-intensive study programs? More specifically:
   a. How do students' expectancies of success and task values change over time?
   b. How closely aligned are students' expectancies of success and subjective task values with each other and does the alignment change over time?
   c. Do students' expectancies of success and subjective task values predict each other over time?

(2) Do the developmental processes of students' expectancies and task values differ as a function of students' personal characteristics (e.g., prior achievement, gender, socioeconomic status)?

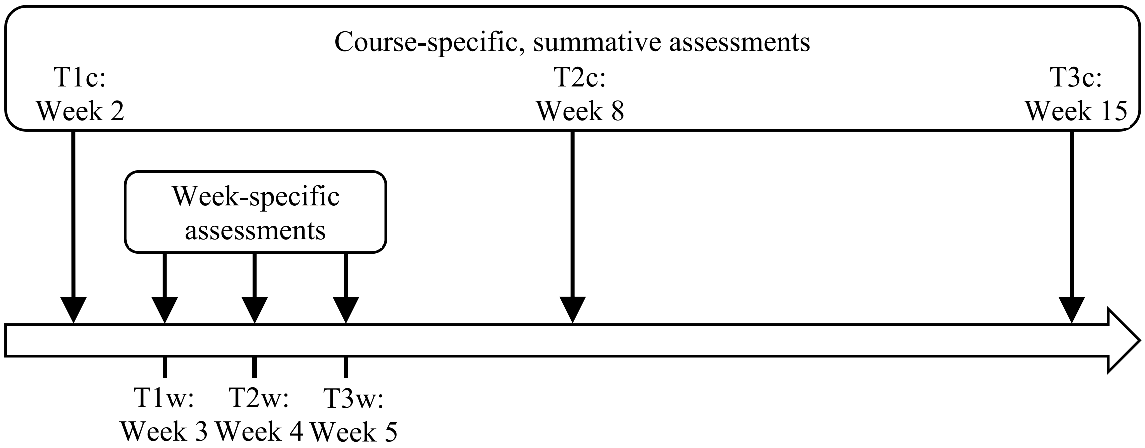
(3) Are potential motivational changes during the semester linked to students' academic success at the end of their first semester in math-intensive study programs?

These central research questions were addressed in two empirical studies (Studies 1a and 1b and Study 2) as well as in further analyses (Study 3) presented in the discussion. Regarding the first main research question, all three empirical studies focused on the developmental processes of students' expectancies of success and subjective task values, examining when and how much these motivational beliefs change over one semester in demanding math courses (Studies 1a and 1b, Study 2), how closely aligned students' expectancies and task values are with each other (Study 2 and Study 3), and whether students' expectancies and task values predict each other over time (Study 3). To address the second research question, the three studies of the present dissertation examined interindividual differences in mean-levels of students' expectancies and task values (Studies 1a and 1b, Study 3), in the change over time (Studies 1a and 1b, Study 2), and the alignment of these motivational beliefs (Study 3) as a function of students' personal characteristics (i.e., prior achievement, gender, SES). With a particular focus on gender, Study 2 further examined gender differences in the alignment of students' expectancies, task values, and self-rated performance. Lastly, for research question three, Studies 1a and 1b examined whether motivational changes during the semester predict students' academic achievement, well-being, and course dropout at the end of their first semester in math-intensive STEM programs.

Drawing on Eccles and colleagues' situated expectancy-value theory (Eccles et al., 1983; Eccles & Wigfield, 2020), the present dissertation used data from the BONNS project, which followed six cohorts of students enrolled in physics, math, or math teacher education programs in required math courses across their first semester at a German university ($N = 1{,}004$). The study design is shown in Figure 2. In all cohorts, three main data collections took place at the beginning, midpoint, and end of the semester focusing on students' expectancies and task values towards their math course. Additionally, in five of the six cohorts (two cohorts in the physics and math teacher education program, respectively, and one cohort in the math study program), three additional data collections in Weeks 3 to 5 of the semester asked students to reflect on their experiences with their mandatory math worksheets in each week. This study design, relying on intensive data collections across four weeks at the beginning of the semester, allowed for fine-grained analyses of the developmental processes of students' expectancies and subjective task values shortly after the transition to postsecondary education and across the first semester in gateway math courses in STEM fields.

Figure 2

Study Design of the BONNS-Study



Note. T = time point, T1c–T3c = course-specific summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet.

Study 1a and Study 1b (*Students' Motivational Trajectories and Academic Success in Math-Intensive Study Programs: Why Short-Term Motivational Assessments Matter*) examined short-term changes in students' expectancies and task values across the first semester (Study 1a) as well as across the first weeks of the semester (Study 1b) in math-intensive STEM programs. The intensive data collections at six time points during the semester allowed for fine-grained analyses of potential motivational declines in gateway math courses that may have been overlooked in prior research, which relied mostly on pre-post designs or three assessments across one semester. Furthermore, Study 1 examined whether students' motivational trajectories differ as a function of their personal characteristics (i.e., gender, SES, prior achievement) and addressed the question of whether potential motivational declines are a warning sign of academic difficulties (i.e., predictors of low academic achievement, dissatisfaction with one's study program, and course dropout at the end of the semester).

Study 2 (*Geschlechtsunterschiede in der Variabilität situationsspezifischer Erwartungs- und Wertüberzeugungen und selbsteingeschätzter Leistung in mathematik-intensiven Studienfächern: Eine Mehrebenenanalyse von motivationalen Schwankungen*) examined potential gender differences in the variability of students' expectancies, task values, and self-assessed performance both across the semester and within a time point. Whereas prior research has focused mostly on mean-level differences in female and male students' math-related expectancies and task values as well as gender differences in the associations between these motivational beliefs and corresponding educational outcomes, this study explored potential gender differences in the alignment of students' expectancies of success, subjective task values, and their self-assessed performance within a given time point (beginning, midpoint, and end-of-term) and over time.

Finally, further analyses in Study 3 (*Searching for Short-Term Motivational Spillover Effects: A Random Intercept Cross-Lagged Panel Analysis of Students' Expectancies and Task Values in Math-Intensive Study Programs*) focused on potential within-person reciprocal links (i.e., motivational spillover effects) over time and the within-person alignment of students' expectancies and subjective task values within a given time point (i.e., their association at each time point). Specifically, Study 3 examined developmental changes in the degree of alignment of students' expectancies of success and subjective task values across the semester, whether these motivational beliefs are reciprocally related to each other over time, and whether there are interindividual differences in the degree of alignment as a function of students' gender, prior achievement, and SES. In contrast to prior research, Study 3 used a random intercept cross-lagged panel approach to examine these developmental processes (i.e., motivational alignment and spillover effects) on the within-person level, after controlling for stable between-person motivational differences.

References I

Anger, C., Kohlisch, E., Koppel, O., & Plünnecke, A. (2022). *MINT-Frühjahrsreport 2022: Demografie, Dekarbonisierung und Digitalisierung erhöhen MINT-Bedarf - Zuwanderung stärkt MINT-Fachkräfteangebot und Innovationskraft*. https://www.iwkoeln.de/fileadmin/user_upload/Studien/Gutachten/PDF/2022/MINT-Fr%C3%BChjahrsreport_2022.pdf

Arens, A. K. (2021). Wertfacetten im Grundschulalter in drei Fächern: Differenzierung, Entwicklung, Geschlechtseffekte und Zusammenhänge zu Noten. *Zeitschrift für Pädagogische Psychologie, 35*(1), 32–52. https://doi.org/10.1024/1010-0652/a000257

Arens, A. K., Schmidt, I., & Preckel, F. (2019). Longitudinal relations among self-concept, intrinsic value, and attainment value across secondary school years in three academic domains. *Journal of Educational Psychology, 111*(4), 663–684. https://doi.org/10.1037/edu0000313

Atkinson, J. W. (1957). Motivational determinants of risk-taking behavior. *Psychological Review, 64*(6), 359–372. https://doi.org/10.1037/h0043445

Atkinson, J. W. (1964). *An introduction to motivation*. Van Nostrand.

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. *Psychological Review, 84*(2), 191–215. https://doi.org/10.1037/0033-295X.84.2.191

Bandura, A. (1997). *Self-efficacy: The exercise of control*. Freeman.

Battle, A., & Wigfield, A. (2003). College women's value orientations toward family, career, and graduate school. *Journal of Vocational Behavior, 62*(1), 56–75. https://doi.org/10.1016/S0001-8791(02)00037-4

Battle, E. S. (1965). Motivational determinants of academic task persistence. *Journal of Personality and Social Psychology, 2*(2), 209–218. https://doi.org/10.1037/h0022442

Battle, E. S. (1966). Motivational determinants of academic competence. *Journal of Personality and Social Psychology, 4*(6), 634–642. https://doi.org/10.1037/h0024028

Beymer, P. N., & Robinson, K. A. (2022). Motivating by measuring motivation? Examining reactivity in a diary study on student motivation. *Contemporary Educational Psychology, 70*, Article 102072. https://doi.org/https://doi.org/10.1016/j.cedpsych.2022.102072

Bong, M. (2001). Role of self-efficacy and task-value in predicting college students' course performance and future enrollment intentions. *Contemporary Educational Psychology, 26*(4), 553–570. https://doi.org/10.1006/ceps.2000.1048

Brandstätter, H., Grillich, L., & Farthofer, A. (2006). Prognose des Studienabbruchs. *Zeitschrift für Entwicklungspsychologie und Pädagogische Psychologie, 38*(3), 121–131. https://doi.org/10.1026/0049-8637.38.3.121

Chen, X. (2013). *STEM attrition: College students' paths into and out of STEM fields. Statistical Analysis Report (NCES 2014-001)*. https://nces.ed.gov/pubs2014/2014001rev.pdf

Chouinard, R., & Roy, N. (2008). Changes in high-school students' competence beliefs, utility value and achievement goals in mathematics. *British Journal of Educational Psychology, 78*(1), 31–50. https://doi.org/10.1348/000709907X197993

Clem, A.-L., Hirvonen, R., Aunola, K., & Kiuru, N. (2021). Reciprocal relations between adolescents' self-concepts of ability and achievement emotions in mathematics and literacy. *Contemporary Educational Psychology, 65*, Article 101964. https://doi.org/10.1016/j.cedpsych.2021.101964

Credé, M., & Niehorster, S. (2012). Adjustment to college as measured by the student adaptation to college questionnaire: A quantitative review of its structure and relationships with correlates and consequences. *Educational Psychology Review, 24*(1), 133–165. https://doi.org/10.1007/s10648-011-9184-5

Denissen, J. J., Zarrett, N. R., & Eccles, J. S. (2007). I like to do it, I'm able, and I know I am: Longitudinal couplings between domain-specific achievement, self-concept, and interest. *Child Development, 78*(2), 430–447. https://doi.org/10.1111/j.1467-8624.2007.01007.x

Dietrich, J., & Lazarides, R. (2019). Gendered development of motivational belief patterns in mathematics across a school year and career plans in math-related fields. *Frontiers in Psychology, 10*. https://doi.org/10.3389/fpsyg.2019.01472

Dietrich, J., Moeller, J., Guo, J., Viljaranta, J., & Kracke, B. (2019). In-the-moment profiles of expectancies, task values, and costs. *Frontiers in Psychology, 10*. https://doi.org/10.3389/fpsyg.2019.01662

Dietrich, J., Viljaranta, J., Moeller, J., & Kracke, B. (2017). Situational expectancies and task values: Associations with students' effort. *Learning and Instruction, 47*, 53–64. https://doi.org/10.1016/j.learninstruc.2016.10.009

Dormann, C., & Griffin, M. A. (2015). Optimal time lags in panel studies. *Psychological Methods, 20*(4), 489–505. https://doi.org/10.1037/met0000041

Dresel, M., & Grassinger, R. (2013). Changes in achievement motivation among university freshmen. *Journal of Education and Training Studies, 1*(2), 159–173. https://doi.org/10.11114/jets.v1i2.147

Du, C., Qin, K., Wang, Y., & Xin, T. (2021). Mathematics interest, anxiety, self-efficacy and achievement: Examining reciprocal relations. *Learning and Individual Differences, 91*, Article 102060. https://doi.org/10.1016/j.lindif.2021.102060

Durik, A. M., Vida, M., & Eccles, J. S. (2006). Task values and ability beliefs as predictors of high school literacy choices: A developmental analysis. *Journal of Educational Psychology, 98*(2), 382–393. https://doi.org/10.1037/0022-0663.98.2.382

Eccles, J. S. (1984). Sex differences in achievement patterns. *Nebraska Symposium on Motivation, 32*, 97–132.

Eccles, J. S. (2005a). Commentary: Studying the development of learning and task motivation. *Learning and Instruction, 15*(2), 161–171. https://doi.org/10.1016/j.learninstruc.2005.04.012

Eccles, J. S. (2005b). Subjective task value and the Eccles et al. model of achievement-related choices. In A. Elliot & C. S. Dweck (Eds.), *Handbook of competence and motivation* (pp. 105–121). The Guilford Press.

Eccles, J. S. (2009). Who am I and what am I going to do with my life? Personal and collective identities as motivators of action. *Educational Psychologist, 44*(2), 78–89. https://doi.org/10.1080/00461520902832368

Eccles, J. S. (2011). Gendered educational and occupational choices: Applying the Eccles et al. model of achievement-related choices. *International Journal of Behavioral Development, 35*(3), 195–201. https://doi.org/10.1177/0165025411398185

Eccles, J. S. (2022). Commentary on within-person designs and motivational science. *Learning and Instruction*, Article 101662. https://doi.org/10.1016/j.learninstruc.2022.101662

Eccles, J. S., Adler, T., Futterman, R., Goff, S., Kaczala, C., Meece, J., & Midgley, C. (1983). Expectancies, values, and academic behaviors. In J. T. Spence (Ed.), *Achievement and achievement motives* (pp. 75–146). Freeman.

Eccles, J. S., & Midgley, C. (1989). Stage-environment fit: Developmentally appropriate classrooms for young adolescents. In C. Ames & R. Ames (Eds.), *Research on motivation in education: Goals and cognitions* (Vol. 3, pp. 139–186). Academic Press.

Eccles, J. S., & Wigfield, A. (1995). In the mind of the actor: The structure of adolescents' achievement task values and expectancy-related beliefs. *Personality and Social Psychology Bulletin, 21*(3), 215–225. https://doi.org/10.1177/0146167295213003

Eccles, J. S., & Wigfield, A. (2020). From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation. *Contemporary Educational Psychology, 61*, Article 101859. https://doi.org/10.1016/j.cedpsych.2020.101859

Eccles, J. S., Wigfield, A., Harold, R. D., & Blumenfeld, P. (1993). Age and gender differences in children's self- and task perceptions during elementary school. *Child Development, 64*(3), 830–847. https://doi.org/10.2307/1131221

Ellis, J., Fosdick, B. K., & Rasmussen, C. (2016). Women 1.5 times more likely to leave STEM pipeline after calculus compared to men: Lack of mathematical confidence a potential culprit. *PloS One, 11*(7). https://doi.org/10.1371/journal.pone.0157447

Fadda, D., Scalas, L. F., Morin, A. J. S., Marsh, H. W., & Gaspard, H. (2020). Value beliefs about math: A bifactor-ESEM representation. *European Journal of Psychological Assessment, 36*(2), 259–268. https://doi.org/10.1027/1015-5759/a000513

Feather, N. T. (1959). Subjective probability and decision under uncertainty. *Psychological Review, 66*(3), 150–164. https://doi.org/10.1037/h0045692

Feather, N. T. (2021). *Expectations and actions: Expectancy-value models in psychology*. Routledge. (Original work published in 1982)

Flake, J. K., Barron, K. E., Hulleman, C., McCoach, B. D., & Welsh, M. E. (2015). Measuring cost: The forgotten component of expectancy-value theory. *Contemporary*

Educational Psychology, 41, 232–244. https://doi.org/10.1016/j.cedpsych.2015.03.002

Fleischer, J., Leutner, D., Brand, M., Fischer, H., Lang, M., Schmiemann, P., & Sumfleth, E. (2019). Vorhersage des Studienabbruchs in naturwissenschaftlich-technischen Studiengängen. *Zeitschrift für Erziehungswissenschaft, 22*(5), 1077–1097. https://doi.org/10.1007/s11618-019-00909-w

Fredricks, J. A., & Eccles, J. S. (2002). Children's competence and value beliefs from childhood through adolescence: Growth trajectories in two male-sex-typed domains. *Developmental Psychology, 38*(4), 519–533. https://doi.org/10.1037/0012-1649.38.4.519

Frenzel, A. C., Goetz, T., Pekrun, R., & Watt, H. M. (2010). Development of mathematics interest in adolescence: Influences of gender, family, and school context. *Journal of Research on Adolescence, 20*(2), 507–537. https://doi.org/10.1111/j.1532-7795.2010.00645.x

Frieze, I. H., Fisher, J., Hanusa, B., McHugh, M. C., & Valle, V. A. (1978). Attributions of the causes of success and failure as internal and external barriers to achievement in women. In J. Sherman & F. Denmark (Eds.), *Psychology of women: Future directions of research.* (pp. 519–552). Psychological Dimensions.

Ganley, C. M., & Lubienski, S. T. (2016). Mathematics confidence, interest, and performance: Examining gender patterns and reciprocal relations. *Learning and Individual Differences, 47*, 182–193. https://doi.org/10.1016/j.lindif.2016.01.002

Gasiewski, J. A., Eagan, M. K., Garcia, G. A., Hurtado, S., & Chang, M. J. (2012). From gatekeeping to engagement: A multicontextual, mixed method study of student academic engagement in introductory STEM courses. *Research in Higher Education, 53*(2), 229–261. https://doi.org/10.1007/s11162-011-9247-y

Gaspard, H., Dicke, A.-L., Flunger, B., Schreier, B., Häfner, I., Trautwein, U., & Nagengast, B. (2015). More value through greater differentiation: Gender differences in value beliefs about math. *Journal of Educational Psychology, 107*(3), 663–677. https://doi.org/10.1037/edu0000003

Gaspard, H., Häfner, I., Parrisius, C., Trautwein, U., & Nagengast, B. (2017). Assessing task values in five subjects during secondary school: Measurement structure and mean level differences across grade level, gender, and academic subject. *Contemporary Educational Psychology, 48*, 67–84. https://doi.org/10.1016/j.cedpsych.2016.09.003

Gaspard, H., Lauermann, F., Rose, N., Wigfield, A., & Eccles, J. S. (2020). Cross-domain trajectories of students' ability self-concepts and intrinsic values in math and language arts. *Child Development, 91*(5), 1800–1818. https://doi.org/10.1111/cdev.13343

Gaspard, H., Wille, E., Wormington, S. V., & Hulleman, C. S. (2019). How are upper secondary school students' expectancy-value profiles associated with achievement and university STEM major? A cross-domain comparison. *Contemporary Educational Psychology, 58*, 149–162. https://doi.org/10.1016/j.cedpsych.2019.02.005

Griffith, A. L. (2010). Persistence of women and minorities in STEM field majors: Is it the school that matters? *Economics of Education Review, 29*(6), 911–922. https://doi.org/10.1016/j.econedurev.2010.06.010

Grigg, S., Perera, H. N., McIlveen, P., & Svetleff, Z. (2018). Relations among math self efficacy, interest, intentions, and achievement: A social cognitive perspective. *Contemporary Educational Psychology, 53*, 73–86. https://doi.org/10.1016/j.cedpsych.2018.01.007

Gueudet, G. (2008). Investigating the secondary–tertiary transition. *Educational Studies in Mathematics, 67*(3), 237–254. https://doi.org/10.1007/s10649-007-9100-6

Guo, J., Marsh, H. W., Morin, A. J. S., Parker, P. D., & Kaur, G. (2015). Directionality of the associations of high school expectancy-value, aspirations, and attainment: A longitudinal study. *American Educational Research Journal, 52*(2), 371–402. https://doi.org/10.3102/0002831214565786

Guo, J., Marsh, H. W., Parker, P. D., Morin, A. J., & Yeung, A. S. (2015). Expectancy-value in mathematics, gender and socioeconomic background as predictors of achievement and aspirations: A multi-cohort study. *Learning and Individual Differences, 37*, 161–168. https://doi.org/10.1016/j.lindif.2015.01.008

Guo, J., Nagengast, B., Marsh, H. W., Kelava, A., Gaspard, H., Brandt, H., Cambria, J., Flunger, B., Dicke, A.-L., Häfner, I., Brisson, B., & Trautwein, U. (2016). Probing the unique contributions of self-concept, task values, and their interactions using multiple value facets and multiple academic outcomes. *AERA Open, 2*(1), 1–20. https://doi.org/10.1177/2332858415626884

Guo, J., Parker, P. D., Marsh, H. W., & Morin, A. J. (2015). Achievement, motivation, and educational choices: A longitudinal study of expectancy and value using a multiplicative perspective. *Developmental Psychology, 51*(8), 1163–1176. https://doi.org/10.1037/a0039440

Harackiewicz, J. M., Canning, E. A., Tibbetts, Y., Priniski, S. J., & Hyde, J. S. (2016). Closing achievement gaps with a utility-value intervention: Disentangling race and social class. *Journal of Personality and Social Psychology, 111*(5), 745–765. https://doi.org/10.1037/pspp0000075

Harter, S. (1990). Causes, correlates, and the functional role of global self-worth: A life-span perspective. In R. J. Sternberg & J. Kolligian (Eds.), *Competence considered* (pp. 67–97). Yale University Press.

Hasenberg, S., & Schmidt-Atzert, L. (2013). Die Rolle von Erwartungen zu Studienbeginn: Wie bedeutsam sind realistische Erwartungen über Studieninhalte und Studienaufbau für die Studienzufriedenheit?. *Zeitschrift für Pädagogische Psychologie, 27*(1-2), 87–93. https://doi.org/10.1024/1010-0652/a000091

Heckhausen, H. (1977). Achievement motivation and its constructs: A cognitive model. *Motivation and Emotion, 1*(4), 283–329. https://doi.org/10.1007/BF00992538

Helmke, A. (1999). From optimism to realism? Development of children's academic self-concept from kindergarten to grade 6. In F. E. Weinert & W. Schneider (Eds.), *Individual Development From 3 to 12: Findings From the Munich Longitudinal Study* (pp. 198–221). Cambridge University Press.

Heublein, U., Ebert, J., Hutzsch, C., Isleib, S., König, R., Richter, J., & Woisch, A. (2017). *Zwischen Studienerwartungen und Studienwirklichkeit: Ursachen des Studienabbruchs, beruflicher Verbleib der Studienabbrecherinnen und Studienabbrecher und Entwicklung der Studienabbruchquote an deutschen Hochschulen*. https://www.dzhw.eu/pdf/pub_fh/fh-201701.pdf

Heublein, U., Richter, J., & Schmelzer, R. (2020). *Die Entwicklung der Studienabbruchquoten in Deutschland*. DZHW Brief, Issue 3. https://www.dzhw.eu/pdf/pub_brief/dzhw_brief_03_2020.pdf

Hong, W., & Bernacki, M. L. (2022). Initial and evolving perceptions of value and cost of engaging in undergraduate science course work and effects on achievement and persistence. *Journal of Educational Psychology, 114*(5), 1005–1027. https://doi.org/10.1037/edu0000717

Isleib, S. (2019). Soziale Herkunft und Studienabbruch im Bachelor- und Masterstudium. In M. Lörz & H. Quast (Eds.), *Bildungs- und Berufsverläufe mit Bachelor und Master* (pp. 307–337). Springer. https://doi.org/10.1007/978-3-658-22394-6_10

Isphording, I., & Qendrai, P. (2019). *Gender differences in student dropout in STEM. IZA Research Report No. 87*. http://ftp.iza.org/report_pdfs/iza_report_87.pdf

Jacobs, J. E., Lanza, S., Osgood, D. W., Eccles, J. S., & Wigfield, A. (2002). Changes in children's self-competence and values: Gender and domain differences across grades one through twelve. *Child Development, 73*(2), 509–527. https://doi.org/10.1111/1467-8624.00421

Kosovich, J. J., Flake, J. K., & Hulleman, C. S. (2017). Short-term motivation trajectories: A parallel process model of expectancy-value. *Contemporary Educational Psychology, 49*, 130–139. https://doi.org/10.1016/j.cedpsych.2017.01.004

Kryshko, O., Fleischer, J., Grunschel, C., & Leutner, D. (2022). Self-efficacy for motivational regulation and satisfaction with academic studies in STEM undergraduates: The mediating role of study motivation. *Learning and Individual Differences, 93*, Article 102096. https://doi.org/10.1016/j.lindif.2021.102096

Lauermann, F., Tsai, Y.-M., & Eccles, J. S. (2017). Math-related career aspirations and choices within Eccles et al.'s expectancy-value theory of achievement-related behaviors. *Developmental Psychology, 53*(8), 1540–1559. https://doi.org/10.1037/dev0000367

Lazarides, R., Rubach, C., & Ittel, A. (2016). Motivational profiles in mathematics: What role do gender, age and parents' valuing of mathematics play? *International Journal of Gender, Science and Technology, 8*(1), 124–143. https://genderandset.open.ac.uk/index.php/genderandset/article/view/406

Lee, Y.-k., Freer, E., Robinson, K. A., Perez, T., Lira, A. K., Briedis, D., Walton, S. P., & Linnenbrink-Garcia, L. (2022). The multiplicative function of expectancy and value in predicting engineering students' choice, persistence, and performance. *Journal of Engineering Education, 111*(3), 531–553. https://doi.org/10.1002/jee.20456

Lee, Y.-k., & Seo, E. (2021). Longitudinal relations between South Korean adolescents' academic self-efficacy and values in mathematics and English. *British Journal of Educational Psychology, 91*(1), 217–236. https://doi.org/10.1111/bjep.12357

Lent, R. W., Sheu, H.-B., Singley, D., Schmidt, J. A., Schmidt, L. C., & Gloster, C. S. (2008). Longitudinal relations of self-efficacy to outcome expectations, interests, and major choice goals in engineering students. *Journal of Vocational Behavior, 73*(2), 328–335. https://doi.org/10.1016/j.jvb.2008.07.005

Mac Iver, D. J., Stipek, D. J., & Daniels, D. H. (1991). Explaining within-semester changes in student effort in junior high school and senior high school courses. *Journal of Educational Psychology, 83*(2), 201–211. https://doi.org/10.1037/0022-0663.83.2.201

Maehr, M. L., & Sjogren, D. D. (1971). Atkinson's theory of achievement motivation: First step toward a theory of academic motivation? *Review of Educational Research, 41*(2), 143–161. https://doi.org/10.3102/00346543041002143

Marsh, H. W. (1990). The structure of academic self-concept: The Marsh/Shavelson model. *Journal of Educational Psychology, 82*(4), 623–636. https://doi.org/10.1037/0022-0663.82.4.623

Marsh, H. W., Pekrun, R., & Lüdtke, O. (2022). Directional ordering of self-concept, school grades, and standardized tests over five years: New tripartite models juxtaposing within- and between-person perspectives. *Educational Psychology Review*. Advance online publication. https://doi.org/10.1007/s10648-022-09662-9

Marsh, H. W., Pekrun, R., Parker, P. D., Murayama, K., Guo, J., Dicke, T., & Arens, A. K. (2019). The murky distinction between self-concept and self-efficacy: Beware of lurking jingle-jangle fallacies. *Journal of Educational Psychology, 111*(2), 331–353. https://doi.org/10.1037/edu0000281

Marsh, H. W., Trautwein, U., Lüdtke, O., Köller, O., & Baumert, J. (2005). Academic self-concept, interest, grades, and standardized test scores: Reciprocal effects models of causal ordering. *Child Development, 76*(2), 397–416. https://doi.org/10.1111/j.1467-8624.2005.00853.x

Meece, J. L., Wigfield, A., & Eccles, J. S. (1990). Predictors of math anxiety and its influence on young adolescents' course enrollment intentions and performance in mathematics. *Journal of Educational Psychology, 82*(1), 60–70. https://doi.org/10.1037/0022-0663.82.1.60

Meyer, J., Fleckenstein, J., & Köller, O. (2019). Expectancy value interactions and academic achievement: Differential relationships with achievement measures. *Contemporary Educational Psychology, 58*, 58–74. https://doi.org/10.1016/j.cedpsych.2019.01.006

Meyer, J., & Strauß, S. (2019). The influence of gender composition in a field of study on students' drop-out of higher education. *European Journal of Education, 54*(3), 443–456. https://doi.org/10.1111/ejed.12357

Moeller, J., Viljaranta, J., Tolvanen, A., Kracke, B., & Dietrich, J. (2022). Introducing the DYNAMICS framework of moment-to-moment development in achievement motivation. *Learning and Instruction*, Article 101653. https://doi.org/10.1016/j.learninstruc.2022.101653

Murphy, M. C., Steele, C. M., & Gross, J. J. (2007). Signaling threat: How situational cues affect women in math, science, and engineering settings. *Psychological Science, 18*(10), 879–885. https://doi.org/10.1111/j.1467-9280.2007.01995.x

Musu-Gillette, L. E., Wigfield, A., Harring, J. R., & Eccles, J. S. (2015). Trajectories of change in students' self-concepts of ability and values in math and college major choice. *Educational Research and Evaluation, 21*(4), 343–370. https://doi.org/10.1080/13803611.2015.1057161

Nagengast, B., Marsh, H. W., Scalas, L. F., Xu, M. K., Hau, K.-T., & Trautwein, U. (2011). Who took the "×" out of expectancy-value theory? A psychological mystery, a substantive-methodological synergy, and a cross-national generalization. *Psychological Science, 22*(8), 1058–1066. https://doi.org/10.1177/0956797611415540

Nagy, G., Trautwein, U., Baumert, J., Köller, O., & Garrett, J. (2006). Gender and course selection in upper secondary education: Effects of academic self-concept and intrinsic value. *Educational Research and Evaluation, 12*(4), 323–345. https://doi.org/10.1080/13803610600765687

Nuutila, K., Tuominen, H., Tapola, A., Vainikainen, M.-P., & Niemivirta, M. (2018). Consistency, longitudinal stability, and predictions of elementary school students' task interest, success expectancy, and performance in mathematics. *Learning and Instruction, 56*, 73–83. https://doi.org/10.1016/j.learninstruc.2018.04.003

OECD (2020). *OECD Economic Surveys: Germany 2020*. OECD Publishing. https://doi.org/10.1787/91973c69-en

OECD (2021). *Education at a Glance 2021*. OECD Publishing. https://doi.org/10.1787/b35a14e5-en

OECD (2019). *Education at a Glance 2019*. OECD Publishing. https://doi.org/10.1787/f8d7880d-en

Parker, P. D., Schoon, I., Tsai, Y.-M., Nagy, G., Trautwein, U., & Eccles, J. S. (2012). Achievement, agency, gender, and socioeconomic background as predictors of postschool choices: A multicontext study. *Developmental Psychology, 48*(6), 1629–1642. https://doi.org/10.1037/a0029167

Parrisius, C., Gaspard, H., Zitzmann, S., Trautwein, U., & Nagengast, B. (2022). The "situative nature" of competence and value beliefs and the predictive power of autonomy support: A multilevel investigation of repeated observations. *Journal of Educational Psychology, 114*(4), 791–814. https://doi.org/10.1037/edu0000680

Parsons, J. E., & Goff, S. B. (1980). Achievement motivation and values: An alternative perspective. In L. J. Fyans (Ed.), *Achievement motivation: recent trends in theory and research* (pp. 349–373). Springer US. https://doi.org/10.1007/978-1-4757-8997-3_15

Perez, T., Cromley, J. G., & Kaplan, A. (2014). The role of identity development, values, and costs in college STEM retention. *Journal of Educational Psychology, 106*(1), 315–329. https://doi.org/10.1037/a0034027

Perez, T., Dai, T., Kaplan, A., Cromley, J. G., Brooks, W. D., White, A. C., Mara, K. R., & Balsai, M. J. (2019). Interrelations among expectancies, task values, and perceived costs in undergraduate biology achievement. *Learning and Individual Differences, 72*, 26–38. https://doi.org/10.1016/j.lindif.2019.04.001

Perez, T., Wormington, S. V., Barger, M. M., Schwartz-Bloom, R. D., Lee, Y. k., & Linnenbrink-Garcia, L. (2019). Science expectancy, value, and cost profiles and their proximal and distal relations to undergraduate science, technology, engineering, and math persistence. *Science Education, 103*(2), 264–286. https://doi.org/10.1002/sce.21490

Pinxten, M., Marsh, H. W., De Fraine, B., Van Den Noortgate, W., & Van Damme, J. (2014). Enjoying mathematics or feeling competent in mathematics? Reciprocal effects on mathematics achievement and perceived math effort expenditure. *British Journal of Educational Psychology, 84*(1), 152–174. https://doi.org/10.1111/bjep.12028

Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: a systematic review and meta-analysis. *Psychological Bulletin, 138*(2), 353–387. https://doi.org/10.1037/a0026838

Robbins, S. B., Lauver, K., Le, H., Davis, D., Langley, R., & Carlstrom, A. (2004). Do psychosocial and study skill factors predict college outcomes? A meta-analysis. *Psychological Bulletin, 130*(2), 261–288. https://doi.org/10.1037/0033-2909.130.2.261

Robinson, K. A., Lee, S. Y., Friedman, S., Christiaans, E., McKeague, M., Pavelka, L., & Sirjoosingh, P. (2022). "You know what, I can do this": Heterogeneous joint trajectories of expectancy for success and attainment value in chemistry. *Contemporary Educational Psychology, 69*, Article 102055. https://doi.org/10.1016/j.cedpsych.2022.102055

Robinson, K. A., Lee, Y.-k., Bovee, E. A., Perez, T., Walton, S. P., Briedis, D., & Linnenbrink-Garcia, L. (2019). Motivation in transition: Development and roles of expectancy, task values, and costs in early college engineering. *Journal of Educational Psychology, 111*(6), 1081–1102. https://doi.org/10.1037/edu0000331

Rokeach, M. (2008). *Understanding human values*. Simon and Schuster. (Original work published in 1979).

Rosenzweig, E. Q., & Wigfield, A. (2016). STEM motivation interventions for adolescents: A promising start, but further to go. *Educational Psychologist, 51*(2), 146–163. https://doi.org/10.1080/00461520.2016.1154792

Rosenzweig, E. Q., Wigfield, A., & Eccles, J. S. (2022). Beyond utility value interventions: The why, when, and how for next steps in expectancy-value intervention research. *Educational Psychologist, 57*(1), 11–30. https://doi.org/10.1080/00461520.2021.1984242

Salmela-Aro, K., Upadyaya, K., Cumsille, P., Lavonen, J., Avalos, B., & Eccles, J. (2021). Momentary task-values and expectations predict engagement in science among Finnish and Chilean secondary school students. *International Journal of Psychology, 56*(3), 415–424. https://doi.org/https://doi.org/10.1002/ijop.12719

Sanabria, T., & Penner, A. (2017). Weeded Out? Gendered Responses to Failing Calculus. *Social Sciences, 6*(2), Article 47. https://doi.org/10.3390/socsci6020047

Scherrer, V., & Preckel, F. (2019). Development of motivational variables and self-esteem during the school career: A meta-analysis of longitudinal studies. *Review of Educational Research, 89*(2), 211–258. https://doi.org/10.3102/0034654318819127

Schnettler, T., Bobe, J., Scheunemann, A., Fries, S., & Grunschel, C. (2020). Is it still worth it? Applying expectancy-value theory to investigate the intraindividual motivational process of forming intentions to drop out from university. *Motivation and Emotion, 44*(4), 491–507. https://doi.org/10.1007/s11031-020-09822-w

Sewasew, D., Schroeders, U., Schiefer, I. M., Weirich, S., & Artelt, C. (2018). Development of sex differences in math achievement, self-concept, and interest from grade 5 to 7. *Contemporary Educational Psychology, 54*, 55–65. https://doi.org/10.1016/j.cedpsych.2018.05.003

Seymour, E., & Hewitt, N. (1997). *Talking about leaving: Why undergraduates leave the sciences*. Westview Press.

Shaw, E. J., & Barbuti, S. (2010). Patterns of persistence in intended college major with a focus on STEM majors. *NACADA Journal, 30*(2), 19–34. https://doi.org/10.12930/0271-9517-30.2.19

Simpkins, S. D., Davis-Kean, P. E., & Eccles, J. S. (2006). Math and science motivation: A longitudinal examination of the links between choices and beliefs. *Developmental Psychology, 42*(1), 70–83. https://doi.org/10.1037/0012-1649.42.1.70

Skaalvik, E. M., & Valås, H. (1999). Relations among achievement, self-concept and motivation in mathematics and language arts: A longitudinal study. *Journal of Experimental Education, 67*(2), 135–149. https://doi.org/10.1080/00220979909598349

Spinath, B., & Spinath, F. M. (2005). Longitudinal analysis of the link between learning motivation and competence beliefs among elementary school children. *Learning and Instruction, 15*(2), 87–102. https://doi.org/10.1016/j.learninstruc.2005.04.008

Spinath, B., & Steinmayr, R. (2008). Longitudinal analysis of intrinsic motivation and competence beliefs: Is there a relation over time? *Child Development, 79*(5), 1555–1569. https://doi.org/10.1111/j.1467-8624.2008.01205.x

Steinmayr, R., & Spinath, B. (2010). Konstruktion und erste Validierung einer Skala zur Erfassung subjektiver schulischer Werte (SESSW). *Diagnostica, 56*(4), 195–211. https://doi.org/10.1026/0012-1924/a000023

Stipek, D., & Mac Iver, D. (1989). Developmental change in children’s assessment of intellectual competence. *Child Development, 60*(3), 521–538. https://doi.org/10.2307/1130719

Sutter, C. C., Hulleman, C. S., Givvin, K. B., & Tucker, M. (2022). Utility value trajectories and their relationship with behavioral engagement and performance in introductory statistics. *Learning and Individual Differences, 93*, Article 102095. https://doi.org/10.1016/j.lindif.2021.102095

Tanaka, A., & Murayama, K. (2014). Within-person analyses of situational interest and boredom: Interactions between task-specific perceptions and achievement goals.

Journal of Educational Psychology, 106(4), 1122–1134. https://doi.org/10.1037/a0036659

Trapmann, S., Hell, B., Weigand, S., & Schuler, H. (2007). Die Validität von Schulnoten zur Vorhersage des Studienerfolgs – Eine Metaanalyse. *Zeitschrift für Pädagogische Psychologie, 21*(1), 11–27. https://doi.org/10.1024/1010-0652.21.1.11

Trautwein, U., Marsh, H. W., Nagengast, B., Lüdtke, O., Nagy, G., & Jonkmann, K. (2012). Probing for the multiplicative term in modern expectancy-value theory: A latent interaction modeling study. *Journal of Educational Psychology, 104*(3), 763–777. https://doi.org/10.1037/a0027470

Viljaranta, J., Tolvanen, A., Aunola, K., & Nurmi, J.-E. (2014). The developmental dynamics between interest, self-concept of ability, and academic performance. *Scandinavian Journal of Educational Research, 58*(6), 734–756. https://doi.org/10.1080/00313831.2014.904419

Wan, S., Lauermann, F., Bailey, D. H., & Eccles, J. S. (2021). When do students begin to think that one has to be either a “math person” or a “language person”? A meta-analytic review. *Psychological Bulletin, 147*(9), 867–889. https://doi.org/10.1037/bul0000340

Wang, M.-T. (2012). Educational and career interests in math: A longitudinal examination of the links between classroom environment, motivational beliefs, and interests. *Developmental Psychology, 48*(6), 1643–1657. https://doi.org/10.1037/a0027247

Wang, M.-T., Eccles, J. S., & Kenny, S. (2013). Not lack of ability but more choice: Individual and gender differences in choice of careers in science, technology, engineering, and mathematics. *Psychological Science, 24*(5), 770–775. https://doi.org/10.1177/0956797612458937

Watermann, R., Daniel, A., & Maaz, K. (2014). Primäre und sekundäre Disparitäten des Hochschulzugangs: erklärungsmodelle, Datengrundlagen und Entwicklungen. *Zeitschrift für Erziehungswissenschaft, 17*, 233–261. https://doi.org/10.1007/s11618-013-0470-5

Watt, H. M. (2004). Development of adolescents’ self-perceptions, values, and task perceptions according to gender and domain in 7th-through 11th-grade Australian students. *Child Development, 75*(5), 1556–1574. https://doi.org/10.1111/j.1467-8624.2004.00757.x

Watt, H. M., Bucich, M., & Dacosta, L. (2019). Adolescents’ motivational profiles in mathematics and science: Associations with achievement striving, career aspirations and psychological wellbeing. *Frontiers in Psychology, 10*. https://doi.org/10.3389/fpsyg.2019.00990

Watt, H. M., Eccles, J. S., & Durik, A. M. (2006). The leaky mathematics pipeline for girls: A motivational analysis of high school enrolments in Australia and the USA. *Equal Opportunities International, 25*(8), 642–659. https://doi.org/10.1108/02610150610719119

Weidinger, A. F., Spinath, B., & Steinmayr, R. (2020). The value of valuing math: Longitudinal links between students’ intrinsic, attainment, and utility values and grades in math. *Motivation Science, 6*(4), 413–422. https://doi.org/10.1037/mot0000179

Weiner, B. (1979). A theory of motivation for some classroom experiences. *Journal of Educational Psychology, 71*(1), 3–25. https://doi.org/10.1037/0022-0663.71.1.3

Wigfield, A. (1994). Expectancy-value theory of achievement motivation: A developmental perspective. *Educational Psychology Review, 6*(1), 49–78. https://doi.org/10.1007/BF02209024

Wigfield, A., & Cambria, J. (2010a). Expectancy-value theory: Retrospective and prospective. In T. C. Urdan & S. A. Karabenick (Eds.), *The decade ahead: Theoretical perspectives on motivation and achievement* (pp. 35–70). Emerald Group Publishing Limited. https://doi.org/10.1108/S0749-7423(2010)000016A005

Wigfield, A., & Cambria, J. (2010b). Students' achievement values, goal orientations, and interest: Definitions, development, and relations to achievement outcomes. *Developmental Review, 30*(1), 1–35. https://doi.org/10.1016/j.dr.2009.12.001

Wigfield, A., & Eccles, J. S. (1992). The development of achievement task values: A theoretical analysis. *Developmental Review, 12*(3), 265–310. https://doi.org/10.1016/0273-2297(92)90011-P

Wigfield, A., & Eccles, J. S. (2000). Expectancy–value theory of achievement motivation. *Contemporary Educational Psychology, 25*(1), 68–81. https://doi.org/10.1006/ceps.1999.1015

Wigfield, A., & Eccles, J. S. (2020). 35 years of research on students' subjective task values and motivation: A look back and a look forward. In A. Elliot (Ed.), *Advances in motivation science* (Vol. 7, pp. 161–198). Elsevier. https://doi.org/10.1016/bs.adms.2019.05.002

Wigfield, A., Eccles, J. S., Fredricks, J. A., Simpkins, S., Roeser, R. W., & Schiefele, U. (2015). Development of achievement motivation and engagement. In M. E. Lamb & R. M. Lerner (Eds.), *Handbook of child psychology and developmental science: Socioemotional processes* (pp. 657–700). John Wiley & Sons, Inc.. https://doi.org/10.1002/9781118963418.childpsy316

Wigfield, A., Eccles, J. S., & Möller, J. (2020). How dimensional comparisons help to understand linkages between expectancies, values, performance, and choice. *Educational Psychology Review, 32*(3), 657–680. https://doi.org/10.1007/s10648-020-09524-2

Wigfield, A., Eccles, J. S., Yoon, K. S., Harold, R. D., Arbreton, A. J. A., Freedman-Doan, C., & Blumenfeld, P. C. (1997). Change in children's competence beliefs and subjective task values across the elementary school years: A 3-year study. *Journal of Educational Psychology, 89*(3), 451–469. https://doi.org/10.1037/0022-0663.89.3.451

Wigfield, A., Rosenzweig, E. Q., & Eccles, J. S. (2017). Achievement values: Interactions, interventions, and future directions. In A. Elliot, C. S. Dweck, & D. S. Yeager (Eds.), *Handbook of competence and motivation: Theory and application* (Vol. 2, pp. 116–134). The Guilford Press.

Yoon, K. S. (1996). *Testing reciprocal causal relations among expectancy, value and academic achievement of early adolescents: A longitudinal study* [Dissertation, University of Michigan].

Zusho, A., Pintrich, P. R., & Coppola, B. (2003). Skill and will: The role of motivation and cognition in the learning of college chemistry. *International Journal of Science Education, 25*(9), 1081–1094. https://doi.org/10.1080/0950069032000052207

2 Contributions of the Cumulative Dissertation

2.1 Study 1a and Study 1b: Students' Motivational Trajectories and Academic Success in Math-Intensive Study Programs: Why Short-Term Motivational Assessments Matter

Benden, D. K., & Lauermann, F. (2022). Students' motivational trajectories and academic success in math-intensive study programs: Why short-term motivational assessments matter. *Journal of Educational Psychology, 114*(5), 1062–1085. https://doi.org/10.1037/edu0000708

Abstract

Students' expectancy-value beliefs play an important role in shaping their educational choices and behaviors. Drawing on Eccles et al.'s situated expectancy-value theory, we investigated short-term changes in students' expectancy-value beliefs in gateway math courses for beginning university students. In Study 1a, we collected data from first-semester students in three math-intensive study programs at the beginning, midpoint, and end of the semester ($N = 1{,}004$). Latent change score analyses revealed a significant decline in students' expectancy, intrinsic value, and utility value, and an increase in perceived psychological and effort costs over the first half of the semester. These maladaptive motivational changes predicted students' end-of-term study program satisfaction, exam performance, and course dropout. Study 1b then explored weekly motivational changes in the very first weeks of the semester using a subsample from Study 1a ($N = 773$). We found that students experienced a "motivational shock" between Weeks 2 and 3 of the semester that coincided with their first performance feedback on mandatory math worksheets. The motivational shock was characterized by a rapid decline in students' intrinsic and utility values, and a significant increase in their perceived cost. Similar to Study 1a, the motivational shock in Study 1b predicted students' end-of-term study program satisfaction, exam performance, and course dropout. Across both studies, female students and students with comparatively lower prior achievement experienced more negative motivational changes. Our studies underscore the importance of considering short-term motivational changes as early warning signs of academic struggles and course dropout in math-intensive fields.

Keywords: motivational changes, situated expectancy-value theory, STEM, academic achievement, dropout tendencies

Educational Impact and Implications Statement

The present study focused on short-term changes in students' academic motivations during their first semester in math-intensive study programs, which are often plagued by particularly high dropout rates. Our analyses revealed significant declines in students' academic motivations in the first weeks of the semester. These motivational declines were a precursor to academic struggles at the end of the first semester at the university (lower study program satisfaction and achievement, higher likelihood of course dropout). Our results suggest that educational interventions that support students' success in math-intensive study domains are needed in the very early stages of their college careers.

Students' Motivational Trajectories and Academic Success in Math-Intensive Study Programs: Why Short-Term Motivational Assessments Matter

Nationally and internationally, there are concerns about the insufficient involvement of talented youth in math-intensive fields such as science, technology, engineering, and mathematics (STEM; Organisation for Economic Co-operation and Development [OECD], 2019; President's Council of Advisors on Science and Technology, 2012). On average, only approximately 27% of bachelor's degree students in OECD member countries choose to pursue a degree in a STEM field (Chen, 2013; OECD, 2019). Furthermore, a relatively high percentage of students who enroll in math-intensive programs drop out, i.e., they leave without completing a degree (Chen, 2013; Heublein & Schmelzer, 2018). In Germany, where our research was conducted, dropout rates in math-intensive programs such as physics, engineering, and mathematics range between 35% and 54% (Heublein & Schmelzer, 2018). Student dropout can incur significant personal and societal costs, including interrupted educational trajectories, lost career opportunities, and psychological strain (Faas et al., 2018; OECD, 2019; Schneider & Yin, 2011). It is therefore important to understand what factors contribute to students' academic struggles and dropout tendencies, especially in math-intensive fields.

Expectancy-value theory provides a powerful framework that describes the motivational underpinnings of achievement-related choices such as the decision to pursue a degree in, persist, or drop out of a STEM program (Eccles et al., 1983; Guo et al., 2015; Lauermann et al., 2017; Perez et al., 2014). Evidence suggests that students' expectancy beliefs ("Can I do this task?") and subjective task values ("Do I want to do this task?") are predictive of their achievement-related choices and behaviors, even when differences in cognitive abilities are accounted for (e.g., Perez et al., 2014; for a review, see Wigfield & Cambria, 2010). Longitudinal research further indicates that students' expectancy beliefs and task values decline—on average—across their educational careers (e.g., Jacobs et al., 2002; Robinson et al., 2019). These motivational declines can be a precursor to later academic struggles and dropout from math-intensive educational and occupational fields (e.g., Gaspard et al., 2020; Robinson et al., 2019). Importantly, recent research indicates that these motivational beliefs are malleable and can thus be targeted in interventions that improve students' participation and persistence in STEM (e.g., Gaspard, Dicke, Flunger, Brisson, et al., 2015; for a review, see Rosenzweig & Wigfield, 2016).

However, our understanding of students' motivational trajectories in math-intensive fields is still limited, especially in the context of higher education. First, most of the available research has examined changes in students' motivations using annual assessments of expectancies and subjective task values (e.g., Jacobs et al., 2002; Watt, 2004), and only a few studies have explored short-term changes in these beliefs (e.g., over the course of a semester or at critical time points such as the transition to higher education; Dresel & Grassinger, 2013; Kosovich et al., 2017). Yet, short-term declines in students' expectancy and value beliefs—especially at the beginning of college—are a precursor to later declines in academic performance, and can thus function as early warning signs of academic struggles and intentions to leave college (Kosovich et al., 2017; Perez et al., 2014). Second, even fewer studies have examined these short-term motivational changes in math-intensive fields where dropout tendencies are particularly severe (Heublein & Schmelzer, 2018). Third, the available evidence is often limited to two or three measurement points during the semester (for an exception, see Johnson et al., 2014); however, more intensive short-term assessments are necessary to better understand the development of students' motivations at critical time points such as the transition to higher education when motivational changes are particularly likely (Eccles & Midgley, 1989). Finally, existing research has focused almost exclusively on a single course or study program (Kosovich et al., 2017; Zusho et al., 2003), which might limit the generalizability of the reported findings.

To address these gaps in the literature, the present study examined short-term changes in students' expected academic success and subjective task values in three math-intensive study programs shortly after the transition to higher education. We focused not only on semester-long motivational changes but also on weekly fluctuations in students' motivations at the beginning of the semester and were thus able to conduct fine-grained analyses of students' experiences at a critical stage in their educational careers. Prior evidence suggests that the majority of students who drop out of higher education do so within the first year of their study program (Heublein & Schmelzer, 2018; OECD, 2019). Furthermore, we focused on required math courses that typically function as a gatekeeper to further engagement and success in math-intensive study programs. Academic struggles and low levels of motivation in such courses have been identified as one of the most critical factors influencing students' decision to drop out of STEM (Heublein et al., 2017; Seymour & Hewitt, 1997).

In the following sections, we discuss new developments in Eccles' expectancy-value theory that specifically focus on students' situational motivations, and we describe potential predictors and consequences of short-term fluctuations in students' academic motivations for their subsequent academic success and well-being.

Expectancy-Value Theory and Developmental Trajectories of Student Motivation: A Situational Perspective

Expectancy-value theory (Eccles et al., 1983) posits that students' expected success in academic domains such as math and science and their subjective valuing of these domains are proximal predictors of important achievement-related choices and behaviors such as students' educational and career decisions, persistence in the face of difficulty, and academic performance (for a review, see Wigfield et al., 2016). A key contribution of this theoretical framework is the differentiation of expectancy and task value components that shape students' domain- and task-specific choices and behaviors such as the decision to persist in or drop out of the STEM domain. The theory distinguishes between students' self-concepts of ability in different academic domains and their task- and time-specific expected success (Eccles & Wigfield, 1995, 2020; Wigfield & Eccles, 2000). Students' self-concepts reflect relatively stable beliefs about their ability in particular domains such as math or science, whereas expectancy refers to students' subjective probability of success on a given task or domain (e.g., an exam or a course assignment). Although these two constructs have often been combined into one composite score, Eccles and Wigfield (2020) point out that they are conceptually distinct and may follow different developmental trajectories. Much of the expectancy-value literature has focused on students' self-concepts of ability (e.g., Jacobs et al., 2002; see also Wigfield & Cambria, 2010), and less is known about the relevance of their task- and time-specific expectancy beliefs for their academic success and well-being (Dietrich et al., 2019; Tanaka & Murayama, 2014).

Additionally, Eccles and colleagues differentiated several components of students' subjective task values (Eccles et al., 1983; Wigfield & Eccles, 2000; Wigfield & Eccles, 2020): Individuals may value a given task or activity because of its importance for one's identity (attainment value), because of the interest in or enjoyment of engaging in the task (intrinsic value), or because of its usefulness for current or future goals (utility value). These three value components address potential reasons for engaging in a given task, whereas the cost component refers to perceived drawbacks (Eccles et al., 1983; Wigfield & Eccles, 2020). Engagement in a given task or activity may be perceived as subjectively costly due to the perceived amount of effort required to be successful (effort cost), concerns about missed opportunities to engage in alternative valued activities or tasks (opportunity cost), and negative emotions that stem from anticipated or experienced failure (psychological cost; Eccles et al., 1983; Perez et al., 2014; Wigfield & Eccles, 2020, see also Flake et al., 2015). As noted previously, these motivational constructs have emerged as powerful predictors of students' educational and occupational choices and behaviors, including students' enrollment in high school courses (Wang, 2012), career aspirations in math- or science-related fields (Nagengast et al., 2011), enrollment in particular college majors (Gaspard et al., 2019), college retention (Robinson et al., 2019) and career attainment in STEM (Lauermann et al., 2017).

Recently, Eccles and Wigfield (2020) pointed out that students' expectancy and subjective task values are not only developmental (i.e., change over time) but also situationally sensitive (i.e., influenced by situational characteristics). Differences in the salience of situational characteristics such as task difficulty or the number of options for action of which a given individual is aware can change the perceived relevance of different value facets, and thus, these facets can carry different weights in influencing students' decision-making at a given point in time. A student's interest in math, for example, might be a key driving force behind choosing to pursue a degree in a STEM field, whereas the cost component might become an increasingly influential determinant of the student's subjective valuing of this domain when he or she faces typical challenges such as demanding coursework or a difficult exam. Accordingly, expectancy-value research should focus not only on the developmental course and long-term implications of these motivational constructs for students' academic choices and behaviors but also on situation-specific influences that shape students' time- and task-specific decision-making (Eccles & Wigfield, 2020; Wigfield & Eccles, 2020). Eccles and Wigfield emphasized the situational nature of the expectancy-value constructs in their theoretical framework by renaming their theory *situated expectancy-value theory* (SEVT; Eccles & Wigfield, 2020).

Educational research on situation-specific motivational fluctuations is still relatively scarce; therefore, it is not yet clear whether, when, and for whom these fluctuations can serve as an early warning sign of academic struggles. Research focusing on long-term developmental processes has typically documented an average decline in students' academic motivations over time (Chouinard & Roy, 2008; Jacobs et al., 2002; Robinson et al., 2019; Watt, 2004), but evidence focusing on short-term motivational changes is less consistent. Several studies have observed short-term declines in students' motivational beliefs that parallel previously documented long-term declines (Dresel & Grassinger, 2013; Kosovich et al., 2017; Perez et al., 2014; Sonnert et al., 2015; Zusho et al., 2003), but other studies have found no change (Hardin & Longhurst, 2016) or an increase in students' motivations (Bong, 2005; Finney & Schraw, 2003). A number of factors might contribute to these mixed results. First, both ability-related and task value-related motivations are more likely to fluctuate over time when they are measured with situation-specific assessments that reference students' lesson-, class- or content-specific expectancies and values (Dietrich et al., 2017; Tanaka & Murayama, 2014; Tsai et al., 2008), as opposed to more global motivations such as students' domain-specific self-concepts of ability and interests (Hardin & Longhurst, 2016; Jansen et al., 2020; Rieger et al., 2017).

Second, some motivational constructs might be more sensitive to situational influences than others, and different constructs can follow different developmental trajectories. For instance, over the course of a semester in an introductory psychology course, Kosovich et al. (2017) found a greater decline in students' expectancy beliefs than in their utility value, and this decline was predicted by students' performance over the course of the semester. Similarly, in a chemistry course for beginning students, Perez et al. (2014) found a greater decline in students' competence beliefs than in their task values (a composite of intrinsic, utility, and attainment value). Perez et al. (2014) also observed a greater increase in students' perceived effort and opportunity cost than in their perceived psychological cost (effort cost emerged as one of the strongest predictors of dropout intentions in this study). Unfortunately, very few studies to date have examined multiple facets of the expectancy-value framework with situation-specific assessments in the same sample, which limits our ability to examine differential developmental trajectories within the same sample and across different situations. Furthermore, with very few exceptions (Perez et al., 2014; Perez et al., 2019), the cost component has been largely neglected in this literature, despite its potential to explain interindividual differences in students' academic achievement and dropout intentions. In the present study, we examine the short-term trajectories of students' expectancy, intrinsic and utility values as well as perceived psychological and effort costs.

Finally, motivational changes can be time specific. For instance, Zusho et al. (2003) reported a decline in students' confidence in their ability to master achievement tasks in introductory chemistry courses from the beginning to the midpoint of the semester but found no further changes in these beliefs towards the end of the semester (see also Hardin & Longhurst, 2016). A period of adaptation may have contributed to this developmental pattern. In addition, motivational changes may be particularly likely at educational transitions because students face new academic demands and have to adjust to a new and unfamiliar educational context (Eccles & Midgley, 1989). To date, most studies of students' short-term motivational changes in higher education have assessed students' motivations only at the beginning and at the end of a given course or semester, and thus, these studies do not sufficiently account for a period of adaptation between these time points. Further research that examines construct- and time-specific differences in students' educational experiences is warranted.

Predictors of Motivational Changes: The Role of Prior Achievement, Gender, Family Background, and Course-Specific Differences

One of the strongest predictors of students' expectancy beliefs and subjective task values is their prior academic performance, which is often operationalized via standardized test scores or grades (e.g., Perez et al., 2014; Robinson et al., 2019). Evidence suggests that students' prior academic achievement in school typically serves as a buffer against motivational declines in college (Robinson et al., 2019; Sonnert et al., 2015). In our study, we focus on students' high school grade point average (GPA) as an indicator of prior performance for several reasons. Students' GPA predicts important life outcomes such as academic success (e.g., degree completion), career success (e.g., wages), and general life satisfaction, even when differences in intelligence and standardized performance are controlled for (Borghans et al., 2016; see also Allensworth & Clark, 2020; Schneider & Preckel, 2017). Furthermore, students' grades are more strongly correlated with their academic motivations than are students' standardized performance or intelligence (Borghans et al., 2016; Lauermann et al., 2020). Finally, German institutions of higher education use students' high school GPA as a selection criterion for college admission (Heublein et al., 2017), and no standardized admission tests (analogous to the SAT or ACT in the US) are available in this educational context.

Even when there are no or only small differences in achievement, prior research has revealed persistent gender differences in STEM-related motivations and educational attainment (OECD, 2019; Wang & Degol, 2017). Gender differences are particularly pronounced in the most math-intensive STEM fields such as physics and math (OECD, 2019), and some studies report higher dropout rates from math-intensive study programs for female students than for male students (Griffith, 2010; Isphording & Qendrai, 2019). With some exceptions (e.g., Lauermann et al., 2017), evidence suggests that compared to male students, female students report lower levels of competence beliefs, intrinsic value, and utility value in the math domain, as well as higher levels of subjective cost (Gaspard, Dicke, Flunger, Schreier, et al., 2015; Nagy et al., 2010; Watt, 2004). However, analyses of situation-specific rather than general math-related motivations and affect (e.g., interest and anxiety) tend to reveal smaller or no gender differences (Goetz et al., 2013; Tsai et al., 2008). Accordingly, male and female students' everyday experiences in the math domain might be more similar than is typically assumed in research that relies on relatively global self-assessments of academic motivation and affect.

Students' family background (i.e., socioeconomic status, SES) is yet another important factor that can influence their decision to pursue higher education, their subsequent academic success, and the likelihood of dropping out of college (Isleib, 2019; Parker et al., 2012; Sackett et al., 2009). Notably, students from different family backgrounds often report similar expectancy beliefs and subjective task values at the beginning of college (Robinson et al., 2019) but achieve different educational and occupational attainments (e.g., achievement, level of job prestige; OECD, 2019; Schoon & Polek, 2011). A number of factors contribute to these social disparities, including differences in the quality of educational opportunities in K-12 schooling, insufficient access to information about performance requirements, financial struggles, and competing time commitments such as employment, which can increase the risk of college dropout (Isleib, 2019; Walpole, 2003).

Finally, students' academic motivations are likely to vary as a function of course- and context-specific influences (e.g., Mac Iver et al., 1991). Some motivational changes may be universal (e.g., motivational declines at educational transitions), whereas others might be course- and context-specific, for instance, due to different instructional and assessment practices (Linnenbrink-Garcia et al., 2016). However, most studies to date have focused on a single course or study program so that the generalizability of identified motivational declines across different courses and study programs remains unclear. Examining students' math-related motivational trajectories across different courses and study programs in the present study allows us to address this gap and identify patterns of motivational change that are relatively generalizable across different math-intensive courses and study programs.

Relatedly, assessment practices such as receiving performance feedback may affect students' motivational trajectories. Prior research has shown that people are often overconfident with respect to their expected performance across a variety of cognitive tasks (Metcalfe, 1998), for instance, their expected grade in introductory economics and quantitative courses in college (Nowell & Alston, 2007). This overconfidence bias may be particularly relevant after the transition to a new educational context such as math-intensive study programs in college: Students' expectations of their performance may not yet be calibrated to the high demands and performance requirements of such programs. Accordingly, receiving performance feedback for the first time may be a precursor to motivational declines.

Motivational Changes as a Predictor of Students' Academic Success

As noted previously, extensive research in the expectancy-value literature corroborates the importance of students' expectancy and subjective task values as proximal psychological predictors of their achievement, effort investment, and persistence in the pursuit of challenging academic goals, even when the effects of background characteristics such as gender or prior achievement are controlled for (for a review, see Wigfield & Cambria, 2010). Substantial evidence indicates that students' motivations and their academic achievement influence each other over time (e.g., Marsh & Martin, 2011; Weidinger et al., 2020). Students' domain-specific self-concepts of ability and their subjective task values predict later academic achievement even after controlling for differences in prior achievement (e.g., Robinson et al., 2019; Steinmayr & Spinath, 2009). Students' motivations are thus key predictors of their academic success in math-intensive fields and play a particularly important role in students' academic success in required gateway courses (Perez et al., 2014). Such courses are critical for students' long-term academic success because they are a prerequisite for enrollment in subsequent courses, students' degree completion, and further engagement in STEM fields (Seymour & Hewitt, 1997).

Importantly, students' academic success is not limited to their academic performance. Affective-motivational aspects such as students' study program satisfaction are also important because they reflect students' well-being in a given academic environment and can be a precursor to later job satisfaction (Nauta, 2007). Students' overall study program satisfaction—i.e., their satisfaction with various aspects of their academic life in a particular field of study—has been linked to their academic achievement (Nauta, 2007), long-term persistence (Lent et al., 2016), and retention in college (Starr et al., 1972). Assessments of students' study program satisfaction typically include components similar to those used to assess job satisfaction (Westermann et al., 1996). These assessments capture students' overall satisfaction with or enjoyment of their studies, satisfaction with the choice of their study program or university, and satisfaction with the content taught in their study program (Nauta, 2007; Westermann et al., 1996). Numerous studies suggest that students' domain- and context-specific academic motivations are key predictors of their overall study program satisfaction and dropout intentions (e.g., Bergey et al., 2018; Perez et al., 2014; Wach et al., 2016). Comparatively few studies have examined students' expectancy-value beliefs as predictors of dropout or retention in college (e.g., Robinson et al., 2019). For instance, Robinson et al. (2019) found that changes in students' expectancy-value beliefs across the first two years in college predicted students' retention in an engineering major at the end of the second year in college. However, we are not aware of any studies that have examined students' expectancy-value beliefs as predictors of course dropout in gateway math courses. In the present study, we examined potential associations between short-term motivational changes at the beginning of the semester and end-of-term exam performance, study program satisfaction, and course dropout.

Indeed, several studies indicate that short-term motivational changes might serve as early warning signs of later academic struggles and dropout intentions in college (Dresel & Grassinger, 2013; Kosovich et al., 2017; Zusho et al., 2003). For instance, in two introductory chemistry courses, Zusho et al. (2003) found that declines in students' self-efficacy and overall task value across three time points during the semester were related to lower levels of end-of-term exam performance. Similarly, significant declines in students' general academic self-concept and task value from the beginning to the end of the semester predicted their dropout intentions at the end of the semester across different study programs at a German university, even when differences in prior achievement (i.e., high school GPA) were statistically controlled for (Dresel & Grassinger, 2013). However, no study to date has examined potential differences in students' short-term motivational trajectories between different task value facets; thus, little is known about whether some facets might be more likely to change than others, and whether such changes might thus serve as warning signs of later academic struggles. Furthermore, with only one exception (Johnson et al., 2014), the available research in higher education has typically focused on two or three time points during the semester, thus providing limited information about the shape of students' motivational trajectories or potentially sensitive time points at which motivational declines are most likely to occur. More intensive, short-term analyses can help us to identify the time points at which motivational interventions might be most fruitful and needed (Rosenzweig & Wigfield, 2016).

The Present Research

The present research (Study 1a and Study 1b) expands upon prior evidence by examining short-term changes in students' expectancy and subjective task values over the course of a semester in gateway math courses in math, physics, and math teacher education programs at a German university. In Study 1a, we examine changes in students' motivations across three time points during the semester (beginning [T1], midpoint [T5], and end of term [T6]) and their links to indicators of students' academic success (end-of-term study program satisfaction, final exam performance, and course dropout). In Study 1b, we focus on a subsample of students from Study 1a and examine weekly and situation-specific changes in students' motivations in four consecutive weeks at the beginning of the semester (T1–T4). Analyses in Study 1b thus focus on the developmental trajectories of students' motivations shortly after the transition to higher education and examine their predictive effects on students' end-of-term performance, study program satisfaction, and course dropout.

Three research questions (RQs) guide our analyses. First (RQ#1), how do students' expectancy, intrinsic and utility values, and psychological and effort costs change throughout the semester (Study 1a) as well as during the very first weeks of the semester (Study 1b)? These analyses allow us to identify particularly sensitive time points at which motivational changes are most likely to occur, whether these changes are temporary and reversible or might serve as warning signs of later academic struggles, and whether different expectancy-value constructs change at the same rate. Due to survey length constraints, we were not able to include all possible task values. We focused on intrinsic and utility values because they have been shown to change more than other values (e.g., attainment value) over short periods of time in college samples (e.g., two years; Robinson et al., 2019). Furthermore, we examined changes in psychological and effort cost: The perceived psychological cost may be particularly likely to change shortly after the transition to higher education in math-intensive study programs because students need to adapt to the high workload and new demands (Seymour & Hewitt, 1997). In addition, effort cost has emerged as a key predictor of students' dropout intentions and retention in STEM majors (Perez et al., 2014; Robinson et al., 2019).

Based on prior research (e.g., Kosovich et al., 2017; Perez et al., 2014), in Study 1a, we expect students' expectancy and task values to decrease and their perceived cost to increase over the semester. We make no specific predictions about the shape of students' motivational trajectories within the four-week period in Study 1b. Potential changes in students' motivations from week to week might represent content-specific, momentary shifts in motivation as students are adjusting to an unfamiliar academic environment, or these changes might be an early sign of academic difficulties. Due to the scarcity of prior research on short-term motivational changes, we refrain from formulating specific predictions regarding differences in the trajectories between the five expectancy-value facets assessed in our study. The few prior studies that are available to date have either found greater changes in students' expectancy or competence-related beliefs than in their task values (Kosovich et al., 2017; Perez et al., 2014; Perez et al., 2019) or similar rates of change (Dresel & Grassinger, 2013). However, these prior findings may not apply to the context of our study, which was conducted in gateway math courses in math-intensive study programs. Students in such programs need to adapt to a high workload and to new math content that is often vastly different from the type of math that is being taught in high school (i.e., learning math as a scientific discipline vs. applied math taught in high school; Gueudet, 2008).

Second (RQ#2), to what extent are students' motivational trajectories related to their individual and family background characteristics (gender, high school GPA, SES), and their specific math course and study program? These analyses allow us to investigate whether and to what extent preexisting differences in students' characteristics, as well as their course-specific experiences, affect students' motivations and subsequent academic outcomes. Some motivational shifts may be universal (e.g., resulting from students' need to adapt to a new context), but others might be context specific or specific to particular groups of students (e.g., as a function of gender, prior achievement, or SES). If there are gender differences in students' motivational trajectories, we expect these differences to favor male over female students (e.g., Sonnert et al., 2015). In line with prior research (Robinson et al., 2019; Sonnert et al., 2015), we also expect that students' high school GPA and SES will function as protective factors against potential motivational declines. Because the math courses were taught by different instructors and across different study programs, we included dummy variables to capture course-specific differences in students' motivations and academic outcomes. In addition, some students in our study had participated in preparatory math courses prior to course enrollment; participation in such preparatory courses was included as a control variable in all analyses.[1]

Third (RQ#3), can short-term changes in students' expectancy-value beliefs serve as warning signs of later academic struggles, i.e., do motivational changes predict students' achievement on their final exam, self-reported study program satisfaction at the end of the semester, and course dropout? We expect that students with comparatively more positive motivational trajectories will perform better on the final exam, will be more satisfied with their study program, and will be less likely to drop out of their math course towards the end of the semester (cf. Dresel & Grassinger, 2013; Kosovich et al., 2017; Robinson et al., 2019). The same research questions were examined in both studies, focusing either on motivational changes across the entire semester (Study 1a) or the first weeks of the semester (Study 1b).

Finally, in Study 1b, we conduct supplemental analyses to determine whether performance feedback practices might contribute to changes in students' motivations at the beginning of the semester. Even though all students in a given course were required to submit mandatory weekly worksheets at the same time, scheduling differences across supplemental tutoring sections caused a delay in the provision of performance feedback for a subset of our sample. Due to these scheduling differences some of the students had received performance feedback at the time of data collection while others had not, which enabled us to examine the effects of receiving performance feedback for the first time on students' subsequent

[1] Such preparatory courses are typical for math-intensive programs at German universities, are free of charge for all admitted students, and may be a buffer against a potential motivational decline.

motivational changes (see Study 1b). We reasoned that the provision of performance feedback in these demanding courses may affect students' motivational trajectories (e.g., receiving performance feedback may contribute to an initial motivational decline), because their performance expectations may not yet be calibrated to the high demands and performance requirements in their study program (Metcalfe, 1998; Nowell & Alston, 2007).

Study 1a

Method

Participants and Procedure

The final sample in Study 1a included 1,004 participants (n = 318 female) from six cohorts of students enrolled in required math courses for beginning students in their respective study program at a German university. Each cohort consisted of students enrolled in the same course, at the same time, and in the same study program. The students were enrolled in physics (n = 366), math (n = 445), or math teacher education (n = 193), and two consecutive cohorts of students were recruited from each study program in the winter terms of the respective academic year (2017 and 2018). The majority of the students with valid demographic data were in their first year (90%), were born in Germany (90%), and indicated German as the language they most frequently speak at home (86%). Student-generated anonymized codes were used to link the longitudinal data. Twenty-seven students failed to provide a code, and seven students used systematic answer patterns such as straight-lining. These cases were not included in the analyses. If an individual participated in more than one course (e.g., courses in math and math teacher education), we analyzed data that were collected only in the study program in which the student was enrolled. Thus, we ensured that there was no overlap between course participants across courses and study programs. This procedure resulted in our final sample of 1,004 students (out of the initial 1,038).

Students participated voluntarily in the study and completed paper-and-pencil questionnaires at the beginning (Week 2, T1), midpoint (Week 8, T5), and end of the semester (Week 15, T6).[2] Data collections took place in regular math lectures. Nearly all students who were present on the day and time of data collection agreed to participate in the study (98%–100%), which allowed us to infer course attendance and attrition. All students were required to complete weekly math worksheets and to submit them in person in the lecture, and all students

[2] Week 1 is typically used for organizational questions, and data collection was not possible at this time. Students received their first course assignments in Week 2 and their first performance feedback in Week 3.

enrolled in a given math course were required to submit their worksheets at the same time. The students received performance feedback in separate tutoring sections, which were scheduled at different times. These tutoring sections were dedicated entirely to a discussion of the weekly math problems (the students were being shown step-by-step solutions on the whiteboard), and no new content was covered. The weekly worksheets were low-stakes assignments that the students had to pass to qualify for the exam, but students' level of performance on these assignments had no relevance for their final grade. Students in five of the six cohorts received scores as performance feedback and needed an overall score of 50% to qualify for the exam, whereas students in one cohort only received a pass/fail feedback and needed to pass 80% of the worksheets. The worksheets were highly demanding; almost no students were able to solve all problems in any given week. The students' achievement on the exam at the end of the semester determined their course grades.

Measures

The students responded to questions about their expectancy-value beliefs at all three time points in Study 1a (T1, T5, and T6) and rated their study program satisfaction at the end of the semester (T6).

Expectancy and Subjective Task Value Beliefs. The students' *expectancy* was measured with three items adapted from Eccles and Wigfield (1995) and Tanaka and Murayama (2014; e.g., "Based on my experiences in this class, I think I will do well on the exam"). *Subjective task values* were assessed using scales adapted from Gaspard, Dicke, Flunger, Brisson, et al. (2015). Two-item scales were used for *intrinsic value* (e.g., "Doing the coursework and the assignments for this class is something I enjoy"), *utility value* (e.g., "Doing the coursework and the assignments for this class is useful for my future"), *psychological cost* (e.g., "Doing the coursework and the assignments for this class is stressful for me"), and *effort cost* (e.g., "Doing the coursework and the assignments for this class drains a lot of my energy"). All items were assessed on a 6-point scale ranging from 1 = *completely disagree* to 6 = *completely agree*. The internal consistencies of these constructs ranged from $\alpha = .67$ to .92 across time points (see Table 1 as well as the online supplemental materials for the full list of items).

Study Program Satisfaction. Five items measuring study program satisfaction were adapted from Nauta (2007), Ditton (1998), and Westermann et al. (1996). Two items focused on students' certainty about their study choice (e.g., "I am certain that my study program is the right choice for me," from 1 = *very uncertain* to 6 = *very certain*); two items captured students' overall satisfaction (e.g., "In general, I am very satisfied with my study program," from 1 = *completely disagree* to 6 = *completely agree*); and one item captured dropout intentions ("I oftentimes think about dropping out of or switching my study program," reverse-scored, from 1 = *completely disagree* to 6 = *completely agree*). The internal consistency of the scale was very good (α = .89).

Course Dropout. Students' lack of attendance at the end of the semester (T6) was used as an indicator of course dropout in our analyses (39% of the sample). The majority of the students dropped out towards the midterm (24% non-attendance at both T5 and T6, and additional 15% non-attendance at T6). This high level of attrition is comparable to prior studies in gateway math courses (e.g., 38% in Rach & Heinze, 2017) and national dropout statistics for math-intensive study programs in Germany (45% in physics, 54% in math; Heublein & Schmelzer, 2018), and lack of course attendance has been shown to be a precursor to later academic difficulties (Schneider & Preckel, 2017).

Exam Performance. The students' scores on the final exam were obtained from the instructor of each math course. Written consent was obtained at T5 or T6, and 91% of all students who were present at these measurement points gave consent. Due to the high levels of course attrition, this percentage of informed consent corresponds to 54% of the total sample. The students' exam scores and course attrition were both included as outcome variables in subsequent analyses. The exam scores were converted into percentages and were z-standardized within each math course to account for instructor- and course-specific grading practices. One of the courses assigned only pass-fail grades (11% of the total sample), and 37 students (4% of the total sample) had submitted a written consent form but did not take the final exam; thus, no achievement data were available for these students.[3]

Personal and Family Background Characteristics. The students reported their gender (34% female; 0 = *male*, 1 = *female*) and high school GPA at the beginning of the study. Students' high school GPA was recoded so that higher scores reflect higher achievement to facilitate the interpretation of results (M = 3.1, SD = 0.64, range from 1 to 4). The students' family background (SES) was coded based on student-reported parental occupations according to the German Classification of Occupations (KldB; Paulus & Matthes, 2013). This classification system differentiates between four job skill levels (1 = *requiring little or no*

[3] We replicated our results (reported subsequently) using a dichotomous pass/fail variable for all students who had achievement data. Our findings were consistent regardless of whether we used this pass/fail variable or the exam scores. However, using the pass/fail variable resulted in somewhat weaker effect sizes, likely because this variable did not differentiate as well between different achievement levels.

education to 4 = *requiring an advanced degree*). The majority of the students (61%) had at least one parent with the highest job level, and less than 1% of the students had parents whose occupation required little or no education. Accordingly, this variable was dichotomized into 0 = *low SES* (for job skill levels 1–3) versus 1 = *high SES* (for job skill level 4). The students' participation in preparatory math courses prior to enrollment (65% had participated) and dummy variables for each math course taught by a different instructor were included as covariates in all analyses. Both physics courses were taught by the same instructor; thus, only one dummy variable was included in this case.

Statistical Analyses

Preliminary analyses examined bivariate correlations and missing data patterns, and included confirmatory factor analyses (CFAs) testing measurement invariance across time points, between the different study programs, and students' gender, family background (SES), and participation in preparatory math courses. Latent change score analyses using M*plus* 8.3 explored short-term motivational changes (see McArdle, 2009). Missing data were handled with full information maximum likelihood estimation (FIML). We fit latent change models for each of the five expectancy-value constructs and a multivariate model including all five constructs (see Figure 1, McArdle, 2009). The latent change scores were modeled such that they assess changes in expectancy and task values from the beginning to the midpoint of the semester (ΔT5T1) and from the midpoint to the end of the semester (ΔT6T5). These change scores allowed us to describe potential discontinuities in the amount of change at the beginning versus towards the end of the semester. We modeled the predictive effects of the initial levels of motivation (T1) on the latent change scores (ΔT5T1), which is recommended when an "intervention" affecting the main variables of interest has taken place after the initial measurement occasion (McArdle, 2009). In the present study, the initial measurement (T1) took place before the students had received their first course assignment, whereas subsequent assessments (T5 and T6) took place after the students had engaged with demanding coursework. Furthermore, following recommendations by Grimm et al. (2012), we included predictive paths between the first (ΔT5T1) and the second (ΔT6T1) latent change scores; these paths model the potential predictive effects of early motivational changes on subsequent changes in students' expectancies and task values.

Table 1

Descriptive Statistics and Observed Bivariate Correlations in Study 1a

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1. Female	—																					
2. SES	.05	—																				
3. High school GPA	.05	.19**	—																			
4. Preparatory course	.03	.11**	.21**	—																		
5. Expectancy T1	−.18**	.04	.16**	−.03	—																	
6. Intrinsic value T1	−.03	.04	.20**	.11**	.43**	—																
7. Utility value T1	−.02	.01	.06	.08*	.31**	.39**	—															
8. Psych. cost T1	.16**	−.08*	−.09**	−.07*	−.51**	−.35**	−.22**	—														
9. Effort cost T1	.05	−.03	−.03	.01	−.44**	−.18**	−.13**	.62**	—													
10. Expectancy T5	−.20**	.03	.23**	.00	.66**	.31**	.17**	−.42**	−.38**	—												
11. Intrinsic value T5	−.04	.03	.25**	.06	.33**	.49**	.21**	−.27**	−.13**	.53**	—											
12. Utility value T5	−.05	.03	.12**	.03	.27**	.28**	.55**	−.20**	−.15**	.34**	.45**	—										
13. Psych. cost T5	.14**	−.06	−.20**	−.07	−.33**	−.21**	−.06	.58**	.42**	−.49**	−.34**	−.13**	—									
14. Effort cost T5	.08*	−.03	−.11**	−.02	−.31**	−.12**	−.01	.41**	.53**	−.41**	−.15**	−.05	.68**	—								
15. Expectancy T6	−.18**	−.02	.18**	−.04	.61**	.30**	.21**	−.38**	−.36**	.78**	.39**	.27**	−.44**	−.38**	—							
16. Intrinsic value T6	−.03	.11*	.15**	.05	.26**	.41**	.21**	−.26**	−.13**	.43**	.64**	.34**	−.31**	−.17**	.50**	—						
17. Utility value T6	−.04	.08	.18**	.05	.25**	.26**	.51**	−.24**	−.16**	.34**	.34**	.67**	−.22**	−.10*	.30**	.45**	—					
18. Psych. cost T6	.12**	−.10*	−.12**	−.05	−.36**	−.27**	−.12**	.58**	.38**	−.46**	−.32**	−.12*	.68**	.52**	−.49**	−.32**	−.18**	—				
19. Effort cost T6	.04	−.03	−.07	.03	−.32**	−.16**	−.05	.41**	.50**	−.42**	−.16**	−.06	.48**	.69**	−.40**	−.18**	−.06	.64**	—			
20. Study satisfaction T6	−.13**	.01	.20**	.04	.45**	.41**	.25**	−.41**	−.30**	.54**	.48**	.39**	−.45**	−.28**	.57**	.56**	.41**	−.42**	−.28**	—		
21. Exam performance	−.12*	.07	.41**	.03	.27**	.17**	.17**	−.25**	−.34**	.39**	.21**	.23**	−.33**	−.32**	.42**	.24**	.22**	−.30**	−.36**	.33**	—	
22. Course dropout	−.04	−.11**	−.39**	−.23**	−.14**	−.17**	.00	.15**	.07*	−.21**	−.26**	−.09*	.16**	.07	[a]	[a]	[a]	[a]	[a]	[a]	[a]	—
M	.34	.61	3.13	.65	3.71	4.74	4.54	3.13	4.31	3.43	4.43	4.29	3.48	4.54	3.44	4.47	4.26	3.43	4.47	4.43	.00	.39
SD	.48	.49	.64	.48	.85	.81	.99	1.24	1.09	.92	0.91	1.06	1.19	1.03	1.00	.90	1.00	1.23	1.00	.93	.99	.49
N	928	811	896	794	887	899	894	899	899	693	695	693	694	695	517	520	518	520	520	520	393	1004
Skewness			−.45		.03	−.75	−.82	.35	−.44	−.14	−.70	−.65	.10	−.73	−.16	−.89	−.57	.28	−.48	−.84	−.05	
Kurtosis			−.64		.51	1.13	.79	−.57	−.05	.33	.84	.40	−.49	.36	.15	1.07	.35	−.47	−.09	.83	−.54	
Cronbach's α					.89	.79	.67	.81	.89	.92	.83	.74	.79	.91	.92	.84	.68	.83	.90	.89		

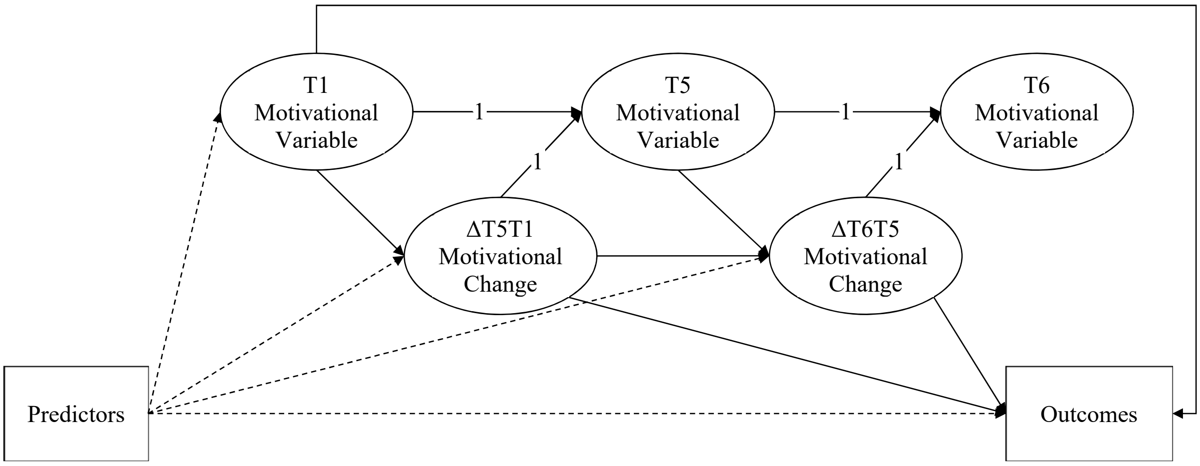
Note. $N = 1{,}004$. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15). Psych. cost = psychological cost.

[a] Course dropout implies that the students were not present at the end-of-semester data collection and no performance data was available, so that correlations could not be computed.

$^{*}p < .05$. $^{**}p < .01$.

Figure 1

Latent Change Model Including Initial Levels of Motivation, Motivational Changes, and Predictor and Outcome Variables in Study 1a



Note. Motivational variables were the five expectancy-value constructs. Analogous models were modeled for each expectancy-value construct. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15). ΔT5T1 = motivational change from the beginning to the midpoint of the semester, ΔT6T5 = motivational change from the midpoint to the end of the semester.

For RQ#1, we modeled a multivariate latent change score model including the five expectancy-value constructs and examined means and variances of the latent change scores. We additionally estimated plausible values and corresponding confidence intervals for all latent change scores (Asparouhov & Muthén, 2010), which allowed us to identify students who experienced significant declines or increases in their expectancies and task values across the three measurement points. To answer RQ#2, we included students' individual characteristics (gender, high school GPA, SES, participation in preparatory math courses) and math course/study program as predictors of their initial motivations and the latent change scores in the model in order to examine differences in students' motivational trajectories as a function of preexisting differences in student characteristics. Finally, for RQ#3, we estimated separate latent change score models for each of the five expectancy-value constructs to examine the predictive effects of students' initial motivations and the latent change scores on students' end-of-term study program satisfaction, exam performance, and course dropout. A multivariate latent change model including the predictive effects of all five expectancy-value constructs and their latent change scores (i.e., 10 latent change scores in total) as predictors of students' academic success resulted in estimation problems and is not reported here. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and achievement, and a second set of analyses using Monte Carlo integration with 5,000 integration points focused on the prediction of course dropout.

Maximum likelihood estimation with robust standard errors (MLR) was used in all analyses. Model fit was evaluated based on the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). Good model fit is indicated by a CFI value of .95 or higher and RMSEA and SRMR values of .06 or lower, whereas acceptable fit is indicated by a CFI value of approximately .90 or higher and RMSEA and SRMR values of .08 or lower (Marsh et al., 2005). For model comparisons, a CFI difference between two models of less than .01 and an RMSEA difference of less than .015 generally indicate a negligible change in overall fit and support the more parsimonious model (Chen, 2007; Cheung & Rensvold, 2002). Analyses including course dropout (a dichotomous outcome variable) used MLR with the LINK = LOGIT option and Monte Carlo integration. For this analysis, model fit indices are not available.

Results

Preliminary Analyses

Descriptive statistics and bivariate correlations are shown in Table 1. All correlations between the expectancy-value constructs and hypothesized predictors and outcomes were in the expected direction. The means reported in Table 1 indicated that students' expectancy, intrinsic value, and utility value decreased over the three time points, on average, whereas the perceived psychological and effort cost increased. Attrition from the math courses (and thus from our study) is represented by the variable "course dropout" and was included as an outcome measure in our final analyses. As shown in Table 1, course dropout was linked to lower SES ($r = -.11$, $p = .002$), lower high school GPA ($r = -.39$, $p < .001$), lower likelihood of participation in preparatory math courses ($r = -.23$, $p < .001$), and less adaptive initial motivations. The students' gender, SES, high school GPA, and participation in preparatory courses as well as instructor-/course-specific dummy variables were included as auxiliary or control variables in all subsequent models (Graham, 2003; Schafer & Graham, 2002).

Measurement Model and Invariance Analyses. Multigroup CFAs including expectancy, intrinsic and utility values, and psychological and effort costs confirmed the same factor structure for these constructs across students' gender, family background (SES), and participation in preparatory math courses. Partial strong measurement invariance was supported across the different study programs (i.e., physics, math, and math teacher education) within each time point. Next, using the full sample, we were able to confirm strong measurement invariance across the three time points included in the study and for all five expectancy-value constructs (Widaman et al., 2010). Strong measurement invariance is a prerequisite for our latent change analyses and imposes equality constraints on the corresponding factor loadings and intercepts at each time point. Correlated residuals between the same indicator assessed at different time points were specified to account for indicator-specific covariances (Little, 2013). All invariance analyses are reported in the online supplemental materials.

Motivational Changes

To address our first research question (RQ#1) regarding the amount and shape of change in students' course-specific motivations in gateway math courses over time, we tested a multivariate latent change score model including all five expectancy-value constructs. The model showed satisfactory fit to the data (χ^2 = 589.42, *df* = 382, CFI = .986, RMSEA = .023, SRMR = .036). The model-estimated means of and variances in the expectancy-value constructs and latent change scores are shown in Table 2. On average, the students reported moderate to high levels of expectancy and subjective task values at the beginning of the semester (T1) and experienced a motivational decline from the beginning towards the midpoint of the semester (ΔT5T1; see Figure 2). This motivational decline was characterized by significant decreases in students' expectancy, intrinsic value, and utility value ($\Delta M = -0.36$ to -0.30, ps < .001) and corresponding increases in perceived psychological and effort costs ($\Delta M = 0.40$ and $\Delta M = 0.26$, ps < .001; see Table 2). The amount of change in students' expectancy, intrinsic value, utility value and perceived psychological and effort cost from the beginning towards the midpoint (ΔT5T1) was comparable across the five different constructs. The only exception was a smaller increase in effort cost compared to the increase in psychological cost and the decrease in students' intrinsic value (ps ≤ .047; see the online supplemental materials for the full results of the Wald tests). The motivational changes from the midpoint towards the end of the semester in students' expectancy, intrinsic value, and utility value were significant (ΔT6T5: $\Delta M = -0.12$ to -0.08, ps < .05) but substantially smaller than the initial motivational decline (ΔT5T1; ps ≤ .008). The amount of change in students' expectancy, intrinsic value, and utility value did not significantly differ from each other (ΔT6T5; ps ≥ .348).[4]

---

[4] Two sets of supplemental analyses were conducted to describe the implications of missing data in both studies and to test the robustness of our findings (see supplemental materials). First, we replicated our analyses with and without the inclusion of students' individual and background characteristics as auxiliary variables. Second, we replicated our latent change score analyses using only the subsample of students who were present for the end-of-term data collection (T6).

Table 2

Latent Means and Variances of Initial Motivations and Latent Change Scores and Amount of Students Experiencing Significant Changes in Their Motivations in Study 1a

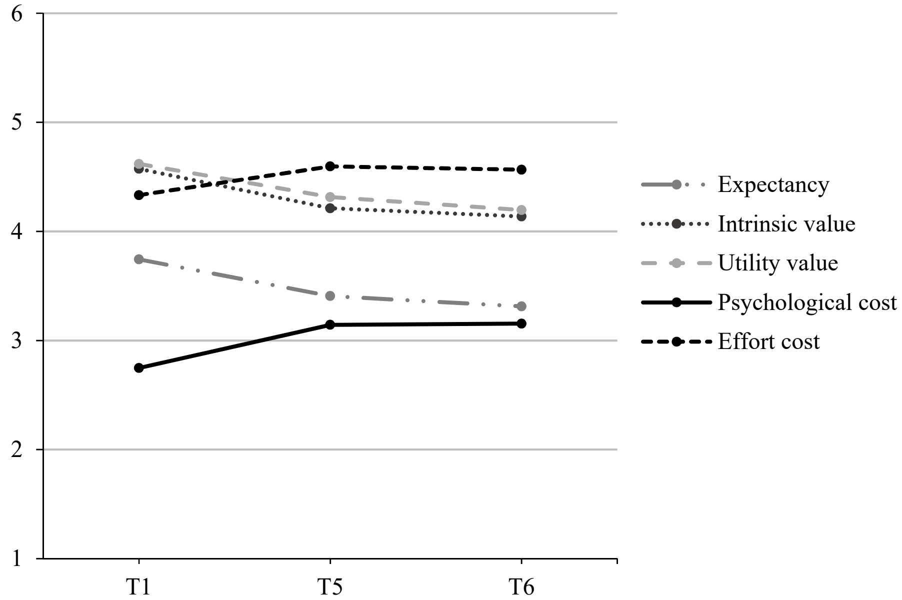
Variable	T1		ΔT5T1		ΔT6T5		ΔT5T1		ΔT6T5	
	M	σ^2	*M*	σ^2	*M*	σ^2	Decrease	Increase	Decrease	Increase
Expectancy	3.74	0.69^{***}	-0.34^{***}	0.45^{***}	-0.09^{**}	0.30^{***}	21% (78%)	4% (22%)	8% (61%)	3% (39%)
Intrinsic value	4.57	0.54^{***}	-0.36^{***}	0.52^{***}	-0.08^{*}	0.33^{***}	17% (77%)	1% (23%)	6% (56%)	2% (44%)
Utility value	4.62	0.88^{***}	-0.30^{***}	0.67^{***}	-0.12^{**}	0.39^{***}	10% (72%)	2% (28%)	5% (60%)	2% (39%)
Psych. cost	2.75	1.01^{***}	0.40^{***}	0.69^{***}	0.01	0.44^{***}	3% (25%)	19% (75%)	4% (50%)	5% (50%)
Effort cost	4.33	1.02^{***}	0.26^{***}	0.83^{***}	−0.03	0.45^{***}	7% (34%)	18% (66%)	6% (55%)	5% (45%)

Note. Plausible values were generated for each latent change score using Bayesian estimation to determine the amount of students experiencing significant changes in their expectancy-value beliefs. The amount of students with negative and positive latent change scores is shown in parentheses. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15). Psych. cost = psychological cost.
$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Analyses of plausible values for all latent change scores (Asparouhov & Muthén, 2010; see Table 2) allowed us to determine the percentage of students who experienced a significant decline or increase in their motivational beliefs (we generated 1,000 plausible values per person for each latent change score using Markov chain Monte Carlo Bayesian estimation). Overall, between 72% and 78% of the students had negative change scores for expectancy, intrinsic value, and utility value, and between 66% and 75% had positive change scores for psychological and effort costs from the beginning towards the midpoint of the semester (ΔT5T1). The analysis of the plausible values and corresponding confidence intervals of the change scores allowed us to examine the proportion of significant changes: Between 10% and 21% of the students experienced significant declines in their expectancy, intrinsic value, and utility value during the first half of the semester, and hardly any students experienced a significant positive change (1%–4%). Analogously, a substantially higher percentage of students experienced significant increases (18%–19%) rather than decreases (3%–7%) in their psychological and effort costs in the first half of the semester. The amount of change in these beliefs from the middle towards the end of the semester was substantially smaller (ΔT6T5; only 2%–8% experienced a significant change from the midpoint towards the end of the semester). Importantly, there were significant interindividual differences in the amount of motivational change experienced by different students, as indicated by the significant variances in all latent change scores (see Table 2). We discuss possible factors that may contribute to these interindividual differences in the following section (corresponding to RQ#2).

Figure 2

Trajectories of Students' Expectancy and Subjective Task Values in Study 1a



Note. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

Predictors of Motivational Changes

To answer our second research question (RQ#2), we included individual characteristics and instructor-/course-specific dummy variables as predictors of students' motivations in our latent change analysis. The model showed satisfactory fit to the data (χ^2 = 868.07, *df* = 525, CFI = .977, RMSEA = .026, SRMR = .031). As shown in Table 3, students' high school GPA was positively related to their initial levels of expectancy, intrinsic value, and utility value and negatively related to perceived cost (T1). In addition, students' high school GPA was a significant positive predictor of changes in their expectancy, intrinsic value, and utility value as well as a significant negative predictor of changes in their psychological cost from the beginning towards the midpoint of the semester (ΔT5T1). Students with higher GPAs not only started the semester with more positive motivational profiles but also experienced comparatively smaller motivational declines (and a smaller increase in psychological cost). However, the potential protective role of prior achievement against declines in desirable academic motivations (e.g., loss of interest) was limited to the beginning of the semester; students' high school GPA did not predict additional changes in expectancies and task values from the midpoint towards the end of the semester (ΔT6T5; see Table 3).

Controlling for differences in high school GPA and family background (see Table 3), we observed that, compared to male students, female students reported somewhat lower levels of expectancy and higher levels of psychological cost at the first measurement point (T1). Both male and female students experienced a motivational decline at the beginning of the semester (ΔT5T1); however, female students experienced a somewhat stronger motivational decline concerning their expectancy of success in the course and perceived utility value, as well as a greater increase in their perceived effort cost. No gender differences emerged for motivational changes from the midpoint towards the end of the semester (ΔT6T5). Students' SES and participation in preparatory math courses had no significant predictive effects on their motivational trajectories, with one exception: Compared to students from more advantageous family backgrounds, students from less advantageous family backgrounds experienced somewhat greater declines in intrinsic value from the midpoint towards the end of the semester (ΔT6T5; see Table 3).

These maladaptive motivational trajectories were universal across all math courses and study programs, but there were some course-specific differences in the percentage of students who experienced a significant negative motivational change. The results were most consistent for the observed declines in students' expectancy and intrinsic value and the observed increase in psychological cost across different courses and study programs (54%–92% of the students in a given course had negative change scores for expectancy and intrinsic value for ΔT5T1, and 61%–91% had a positive change score for psychological cost). Course-specific plausible values are reported in the online supplemental materials.

Motivational Changes as a Predictor of Students' Academic Success

To answer our third research question (RQ#3), we examined the predictive effects of students' initial motivations (T1) and motivational change scores (ΔT5T1 and ΔT6T5) as predictors of their end-of-term study program satisfaction, exam performance, and course dropout, controlling for students' gender, SES, high school GPA, and participation in preparatory math courses as well as instructor-/course-specific dummy variables. These analyses allowed us to determine the potential of short-term motivational changes to serve as early warning signs of later academic difficulties.

Table 3

Standardized Path Coefficients for Predictors of Initial Motivations and Motivational Changes in Study 1a

Predictors	T1	ΔT5T1	ΔT6T5
Expectancy			
Female	−.19***	−.18***	−.02
SES	.01	.02	−.04
High school GPA	.24***	.23***	.11
Preparatory course	−.06	.01	−.04
Math1	−.11**	.17***	−.23***
Math2	−.13**	−.05	−.14*
Teacher1	−.07*	.16***	.00
Teacher2	−.04	.18***	−.06
Intrinsic value			
Female	−.03	−.03	.01
SES	−.01	.01	.13*
High school GPA	.25***	.16**	−.01
Preparatory course	.08*	−.03	.02
Math1	−.15***	.29***	−.24**
Math2	−.17***	.03	−.17*
Teacher1	−.19***	.12*	.05
Teacher2	−.11*	.18***	−.13†
Utility value			
Female	−.02	−.10*	.01
SES	−.02	.05	.07
High school GPA	.11**	.10*	.13
Preparatory course	.08†	−.07	−.01
Math1	−.25***	.09†	−.24***
Math2	−.35***	.00	−.25**
Teacher1	−.23***	.00	−.07
Teacher2	−.31***	.24***	−.29**
Psychological cost			
Female	.16***	.08†	−.09
SES	−.06†	.01	−.04
High school GPA	−.12**	−.17***	.04
Preparatory course	−.04	−.01	.05
Math1	.16***	−.17***	.07
Math2	.26***	−.12*	−.02
Teacher1	.16***	−.17***	.00
Teacher2	.13***	−.18***	.03
Effort cost			
Female	.05	.08*	−.10†
SES	−.03	.00	.02
High school GPA	−.09*	−.06	−.05
Preparatory course	.02	−.02	.10†
Math1	.20***	−.12**	−.04
Math2	.24***	−.17**	−.10†
Teacher1	.10**	−.21***	−.10
Teacher2	.12**	−.20***	−.05

Note. Predictive effects of levels of motivation on motivational changes (T1 → ΔT5T1, T5 → ΔT6T5) as well as predictive effects of early motivational changes on subsequent changes (ΔT5T1 → ΔT6T5) are not shown. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15). Math1, Math2, Teacher1 and Teacher2 = dummy variables for the respective math courses and study programs.

$^{†}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

The latent change models for each of the five expectancy-value constructs, including all control variables as predictors and end-of-term study program satisfaction and exam performance as outcomes, showed satisfactory fit to the data (range of values: χ^2 = 178.79 to 272.27, *df* = 97 to 158, CFI = .957 to .982, RMSEA = .027 to .041, SRMR = .031 to .041). Residual covariances were allowed for items capturing similar content: the two items referencing students' study choice satisfaction and the two items referencing students' overall satisfaction with their study program. Standardized parameter estimates for the predictive effects of students' initial motivational beliefs and motivational changes are shown in Table 4 (see the online supplemental materials for the full results, including all covariates).

Students' initial levels of motivation (T1) significantly predicted their end-of-term study program satisfaction and exam performance in each of the five latent change models. Furthermore, controlling for differences in initial expectancy and task value beliefs and all remaining covariates, we observed that the latent change scores from the beginning towards the midpoint of the semester (ΔT5T1) significantly predicted students' end-of-term study program satisfaction and exam performance across all five models (see Table 4). The only exception was a nonsignificant effect of changes in utility value on exam performance (p = .055). Students who experienced stronger declines in expectancy, intrinsic value, and utility value and comparatively greater increases in psychological and effort costs at the beginning of the semester (ΔT5T1) were less satisfied with their study program at the end of the semester and performed worse on their final exam.

Additional changes in students' expectancy, intrinsic and utility values, and effort cost in the second half of the semester (ΔT6T5) had significant incremental predictive effects on their end-of-term study program satisfaction. Among the five expectancy-value constructs included in this study, only changes in students' expected success and intrinsic value towards the end of the semester (ΔT6T5) had significant incremental predictive effects on their end-of-term exam performance. This pattern of results suggests that the initial motivational decline experienced by students can serve as an early warning sign of later academic difficulties. Students' motivational beliefs were far less variable towards the end of the semester, and changes in these beliefs had negligible incremental predictive effects as a result, despite being more proximal in time to the final exam. Overall, the latent change models explained between 24% and 58% of the variance in students' study program satisfaction and between 31% and 41% of the variance in their exam performance (see Table 4).

Table 4

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in Study 1a

Model and predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Covariates	[a]	[a]	[a]	
R^2	.12	.28	.26	
Expectancy				
T1	$.62^{***}$	$.31^{***}$	$-.17^{***}$	0.84
ΔT5T1	$.39^{***}$	$.27^{***}$	$-.22^{***}$	0.81
ΔT6T5	$.18^{**}$	$.14^{*}$	[b]	
R^2	.51	.41	.31	
Intrinsic value				
T1	$.70^{***}$	$.24^{***}$	$-.18^{***}$	0.84
ΔT5T1	$.48^{***}$	$.20^{**}$	$-.23^{**}$	0.80
ΔT6T5	$.31^{***}$	$.16^{*}$	[b]	
R^2	.58	.36	.31	
Utility value				
T1	$.49^{***}$	$.18^{**}$	.04	1.04
ΔT5T1	$.47^{***}$	$.16^{\dagger}$	−.07	0.93
ΔT6T5	$.26^{*}$	.02	[b]	
R^2	.35	.31	.26	
Psychological cost				
T1	$-.58^{***}$	$-.35^{***}$	$.11^{*}$	1.12
ΔT5T1	$-.35^{***}$	$-.23^{**}$	.04	1.04
ΔT6T5	$-.11^{\dagger}$	−.03	[b]	
R^2	.36	.36	.27	
Effort cost				
T1	$-.42^{***}$	$-.39^{***}$	$.10^{*}$	1.10
ΔT5T1	$-.22^{**}$	$-.17^{**}$	.03	1.03
ΔT6T5	$-.14^{*}$	−.09	[b]	
R^2	.24	.38	.27	

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set focused on the prediction of course dropout. *OR* = odds ratio. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

[a] Covariates were students' gender, SES, high school GPA, participation in preparatory courses, and dummies for the math courses. See the online supplemental materials for the full results, including all covariates.

[b] Students' attrition from their math course implied that no course-specific motivational assessments were available at the end of the semester (T6). The analyses therefore included only the latent change score from the beginning towards the midpoint of the semester.

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Finally, an analogous set of latent change models was conducted for the prediction of students' course dropout. Students' attrition from their math course implied that no course-specific motivational assessments were available at the end of the semester (T6). Accordingly, the analyses included latent change scores only from the beginning towards the midpoint of the semester (ΔT5T1). Students' initial levels of expectancy and intrinsic value (T1) had negative predictive effects and their initial perceived cost had positive predictive effects on students' end-of-term course dropout (see Table 4). The more positive students' motivational profiles were at the beginning of the semester (T1), the lower the likelihood of attrition from the course.

In addition, the motivational decline in students' expectancy and intrinsic value towards the midterm (ΔT5T1) negatively predicted students' course dropout. Students who experienced smaller declines in their expectancy and intrinsic value (i.e., one standard deviation above the sample mean of the change score) were 19% to 20% less likely to drop out of their math course than students with mean-level motivational declines. Overall, the latent change models explained between 26% and 31% of the variance in course dropout.

Summary

The main results in Study 1a suggest that changes in students' motivational beliefs were most likely to occur in the first half of the semester and that these changes were generally maladaptive, i.e., they were characterized by declines in course-specific expectancy beliefs, intrinsic and utility values, and increases in psychological and effort costs (RQ#1). Some students experienced more maladaptive motivational changes than others as a function of their prior achievement and gender (RQ#2). Students' negative motivational changes at the beginning of the semester were a precursor to later academic difficulties, including lower levels of study program satisfaction, end-of-term achievement, and course attendance at the end of the semester (RQ#3).

Study 1b

Study 1b expanded upon Study 1a by conducting fine-grained analyses of students' motivational experiences during the very first weeks of the semester (T1–T4, corresponding to Weeks 2–5 of the semester). These analyses allow us to describe motivational changes shortly after the transition to higher education, to identify at what time point students' course-specific motivations typically begin to decline, and to determine whether situation-specific weekly shifts in students' motivations are related to their personal and background characteristics and are predictive of their end-of-term academic success. The research questions tested in Study 1b were analogous to those in Study 1a and focused on the amount and shape of change in students' motivations (RQ#1), the hypothesized predictors of these motivational changes (RQ#2), and the potential predictive effects of students' motivations on end-of-term academic outcomes (RQ#3). Unlike Study 1a, however, Study 1b focused on weekly motivational changes at the beginning of the semester and used motivational assessments that were not only course specific but also situation specific (i.e., focused on students' perceptions of the coursework that was covered that week). Furthermore, Study 1b allowed us to take advantage of scheduling differences in two of the math courses included in the study. Even though all students in these two courses had to submit their weekly worksheets in their math lecture at the same time, some students attended tutoring sections that were scheduled prior to rather than after their respective lectures. The students who attended a tutoring section prior to their lecture had already received feedback on their worksheet from the previous week at the time of data collection, whereas those whose section took place after the lecture had not. We compared the motivational profiles of these students in supplementary analyses.

Method

Participants and Procedure

Study 1b included five of the six cohorts from Study 1a (i.e., $N = 773$; one of the math cohorts did not participate in the weekly data collections). Study 1b was conducted at the same time and in the same lectures as Study 1a but included additional measurement points at the beginning of the semester. Specifically, in addition to the first data collection at the beginning of the semester (Week 2, T1), Study 1b included weekly surveys in three consecutive weeks (Weeks 3–5, T2–T4). Analogous to Study 1a, the data were collected in the same math lectures when the students were required to submit their solutions to the weekly math worksheets. As noted previously, the students had to pass these worksheets to qualify for their final exam but their course grade was determined solely by their performance on the final exam.

The potential effect of receiving delayed performance feedback on students' motivational trajectories was examined in supplemental analyses across two math courses in which the timing of receiving performance feedback varied between students ($n = 296$; one course in the math program and one in the math teacher education program). In these courses, approximately two-thirds of the students had received their weekly performance feedback at the time of data collection each week, whereas one-third of the students had not because their tutoring section was scheduled after the lecture in which we collected the data.

Measures

Weekly Expectancy and Subjective Task Value Beliefs. Students' expectancy-value beliefs were assessed each week using single items to reduce the survey length and, thus, the potential negative effects of survey fatigue due to repeated exposure to the same items over time (for a similar approach, see Martin et al., 2015; Tanaka & Murayama, 2014). The items focused on the content that was taught and practiced each week in the worksheets and were preceded by the following statement: "Think about the current worksheet you have turned in this week." Students' expectancy was assessed with the item "If the content of the current worksheet comes up on the exam: How well do you think will you perform on the exam?" (1 = *very poorly* to 6 = *very well*). Intrinsic and utility values and perceived psychological and effort costs were assessed with the following items: "Doing this week's assignments is something I enjoyed/…was generally useful/…was stressful for me/…drained a lot of my energy" (1 = *completely disagree* to 6 = *completely agree*).

End-of-Term Academic Outcomes. Analogous to Study 1a, students' study program satisfaction, exam performance, and course dropout were included as outcome variables. One set of analyses focused on the prediction of students' study program satisfaction and exam performance, and a separate set focused on potential course dropout.

Personal and Family Background Characteristics. Analogous to Study 1a, students' gender (36% female), SES (60% high SES), high school GPA (M = 3.1, SD = 0.65), and participation in preparatory math courses (63% participation) as well as instructor-/course-specific dummy variables were included as covariates in all models.

Delayed Performance Feedback. Of the students whose tutoring sections were scheduled either prior to or after their math lecture, 69% of the students received their first performance feedback between T1 and T2, whereas 31% received their first performance feedback between T2 and T3. The timing of students' weekly performance feedback was included as a binary predictor in the analyses (0 = *regular feedback*, 1 = *delayed feedback*). Students in both math courses received scores that reflected what proportion of the math problems were solved correctly on each worksheet.

Statistical Analyses

We used latent change models to examine potential changes in students' expectancy and task values during the first weeks after the transition to higher education in demanding, gateway math courses. Our use of weekly single-item indicators resulted in fully saturated measurement models. Plausible values were estimated for all latent change scores to determine the percentage of students experiencing significant motivational changes from week to week.

Results

Descriptive statistics and correlations between the situation-specific motivational variables across the four-week period are shown in Table 5 and were consistent with our expectations and with the correlational patterns reported in Study 1a. The means reported in Table 5 indicated that students' expectancy, intrinsic value, and utility value decreased sharply from T1 to T2 and remained relatively stable after this initial decline, whereas their psychological and effort costs showed a corresponding increase from T1 to T2 but fluctuated in the following weeks (from T2 through T4).

Motivational Changes

To answer our first research question (RQ#1) concerning the amount and shape of change in students' motivational beliefs, we fit a fully saturated latent change model for all expectancy-value constructs and their corresponding change scores. The model-estimated means of and variances in students' initial motivations and the latent change scores are shown in Table 6. These analyses revealed a "motivational shock" from T1 (Week 2) to T2 (Week 3) that was characterized by a rapid and significant decline in intrinsic and utility values ($\Delta M = -0.92$ and $\Delta M = -0.47$, ps < .001), a somewhat less pronounced but significant decline in students' expectancy ($\Delta M = -0.23$, $p < .001$), and a significant increase in psychological and effort costs ($\Delta M = 0.68$ and $\Delta M = 0.35$, ps < .001; see Figure 3). The mean-level changes were smaller in the following weeks ($\Delta M = -0.08$ to 0.06 for expectancy, intrinsic value, and utility value; $\Delta M = -0.39$ to 0.17 for psychological and effort costs). With the exception of effort cost, students' motivations stabilized at lower levels than their initial status (T1) by the end of the fourth weekly assessment (T4; ps < .001; see the online supplemental materials for the full results of the Wald tests). Additionally, the Wald tests indicated that the magnitude of the initial motivational shock varied between the expectancy-value constructs (ΔT2T1). Intrinsic value showed the most rapid decline compared to the other motivational facets (ps < .001), whereas the decline in students' expectancy was the smallest compared to the changes in the other motivational facets (ps ≤ .024). There was a greater increase in psychological cost than in effort cost ($p < .001$).

Analyses of plausible values for these latent change scores indicated that approximately 27% to 48% of all students experienced the initial motivational shock between T1 and T2 (see Table 6). Specifically, nearly half (48%) of all students experienced a sharp decline in their intrinsic value, and 27% to 41% of all students experienced significant declines in their expectancy of success and utility value and corresponding increases in their perceived cost. A substantially smaller proportion of students experienced positive changes in their motivations during this time (ΔT2T1, 7%–18%; see Table 6). This motivational shock coincided with the first time the students had received performance feedback on their weekly assignments. Analogous to Study 1a, we found significant interindividual differences in the amount of change in students' motivations across the four-week period, as indicated by the significant variances in all latent change scores (see Table 6).

Table 5

Descriptive Statistics and Observed Bivariate Correlations in Study 1b

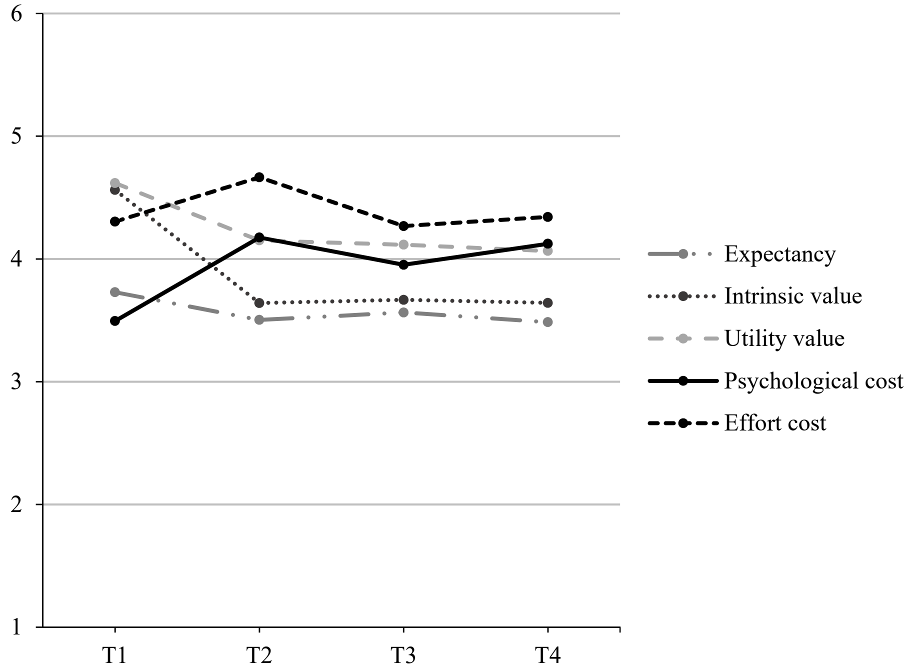
Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. Expectancy T1	—																			
2. Intrinsic value T1	.44**	—																		
3. Utility value T1	.27**	.34**	—																	
4. Psych. cost T1	−.49**	−.39**	−.23**	—																
5. Effort cost T1	−.43**	−.25**	−.07	.59**	—															
6. Expectancy T2	.50**	.24**	.05	−.27**	−.23**	—														
7. Intrinsic value T2	.22**	.31**	.05	−.13*	−.07	.48**	—													
8. Utility value T2	.16**	.23**	.26**	−.10*	.01	.31**	.53**	—												
9. Psych. cost T2	−.24**	−.12**	.02	.31**	.29**	−.43**	−.30**	−.12**	—											
10. Effort cost T2	−.21**	−.05	.12**	.20**	.33**	−.42**	−.21**	−.03	.74**	—										
11. Expectancy T3	.56**	.28**	.14**	−.35**	−.34**	.55**	.24**	.13**	−.28**	−.27**	—									
12. Intrinsic value T3	.39**	.41**	.18**	−.26**	−.20**	.33**	.40**	.28**	−.18**	−.11*	.54**	—								
13. Utility value T3	.32**	.31**	.31**	−.18**	−.11**	.19**	.22**	.42**	−.08	.01	.34**	.58**	—							
14. Psych. cost T3	−.40**	−.27**	−.09*	.46**	.45**	−.34**	−.16**	−.08	.47**	.39**	−.53**	−.38**	−.22**	—						
15. Effort cost T3	−.33**	−.19**	−.02	.36**	.46**	−.31**	−.09*	−.02	.40**	.46**	−.45**	−.25**	−.07	.77**	—					
16. Expectancy T4	.48**	.26**	.07	−.35**	−.37**	.52**	.27**	.19**	−.27**	−.25**	.57**	.35**	.26**	−.36**	−.31**	—				
17. Intrinsic value T4	.28**	.33**	.05	−.22**	−.14**	.34**	.48**	.34**	−.14**	−.06	.30**	.45**	.29**	−.14**	.00	.56**	—			
18. Utility value T4	.19**	.33**	.29**	−.18**	−.07	.23**	.29**	.47**	−.03	.05	.28**	.38**	.52**	−.12**	−.01	.39**	.56**	—		
19. Psych. cost T4	−.30**	−.14**	.03	.34**	.34**	−.28**	−.15**	−.10*	.46**	.34**	−.27**	−.19**	−.12**	.48**	.40**	−.43**	−.34**	−.16**	—	
20. Effort cost T4	−.25**	−.08	.07	.26**	.41**	−.26**	−.06	.00	.39**	.40**	−.25**	−.14**	−.04	.43**	.46**	−.36**	−.13**	.01	.73**	—
M	3.73	4.57	4.62	3.49	4.31	3.56	3.70	4.17	4.13	4.62	3.60	3.72	4.13	3.92	4.25	3.55	3.71	4.09	4.11	4.34
SD	.90	.87	1.13	1.35	1.15	1.08	1.20	1.07	1.33	1.24	1.10	1.10	1.03	1.39	1.25	1.03	1.14	1.03	1.25	1.18
N	684	692	683	691	693	617	619	615	621	620	582	585	583	584	585	557	557	554	553	555
Skewness	−.16	−.44	−.88	.11	−.37	−.11	−.38	−.70	−.43	−.80	−.39	−.56	−.57	−.20	−.36	−.30	−.47	−.71	−.27	−.52
Kurtosis	.29	.39	.74	−.70	−.34	−.19	−.34	.42	−.61	.00	.05	.02	.34	−.85	−.54	−.05	−.16	.61	−.64	−.24

Note. $N = 773$. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester. Psych. cost = psychological cost.

$^{*}p < .05$. $^{**}p < .01$.

Figure 3

Trajectories of Students' Expectancy and Subjective Task Values in Study 1b



Note. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester.

Table 6

Latent Means and Variances of Initial Motivations and Latent Change Scores and Amount of Students Experiencing Significant Changes in Their Motivations in Study 1b

Variable	T1		ΔT2T1		ΔT3T2		ΔT4T3		ΔT2T1		ΔT3T2		ΔT4T3	
	M	σ^2	*M*	σ^2	*M*	σ^2	*M*	σ^2	Decr.	Incr.	Decr.	Incr.	Decr.	Incr.
Expectancy	3.73	0.83^{***}	-0.23^{***}	0.99^{***}	0.06	1.06^{***}	$-0.08^{\dagger}$	0.97^{***}	27% (60%)	16% (36%)	18% (45%)	21% (51%)	20% (52%)	13% (44%)
Intrinsic value	4.56	0.77^{***}	-0.92^{***}	1.52^{***}	0.03	1.58^{***}	−0.03	1.37^{***}	48% (83%)	7% (14%)	21% (49%)	21% (48%)	20% (51%)	18% (46%)
Utility value	4.62	1.27^{***}	-0.47^{***}	1.81^{***}	−0.03	1.28^{***}	−0.05	1.03^{***}	36% (67%)	16% (29%)	20% (52%)	19% (46%)	18% (51%)	15% (46%)
Psych. cost	3.49	1.82^{***}	0.68^{***}	2.49^{***}	-0.22^{***}	2.01^{***}	0.17^{**}	1.88^{***}	15% (28%)	41% (69%)	28% (55%)	19% (42%)	16% (45%)	24% (52%)
Effort cost	4.30	1.33^{***}	0.35^{***}	1.85^{***}	-0.39^{***}	1.71^{***}	0.07	1.63^{***}	18% (37%)	34% (60%)	32% (65%)	15% (34%)	17% (46%)	23% (51%)

Note. Plausible values were generated for each latent change score using Bayesian estimation to determine the amount of students experiencing significant changes in their expectancy-value beliefs. The amount of students with negative and positive latent change scores is shown in parentheses. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester. Psych. cost = psychological cost. Decr. = decrease, Incr. = increase. † *p* < .10. * *p* < .05. ** *p* < .01. *** *p* < .001.

Predictors of Motivational Changes

Next, we examined whether students' short-term motivational trajectories differed as a function of their personal and family background characteristics and respective math course (RQ#2). In general, the results were analogous to those in Study 1a. As shown in Table 7, students' high school GPA was a negative predictor of all three estimated latent change scores for students' expectancy (ΔT2T1, ΔT3T2, ΔT4T3) and a negative predictor of the first two latent change scores for intrinsic value (ΔT2T1, ΔT3T2). Thus, high school GPA served as a buffer against declines in these motivational beliefs across the four-week period. However, students' high school GPA was not consistently linked to changes in their utility value and perceived cost. Notably, and in contrast to Study 1a, students' high school GPA was a positive predictor of the initial increase in their psychological and effort costs; students with comparatively higher levels of prior achievement experienced stronger increases in their perceived cost in the first two weeks of the semester (ΔT2T1). This result suggests that relative to low-achieving students, high-achieving students may be more likely to increase their level of effort in the face of challenging coursework. We return to this point in the discussion.

Similar to Study 1a, we found small but significant gender differences in students' motivational trajectories in the first weeks of the semester (see Table 7). The initial decline in students' expectancy was more pronounced for female students than for male students, and there was a tendency towards a greater decline in female students' intrinsic value (ΔT2T1). Additionally, male students showed a greater decline in psychological and effort costs than female students after the initial motivational shock (ΔT3T2), which is a sign of potential "recovery" from the motivational shock that appears to be gender specific. Students' SES significantly predicted the initial decline in intrinsic and utility values (ΔT2T1) but was unrelated to further changes in their task values and expectancy across the four-week period. Students who had participated in optional preparatory math courses experienced a slightly greater recovery in their effort cost after the initial motivational shock (ΔT3T2), but they also experienced a greater increase in their psychological cost towards the end of the four-week period (ΔT4T3).

The identified motivational shock was observed in all math courses and study programs, but the amount of change varied across courses (see the course-specific plausible values in the online supplemental materials). The sharp decline in students' intrinsic value was universal across courses (ΔT2T1), whereas the onset of the decline in students' expectancy beliefs and utility value and the corresponding increase in their perceived cost varied across different courses.

Table 7

Standardized Path Coefficients for Predictors of Initial Motivations and Motivational Changes in Study 1b

Predictors	T1	ΔT2T1	ΔT3T2	ΔT4T3
Expectancy				
Female	$-.16^{***}$	$-.11^{**}$	$-.04$	$-.03$
SES	$-.03$	$.02$	$.02$	$.01$
High school GPA	$.24^{***}$	$.09^{*}$	$.15^{***}$	$.11^{*}$
Preparatory course	$-.05$	$.01$	$.03$	$.00$
Math2	$-.15^{***}$	$.29^{***}$	$-.15^{**}$	$-.27^{***}$
Teacher1	$-.09^{*}$	$.18^{***}$	$.01$	$-.05$
Teacher2	$-.08^{*}$	$.31^{***}$	$-.18^{***}$	$-.17^{**}$
Intrinsic value				
Female	$-.02$	$-.06^{\dagger}$	$-.03$	$-.02$
SES	$-.03$	$.08^{*}$	$-.04$	$.00$
High school GPA	$.18^{***}$	$.10^{*}$	$.07^{*}$	$.07$
Preparatory course	$.05$	$.04$	$.03$	$-.02$
Math2	$-.16^{***}$	$.28^{***}$	$-.07^{\dagger}$	$-.20^{**}$
Teacher1	$-.12^{**}$	$.20^{***}$	$-.04$	$-.07$
Teacher2	$-.10^{*}$	$.24^{***}$	$-.17^{***}$	$-.10^{\dagger}$
Utility value				
Female	$-.03$	$-.03$	$-.05$	$-.02$
SES	$.00$	$.07^{*}$	$.06$	$-.01$
High school GPA	$.07^{*}$	$.05$	$.08^{*}$	$.00$
Preparatory course	$.10^{*}$	$.02$	$.02$	$-.06$
Math2	$-.31^{***}$	$.11^{**}$	$-.15^{**}$	$-.22^{**}$
Teacher1	$-.24^{***}$	$.09^{**}$	$-.03$	$-.09^{\dagger}$
Teacher2	$-.30^{**}$	$.13^{***}$	$-.12^{**}$	$-.08$
Psychological cost				
Female	$.15^{***}$	$-.03$	$.07^{*}$	$.01$
SES	$-.05$	$-.01$	$-.02$	$.06$
High school GPA	$-.11^{**}$	$.08^{*}$	$-.03$	$-.09^{\dagger}$
Preparatory course	$-.03$	$-.03$	$-.06$	$.11^{*}$
Math2	$.30^{***}$	$-.32^{***}$	$.07$	$.15^{*}$
Teacher1	$.18^{***}$	$-.12^{***}$	$-.05$	$.02$
Teacher2	$.17^{***}$	$-.22^{***}$	$.14^{***}$	$.04$
Effort cost				
Female	$.07^{\dagger}$	$-.02$	$.06^{\dagger}$	$-.03$
SES	$.00$	$.03$	$-.04$	$-.01$
High school GPA	$-.11^{**}$	$.09^{**}$	$-.04$	$-.04$
Preparatory course	$.03$	$.02$	$-.07^{*}$	$.05$
Math2	$.25^{***}$	$-.43^{***}$	$.06$	$.20^{**}$
Teacher1	$.09^{*}$	$-.15^{***}$	$-.06$	$.05$
Teacher2	$.12^{**}$	$-.30^{***}$	$.12^{**}$	$.09$

Note. Predictive effects of levels of motivation on motivational changes (T1 → ΔT2T1, T2 → ΔT3T2, T3 → ΔT4T3) as well as predictive effects of early motivational changes on subsequent changes (ΔT2T1 → ΔT3T2, ΔT3T2 → ΔT4T3) are not shown. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester. Math2, Teacher1 and Teacher2 = dummy variables for the respective math courses and study programs.
$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Supplemental Analyses of Delayed Performance Feedback. Finally, supplemental analyses were conducted to examine whether the delay in receiving performance feedback each week had a significant effect on students' motivational trajectories. Receiving delayed performance feedback had a significant positive effect on changes in students' expectancy and a significant negative effect on change in students' psychological and effort costs (ΔT2T1; see Table 8). Students who received their first performance feedback on the mandatory worksheets a week later, and thus did not know their level of performance at the time of data collection (T2, which corresponded to Week 3), experienced a smaller decline in their expected success as well as smaller increases in their psychological and effort costs from T1 (Week 2) to T2 (Week 3) than students who had already received performance feedback. No significant differences in students' motivational trajectories between the two groups emerged for the remaining change scores (ΔT3T2, ΔT4T3). This finding suggests that receiving performance feedback appears to be a contributing factor to the motivational shock experienced in the first weeks of the semester.[5]

Motivational Changes as a Predictor of Students' Academic Success

Analogous to Study 1a and corresponding to our third research question (RQ#3), we modeled separate latent change models for the five expectancy-value constructs as predictors of students' end-of-term academic success. These models showed satisfactory fit to the data (range of values: χ^2 = 91.86 to 103.23, df = 51, CFI = .968 to .980, RMSEA = .032 to .036, SRMR = .033 to .038; see the online supplemental materials). Standardized parameter estimates for the predictive effects of the latent change scores (ΔT2T1, ΔT3T2, ΔT4T3) on students' end-of-term study program satisfaction and exam performance, controlling for students' background characteristics and math course, are shown in Table 9 (see the online supplemental materials for the full results, including all covariates).

[5] These two groups of students did not differ with regard to prior achievement (high school GPA: $M_{\text{regularFeedback}}$ = 3.22, $M_{\text{delayedFeedback}}$ = 3.23; $F(1, 264) = 0.012$, $p = .911$) and the number of points they received on their worksheet ($M_{\text{regularFeedback}}$ = 64.5, $M_{\text{delayedFeedback}}$ = 59.2; $F(1, 213) = 2.358$, $p = .126$).

Table 8

Predictive Effects of Delayed Performance Feedback on Motivational Changes in Study 1b

Predictors	T1	ΔT2T1	ΔT3T2	ΔT4T3
Expectancy				
Female	−.19**	−.12†	−.14*	.04
SES	.01	−.03	−.01	.03
High school GPA	.07	.06	.16**	.07
Preparatory course	−.10†	.10	.01	−.02
Math2	.02	−.15*	.09	.01
Delayed feedback	−.07	.14*	.08	−.03
Intrinsic value				
Female	−.03	−.01	−.05	.04
SES	.04	−.01	−.11†	.05
High school GPA	.09	.10	.02	−.05
Preparatory course	−.04	.07	−.02	−.04
Math2	.01	−.05	.21***	−.01
Delayed feedback	−.10	.05	−.01	−.03
Utility value				
Female	−.08	.02	−.01	−.08
SES	.04	−.03	.09	.07
High school GPA	−.02	.08†	.05	−.07
Preparatory course	.10	−.01	−.04	−.10
Math2	.13*	−.06	.05	−.06
Delayed feedback	−.08	.06	.01	−.04
Psychological cost				
Female	.13*	−.09†	.14*	.04
SES	−.11†	−.07	.05	.00
High school GPA	−.08	.09	−.04	−.13†
Preparatory course	.02	−.10†	−.01	.22**
Math2	.04	−.01	−.14*	.11†
Delayed feedback	.06	−.12*	−.02	.07
Effort cost				
Female	.07	−.08	.14*	.07
SES	.00	−.02	.07	−.01
High school GPA	−.07	.09	.00	−.05
Preparatory course	.10	−.01	−.06	.13†
Math2	.05	.00	−.15*	.10
Delayed feedback	−.01	−.14*	−.07	.04

Note. n = 296. Predictive effects of levels of motivation on motivational changes (T1 → ΔT2T1, T2 → ΔT3T2, T3 → ΔT4T3) as well as predictive effects of early motivational changes on subsequent changes (ΔT2T1 → ΔT3T2, ΔT3T2 → ΔT4T3) are not shown. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester. Math2 = dummy variable for the respective math course and study program.

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Controlling for students' initial motivations (T1) and all hypothesized control variables, we observed that the motivational shock in the first weeks of the semester (ΔT2T1) emerged as a significant predictor of students' study program satisfaction and exam performance across all five expectancy-value models. The only exception was a nonsignificant predictive effect of students' experienced change in intrinsic value on their exam performance (p = .056). Thus, the greater the motivational shock experienced by students in the very first weeks of the semester, the less satisfied they were with their study program, and the worse they performed on their final exam. In addition, students who experienced a greater recovery or smaller additional declines in their motivations after the initial shock (ΔT3T2) were comparatively more satisfied with their study program and had superior performance on the final exam. Only three of the tested predictive effects failed to reach significance (changes in intrinsic value failed to predict students' exam performance, p = .067, and changes in effort cost, p = .084, and psychological cost, p = .110, failed to predict their end-of-term study program satisfaction). Further motivational changes in the following week (ΔT4T3) had mostly nonsignificant incremental predictive effects on students' end-of-term study program satisfaction and exam performance across the five models. Overall, the latent change models explained between 20% and 41% of the variance in students' study program satisfaction and between 32% and 39% of the variance in their exam performance.

Finally, a set of latent change models for the prediction of students' course dropout was tested (see Table 9). Controlling for students' initial motivations and background characteristics, we observed that all three latent change scores for students' expectancy and intrinsic value (ΔT2T1, ΔT3T2, ΔT4T3) had negative predictive effects on students' course dropout. Students who experienced a smaller motivational shock in their expectancy and intrinsic value (ΔT2T1, i.e., one standard deviation above the sample mean), as well as a greater recovery in their expectancy and intrinsic value in the following weeks (ΔT3T2, ΔT4T3), were between 13% and 25% less likely to drop out of their math course. Across all four time points, changes in cost and utility value failed to predict course dropout, with only one exception (change in perceived utility at the end of the observation period, ΔT4T3, p = .032). Overall, the latent change models explained between 24% and 30% of the variance in course dropout.

Summary

The analyses in Study 1b expand upon the evidence presented in Study 1a by demonstrating a "motivational shock" in the very first weeks of the semester that is characterized by a rapid decline in students' academic motivations and, in particular, in their intrinsic interest (RQ#1). Although, on average, students' motivational beliefs appear to stabilize during the following weeks—a potential sign of adaptation to the new learning environment and demands—students experience an overall motivational decline by the end of the observation period (T1–T4). The first provision of weekly performance feedback appeared to contribute to this motivational shock. Female students and students with comparatively lower prior performance experienced more negative motivational trajectories (RQ#2). The observed motivational shock in the very first weeks of the semester was predictive of end-of-term academic outcomes and can thus be interpreted as an early warning sign of later academic difficulties (RQ#3).

Table 9

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in Study 1b

Model and predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Covariates	[a]	[a]	[a]	
R^2	.11	.27	.24	
Expectancy				
T1	$.64^{***}$	$.33^{***}$	$-.22^{***}$	0.80
ΔT2T1	$.40^{***}$	$.38^{***}$	$-.23^{**}$	0.80
ΔT3T2	$.26^{**}$	$.20^{**}$	$-.29^{***}$	0.75
ΔT4T3	.09	.02	$-.14^{*}$	0.87
R^2	.41	.39	.30	
Intrinsic value				
T1	$.55^{***}$	$.26^{***}$	$-.22^{***}$	0.80
ΔT2T1	$.37^{***}$	$.20^{\dagger}$	$-.26^{***}$	0.77
ΔT3T2	$.28^{***}$	$.17^{\dagger}$	$-.29^{***}$	0.75
ΔT4T3	.04	.02	$-.14^{*}$	0.87
R^2	.33	.34	.29	
Utility value				
T1	$.47^{***}$	$.23^{**}$	.00	1.00
ΔT2T1	$.37^{**}$	$.26^{*}$	−.05	0.95
ΔT3T2	$.30^{**}$	$.21^{*}$	−.09	0.91
ΔT4T3	.11	−.02	$-.14^{*}$	0.87
R^2	.20	.32	.25	
Psychological cost				
T1	$-.58^{***}$	$-.40^{***}$	$.15^{*}$	1.16
ΔT2T1	$-.44^{***}$	$-.41^{***}$	.11	1.12
ΔT3T2	−.14	$-.29^{**}$	.09	1.09
ΔT4T3	.01	$-.13^{\dagger}$	.07	1.07
R^2	.31	.34	.25	
Effort cost				
T1	$-.38^{***}$	$-.37^{***}$	$.09^{\dagger}$	1.10
ΔT2T1	$-.30^{**}$	$-.28^{**}$	.02	1.02
ΔT3T2	$-.15^{\dagger}$	$-.24^{**}$	.00	1.00
ΔT4T3	−.03	$-.20^{**}$	.00	1.00
R^2	.20	.35	.24	

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set focused on the prediction of course dropout. *OR* = odds ratio. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester.

[a] Covariates were students' gender, SES, high school GPA, participation in preparatory courses, and dummies for the math courses. See online supplemental materials for full results, including all covariates.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

General Discussion

Our research focused on the development of students' expectancy and subjective task values shortly after the transition to higher education in math-intensive study programs and examined interindividual differences in students' motivational trajectories and the predictive effects of these motivational changes on students' academic success. Our findings in both studies underscore the importance of examining short-term changes in students' expectancy and subjective task values after the transition to higher education. First, whereas Study 1a corroborates prior research that has documented a motivational decline over the course of a semester (Kosovich et al., 2017; Zusho et al., 2003), Study 1b is the first to document a motivational shock in the very first weeks of the semester in demanding gateway math courses. In addition, we found motivational declines in all math courses, indicating that these declines were fairly generalizable across the different math-intensive study programs in our study. Second, we found that students' situated expectancy and task value beliefs did not follow the same trajectory across the first weeks of the semester in Study 1b, which underscores the importance of considering different facets of SEVT to better understand students' educational experiences. Third, the identified motivational declines across both studies significantly predicted students' end-of-term study program satisfaction, exam performance, and course dropout. Thus, our data suggest that short-term motivational declines function as early warning signs of academic difficulties and dropout tendencies. Finally, our findings have implications for the design of motivational interventions and suggest that construct- and context-specific interventions are needed in the very first weeks of the semester to support students' academic success and to potentially prevent dropout from math-intensive study programs. We discuss our main findings in detail in the following sections.

Motivational Changes: Why Short-Term Assessments Matter

Consistent with prior evidence (Kosovich et al., 2017; Perez et al., 2014; Zusho et al., 2003), Study 1a revealed a motivational decline over one semester after the transition to higher education. Whereas prior research had mostly studied composite scores of students' task value (Dresel & Grassinger, 2013; Zusho et al., 2003) or focused on single task value facets (e.g., utility value; Kosovich et al., 2017), we examined the trajectories of different facets of the expectancy-value framework over one semester in gateway math courses. We found that students' expectancy, intrinsic value, and utility value decreased and that their perceived psychological and effort costs increased across the semester. This motivational decline was mostly limited to the first half of the semester, which is in line with prior evidence in introductory college courses that has documented greater declines in students' motivations in the first half than in the second half of a semester (Kosovich et al., 2017; Zusho et al., 2003).

Importantly, our analyses in Study 1b extend prior research by documenting a motivational shock in the very first weeks of the semester that is characterized by a sharp decline in students' intrinsic and utility values, a comparatively smaller decline in their expected success, and an increase in their perceived psychological and effort costs. Study 1a indicated a much smaller motivational decline across the first half of the semester, compared to the sizeable motivational shock in the first weeks of the semester observed in Study 1b. This discrepancy suggests that students partially recovered from the initial motivational shock by mid-semester. Thus, students' motivations do not appear to show a steady decline over one semester but, instead, change in a nonlinear fashion shortly after the transition to higher education. This developmental pattern of students' expectancy-value beliefs is consistent with the assumption of a period of adaptation to the new learning environment (Eccles & Midgley, 1989).

In addition, our results suggest that different expectancy-value beliefs do not change at the same rate after the transition to higher education. Even though the trajectories of students' course-specific motivations in Study 1a were similar for the five expectancy-value constructs, we found that students' situated expectancies and task values did not follow the same trajectory in Study 1b. The initial motivational shock was particularly pronounced for students' subjective task values, which appear to be more sensitive to the new educational context in math-intensive study programs than students' expectancy. In addition, students' initial task values were somewhat higher than their initial levels of expectancy (with the exception of psychological cost, which was comparable) so that there was greater potential for change in students' task values than in expectancy.

The transition from school math to learning university-level math might be a contributing factor to the strong declines in students' intrinsic and utility values and the corresponding increase in their perceived cost. This transition is accompanied by a shift in the nature of math content from applied math in school to math as a scientific discipline (Gueudet, 2008). Thus, students might have unrealistic expectations of the math content and day-to-day coursework in university math courses, which might explain the rapid changes in their subjective task values.

Relatedly, our finding that students' expectancy beliefs changed at a smaller rate after the transition to higher education than their task values differs from prior studies, which found greater declines in students' expectancy or competence-related beliefs than in their task values (Kosovich et al., 2017; Perez et al., 2014; Perez et al., 2019; but see Zusho et al., 2003). Context-specific differences in the type of performance evaluations and exams may contribute to these discrepancies (Church et al., 2001). Prior studies in the US have shown that students' exam performance during the semester significantly predicts declines in competence-related beliefs (Kosovich et al., 2017; Perez et al., 2014). In contrast, German students usually do not take graded exams during the semester. In our study, as is typical for German universities, students had to pass weekly worksheets to quality for the final exam, but they were allowed to collaborate with other students and their level of performance on the worksheets had no bearing on their final grade. The lack of high-stakes exams during the semester may thus explain the smaller decline in expectancy than in task values in Study 1b.

Furthermore, students' psychological cost showed a larger increase than their effort cost across both studies, which deviates from previous research in which the opposite pattern was found (Perez et al., 2014; Perez et al., 2019; Robinson et al., 2019). However, the students in our study reported high effort cost already at the beginning of the semester (compared to moderate levels of psychological cost), likely due to preconceptions about the high workload in math-intensive study programs or their experiences with the coursework in preparatory math courses. Thus, even though effort cost did not change as much, it remained at a relatively high level throughout the study. The stronger increase in students' psychological rather than effort cost in our study may at least in part be due to assessment differences relative to prior research. We assessed psychological cost using situation-specific measures (e.g., feeling stressed or nervous while working on the weekly assignments), whereas the assessments used in prior research have often referenced relatively stable and global attitudes towards failure or declines in students' self-esteem (e.g., Perez et al., 2014).

Predictors of Motivational Changes

Across both studies, we found relatively small but notable differences in students' motivational trajectories as a function of their gender, SES, prior achievement (i.e., high school GPA), and participation in preparatory math courses. Notably, however, our sample consisted primarily of male, high-achieving students from high-SES backgrounds, which may diminish the predictive power of these variables. Nevertheless, our findings indicate that female students and students with comparatively lower high school GPAs are at risk of experiencing more negative motivational trajectories across the transition to higher education. These results are consistent with prior evidence showing that prior achievement serves as a buffer against later motivational declines (Robinson et al., 2019; Sonnert et al., 2015). Unexpectedly, we found that students' psychological and effort costs in Study 1b increased more for students with comparatively higher high school GPAs. This result suggests that high- and low-achieving students may show different processes of adaptation to the high demands of their math-intensive study programs. High-achieving students may be more likely to increase their level of effort in the face of challenge and negative feedback, thus leading to higher levels of perceived cost, whereas low-achieving students may instead adjust their levels of aspiration and expected success (Vancouver et al., 2008; Vancouver et al., 2002). Even though the observed gender differences in students' motivational trajectories were relatively small, they consistently favored male students over female students, which is in line with prior evidence (Robinson et al., 2019; Sonnert et al., 2015; Watt, 2004). The identified gender differences were mostly limited to students' expectancy and perceived cost, suggesting that gender stereotypes may play a role in the development of female students' expectancy and cost perceptions (Ertl et al., 2017).

Notably, motivational declines were observed in all math courses, which points to a relatively generalizable process of adjusting to the instructional climate of math-intensive study programs in our sample (e.g., high workload, instructors' fixed ability mindsets, grading on a curve; see Seymour & Hewitt, 1997; Sonnert et al., 2015). However, course-specific differences in students' motivational trajectories emerged as well; whereas the sharp decline in students' intrinsic value shortly after the transition to college was observed in all courses, students' expectancy, utility value, and perceived cost changed rapidly in some courses but more gradually in others. Course-specific differences in the math content covered each week or different instructional practices may be a contributing factor to these discrepancies.

Finally, the supplemental analyses in Study 1b showed that not only the exposure to challenging content but also receiving performance feedback is a contributing factor to the students' motivational shock in the first weeks of the semester. Accordingly, the provision of motivationally supportive performance feedback might be a promising avenue to decrease the motivational shock experienced by students at the beginning of the semester. Such feedback practices include, for instance, formative feedback practices that instruct students on how to improve their study strategies and performance as well as instructional adaptations that take into account the needs of individual students (Fong et al., 2019; Jonsson, 2013; Shute, 2008).

Motivational Changes as a Predictor of Students' Academic Success

Our analyses across both studies revealed that short-term changes in students' expectancy and subjective task values—including the motivational shock observed in Study 1b—were predictive of their end-of-term exam performance, study program satisfaction, and course dropout. Thus, not only are the motivational declines shortly after the transition to higher education a sign of students' adaptation to the new educational context and demands of math-intensive study programs, but they also serve as predictors of students' academic success at the end of their first semester in college (see also Dresel & Grassinger, 2013; Kosovich et al., 2017). Our results thus point to the potential of early motivational interventions to reduce student dropout and improve students' well-being and performance in math-intensive study programs. Maladaptive motivational changes were most likely to occur in the first weeks of the semester; thus, motivational interventions should be administered in the early stages of students' college careers (Canning et al., 2018; Hulleman et al., 2017). For instance, Canning et al. (2018) found that writing about the perceived usefulness of the course content improved students' final exam grades in an introductory biology course and increased students' likelihood of enrolling in a subsequent course. Notably, students who were most at risk for low academic achievement (i.e., students with a history of poor performance) benefitted the most if the intervention was administered in the first weeks of the semester. Our study suggests that students' motivations are most likely to decline during this time.

Furthermore, students' task values were more vulnerable to motivational declines than students' expectancy in the first weeks of the semester. Therefore, interventions targeting students' valuing of academic content are needed to support students' academic success in math-intensive programs. Emerging evidence suggests that motivational interventions based on Eccles et al.'s SEVT can benefit not only the values that are explicitly targeted in these interventions (e.g., utility and intrinsic values) but also nontargeted facets of the expectancy-value framework (Hulleman et al., 2017; Rosenzweig et al., 2020). For instance, Rosenzweig et al. (2020) found that a cost reduction and a utility value intervention improved students' exam scores in a physics course in college by boosting initially lower-performing students' competence-related beliefs. Implementing motivational interventions shortly after the transition to higher education that target students' subjective task values may thus be a fruitful approach to buffering students from motivational declines and thus increasing their academic success and retention in math-intensive study programs.

Limitations and Directions for Future Research

Our research is the first to examine short-term changes in students' expectancy and subjective task values immediately after the transition to higher education in math-intensive study programs and to document a motivational shock experienced by students in the first weeks of college. However, several limitations must be considered in the interpretation of our findings. First, our research focused specifically on math courses at the beginning of higher education, as such courses typically function as gatekeepers in the STEM domain (Seymour & Hewitt, 1997). Therefore, the generalizability of the identified motivational shock to other domains remains unclear. Research in the school context has shown greater declines in students' motivations in math courses than in English courses over one academic term (Mac Iver et al., 1991). It is thus possible that the motivational shock is at least partially inherent to the context of (university) math, and to a lesser extent linked to a general process of adapting to higher education. Further research in other contexts and study domains is therefore needed.

Second, our study focused on the short-term development of students' expectancy and task values since academic difficulties in gateway math courses can stall students' progression towards a STEM degree (Seymour & Hewitt, 1997), and the majority of students who drop out of math-intensive study programs do so within their first year in college (Heublein et al., 2017). However, analyses beyond this critical period are needed to examine the potential long-term consequences of the motivational shock for students' degree completion, overall GPA, and study program dropout.

Third, 39% of the students were no longer attending their math course by the end of the semester, which we defined as course dropout. However, even though this high level of attrition is similar to the dropout rates reported in other studies in gateway math courses (e.g., 38%; Rach & Heinze, 2017), we were unable to unambiguously determine the reason why these students were not present in class. Monitoring students' behaviors outside of class would have been necessary to answer this question.

Fourth, even though our study is one of the first to assess short-term changes in different facets of the expectancy-value framework, we did not include students' attainment value and opportunity cost in our study due to length constraints and concerns about survey fatigue. Relatedly, our reliance on two-item scales in Study 1a and single-items in Study 1b is a limitation because we used a limited number of indicators to describe different facets of the expectancy-value framework. In recent years, broader measures tapping different subfacets of the expectancy-value framework have been developed (e.g., utility for daily life vs. utility for job; Gaspard, Dicke, Flunger, Schreier, et al., 2015). Examining a broader array of constructs and corresponding short-term changes may provide further insight into which facets may be particularly malleable after the transition to a new educational context and could thus be targeted in educational interventions.

Finally, the sample of our research was relatively homogeneous in terms of the students' gender, family background, and prior achievement, and the covariates included in our study were insufficient to explain the motivational shock found in our study. More work is needed to better understand which factors contribute to students' recovery from the initial motivational shock and to support students who are most at risk of negative motivational trajectories after the transition to higher education. Such factors might include students' mindset beliefs about the fixedness or malleability of their abilities or students' perceptions of their instructors' mindset beliefs (Dweck & Yeager, 2019; Muenks et al., 2020). Relatedly, our latent change score analyses were limited to average trajectories of students' expectancy-value beliefs across the first weeks and first semester at university. Other methodological approaches such as growth mixture modeling (Muthén, 2004) would be suitable to explore if there are groups of students with qualitatively different trajectories across the first semester in math-intensive study programs and may be able to identify specific at-risk-groups that could benefit from early interventions (e.g., Gaspard et al., 2020).

Conclusion

Understanding the reasons for students' decisions to persist in or drop out of math-intensive study programs is an important objective to increase the involvement of talented youth in the STEM domain. Our study examined the developmental trajectories of students' expectancy-value beliefs shortly after the transition to higher education and investigated the role of short-term motivational changes as potential warning signs of later academic difficulties in gatekeeper math courses. Our analyses suggest that students experienced a motivational shock immediately after the transition to higher education that was in part linked to their first performance feedback. Our analyses identified interindividual differences in students' motivational trajectories as a function of their gender, prior achievement, SES, and their respective math course and study program. However, a motivational shock was observed in all courses, suggesting that many students were experiencing a period of adaptation to the high demands and the instructional climate in the math-intensive study programs included in our study. The motivational shock served as a risk factor for later academic difficulties and course dropout at the end of the first semester in college. Thus, analyses of motivational trajectories should consider not only the long-term but also the short-term changes in students' motivations to better understand their decisions to persist in or drop out of math-intensive programs. Short-term motivational changes are not only a concomitant of students' adaptation to a novel and challenging learning environment but also a predictor of their subsequent performance, persistence, and well-being in the STEM domain.

References

Allensworth, E. M., & Clark, K. (2020). High school GPAs and ACT scores as predictors of college completion: Examining assumptions about consistency across high schools. *Educational Researcher, 49*(3), 198–211. https://doi.org/10.3102/0013189X20902110

Asparouhov, T., & Muthén, B. (2010). *Plausible values for latent variables using Mplus*. http://www.statmodel.com/download/Plausible.pdf

Bergey, B. W., Parrila, R. K., & Deacon, S. H. (2018). Understanding the academic motivations of students with a history of reading difficulty: An expectancy-value-cost approach. *Learning and Individual Differences, 67*, 41–52. https://doi.org/10.1016/j.lindif.2018.06.008

Bong, M. (2005). Within-grade changes in Korean girls' motivation and perceptions of the learning environment across domains and achievement levels. *Journal of Educational Psychology, 97*(4), 656–672. https://doi.org/10.1037/0022-0663.97.4.656

Borghans, L., Golsteyn, B. H., Heckman, J. J., & Humphries, J. E. (2016). What grades and achievement tests measure. *Proceedings of the National Academy of Sciences, 113*(47), 13354–13359. https://doi.org/10.1073/pnas.1601135113

Canning, E. A., Harackiewicz, J. M., Priniski, S. J., Hecht, C. A., Tibbetts, Y., & Hyde, J. S. (2018). Improving performance and retention in introductory biology with a utility-value intervention. *Journal of Educational Psychology, 110*(6), 834–849. https://doi.org/10.1037/edu0000244

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal, 14*(3), 464–504. https://doi.org/10.1080/10705510701301834

Chen, X. (2013). *STEM attrition: College students' paths into and out of STEM fields. Statistical Analysis Report (NCES 2014-001)*. National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. https://nces.ed.gov/pubs2014/2014001rev.pdf

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling, 9*(2), 233–255. https://doi.org/10.1207/S15328007SEM0902_5

Chouinard, R., & Roy, N. (2008). Changes in high-school students' competence beliefs, utility value and achievement goals in mathematics. *British Journal of Educational Psychology, 78*(1), 31–50. https://doi.org/10.1348/000709907X197993

Church, M. A., Elliot, A. J., & Gable, S. L. (2001). Perceptions of classroom environment, achievement goals, and achievement outcomes. *Journal of Educational Psychology, 93*(1), 43–54. https://doi.org/10.1037/0022-0663.93.1.43

Dietrich, J., Moeller, J., Guo, J., Viljaranta, J., & Kracke, B. (2019). In-the-Moment Profiles of Expectancies, Task Values, and Costs. *Frontiers in Psychology, 10*. https://doi.org/10.3389/fpsyg.2019.01662

Dietrich, J., Viljaranta, J., Moeller, J., & Kracke, B. (2017). Situational expectancies and task values: Associations with students' effort. *Learning and Instruction, 47*, 53–64. https://doi.org/10.1016/j.learninstruc.2016.10.009

Ditton, H. (1998). Studieninteresse, kognitive Fähigkeiten und Studienerfolg [Interest in studying, cognitive abilities, and study success]. In J. Abel & C. Tarnai (Eds.), *Pädagogisch-psychologische Interessenforschung in Studium und Beruf* (pp. 45–59). Waxmann.

Dresel, M., & Grassinger, R. (2013). Changes in achievement motivation among university freshmen. *Journal of Education and Training Studies, 1*(2), 159–173. https://doi.org/10.11114/jets.v1i2.147

Dweck, C. S., & Yeager, D. S. (2019). Mindsets: A view from two eras. *Perspectives on Psychological Science, 14*(3), 481–496. https://doi.org/10.1177/1745691618804166

Eccles, J. S., Adler, T., Futterman, R., Goff, S., Kaczala, C., Meece, J., & Midgley, C. (1983). Expectancies, values, and academic behaviors. In J. T. Spence (Ed.), *Achievement and achievement motives* (pp. 75–146). Freeman.

Eccles, J. S., & Midgley, C. (1989). Stage-environment fit: Developmentally appropriate classrooms for young adolescents. In C. Ames & R. Ames (Eds.), *Research on motivation in education: Goals and cognitions* (Vol. 3, pp. 139–186). Academic Press.

Eccles, J. S., & Wigfield, A. (1995). In the mind of the actor: The structure of adolescents' achievement task values and expectancy-related beliefs. *Personality and Social Psychology Bulletin, 21*(3), 215–225. https://doi.org/10.1177/0146167295213003

Eccles, J. S., & Wigfield, A. (2020). From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation. *Contemporary Educational Psychology, 61*. https://doi.org/10.1016/j.cedpsych.2020.101859

Ertl, B., Luttenberger, S., & Paechter, M. (2017). The impact of gender stereotypes on the self-concept of female students in STEM subjects with an under-representation of females. *Frontiers in Psychology, 8*. https://doi.org/10.3389/fpsyg.2017.00703

Faas, C., Benson, M. J., Kaestle, C. E., & Savla, J. (2018). Socioeconomic success and mental health profiles of young adults who drop out of college. *Journal of Youth Studies, 21*(5), 669–686. https://doi.org/10.1080/13676261.2017.1406598

Finney, S. J., & Schraw, G. (2003). Self-efficacy beliefs in college statistics courses. *Contemporary Educational Psychology, 28*(2), 161–186. https://doi.org/10.1016/S0361-476X(02)00015-2

Flake, J. K., Barron, K. E., Hulleman, C., McCoach, B. D., & Welsh, M. E. (2015). Measuring cost: The forgotten component of expectancy-value theory. *Contemporary Educational Psychology, 41*, 232–244. https://doi.org/10.1016/j.cedpsych.2015.03.002

Fong, C. J., Patall, E. A., Vasquez, A. C., & Stautberg, S. (2019). A meta-analysis of negative feedback on intrinsic motivation. *Educational Psychology Review, 31*, 121–162. https://doi.org/10.1007/s10648-018-9446-6

Gaspard, H., Dicke, A.-L., Flunger, B., Brisson, B. M., Häfner, I., Nagengast, B., & Trautwein, U. (2015). Fostering adolescents' value beliefs for mathematics with a relevance intervention in the classroom. *Developmental Psychology, 51*(9), 1226–1240. https://doi.org/10.1037/dev0000028

Gaspard, H., Dicke, A.-L., Flunger, B., Schreier, B., Häfner, I., Trautwein, U., & Nagengast, B. (2015). More value through greater differentiation: Gender differences in value beliefs about math. *Journal of Educational Psychology, 107*(3), 663–677. https://doi.org/10.1037/edu0000003

Gaspard, H., Lauermann, F., Rose, N., Wigfield, A., & Eccles, J. S. (2020). Cross-domain trajectories of students' ability self-concepts and intrinsic values in math and language arts. *Child Development, 91*(5), 1800–1818. https://doi.org/10.1111/cdev.13343

Gaspard, H., Wille, E., Wormington, S. V., & Hulleman, C. S. (2019). How are upper secondary school students' expectancy-value profiles associated with achievement and university STEM major? A cross-domain comparison. *Contemporary Educational Psychology, 58*, 149–162. https://doi.org/10.1016/j.cedpsych.2019.02.005

Goetz, T., Bieg, M., Lüdtke, O., Pekrun, R., & Hall, N. C. (2013). Do girls really experience more anxiety in mathematics? *Psychological Science, 24*(10), 2079–2087. https://doi.org/10.1177/0956797613486989

Graham, J. W. (2003). Adding missing-data-relevant variables to FIML-based structural equation models. *Structural Equation Modeling, 10*(1), 80–100. https://doi.org/10.1207/S15328007SEM1001_4

Griffith, A. L. (2010). Persistence of women and minorities in STEM field majors: Is it the school that matters? *Economics of Education Review, 29*(6), 911–922. https://doi.org/10.1016/j.econedurev.2010.06.010

Grimm, K. J., An, Y., McArdle, J. J., Zonderman, A. B., & Resnick, S. M. (2012). Recent changes leading to subsequent changes: Extensions of multivariate latent difference score models. *Structural Equation Modeling, 19*(2), 268–292. https://doi.org/10.1080/10705511.2012.659627

Gueudet, G. (2008). Investigating the secondary–tertiary transition. *Educational Studies in Mathematics, 67*(3), 237–254. https://doi.org/10.1007/s10649-007-9100-6

Guo, J., Parker, P. D., Marsh, H. W., & Morin, A. J. (2015). Achievement, motivation, and educational choices: A longitudinal study of expectancy and value using a multiplicative perspective. *Developmental Psychology, 51*(8), 1163–1176. https://doi.org/10.1037/a0039440

Hardin, E. E., & Longhurst, M. O. (2016). Understanding the gender gap: Social cognitive changes during an introductory stem course. *Journal of Counseling Psychology, 63*(2), 233–239. https://doi.org/10.1037/cou0000119

Heublein, U., Ebert, J., Hutzsch, C., Isleib, S., König, R., Richter, J., & Woisch, A. (2017). *Zwischen Studienerwartungen und Studienwirklichkeit: Ursachen des Studienabbruchs, beruflicher Verbleib der Studienabbrecherinnen und Studienabbrecher und Entwicklung der Studienabbruchquote an deutschen Hochschulen [Between study expectations and reality: Causes of student dropout, occupational status of dropouts, and the development of dropout rates at German universities]*. Deutsches Zentrum für Hochschul-und Wissenschaftsforschung (DZHW). https://www.dzhw.eu/pdf/pub_fh/fh-201701.pdf

Heublein, U., & Schmelzer, R. (2018). *Die Entwicklung der Studienabbruchquoten an den deutschen Hochschulen [The development of dropout rates at German universities]*. Deutsches Zentrum für Hochschul- und Wissenschaftsforschung (DZHW). https://www.dzhw.eu/pdf/21/studienabbruchquoten_absolventen_2016.pdf

Hulleman, C. S., Kosovich, J. J., Barron, K. E., & Daniel, D. B. (2017). Making connections: Replicating and extending the utility value intervention in the classroom. *Journal of Educational Psychology, 109*(3), 387–404. https://doi.org/10.1037/edu0000146

Isleib, S. (2019). Soziale Herkunft und Studienabbruch im Bachelor- und Masterstudium [Social background and student dropout in bachelor and master programs]. In M. Lörz & H. Quast (Eds.), *Bildungs- und Berufsverläufe mit Bachelor und Master* (pp. 307–337). Springer. https://doi.org/10.1007/978-3-658-22394-6_10

Isphording, I., & Qendrai, P. (2019). *Gender differences in student dropout in STEM (IZA research report no. 87)*. Institute of Labor Economics (IZA). http://ftp.iza.org/report_pdfs/iza_report_87.pdf

Jacobs, J. E., Lanza, S., Osgood, D. W., Eccles, J. S., & Wigfield, A. (2002). Changes in children's self-competence and values: Gender and domain differences across grades one through twelve. *Child Development, 73*(2), 509–527. https://doi.org/10.1111/1467-8624.00421

Jansen, M., Lüdtke, O., & Robitzsch, A. (2020). Disentangling different sources of stability and change in students' academic self-concepts: An integrative data analysis using the STARTS model. *Journal of Educational Psychology, 112*(8), 1614–1631. https://doi.org/10.1037/edu0000448

Johnson, M. L., Edwards, O. V., & Dai, T. (2014). Growth trajectories of task value and self-efficacy across an academic semester. *Universal Journal of Educational Research, 2*(1), 10–18. https://doi.org/10.13189/ujer.2014.020102

Jonsson, A. (2013). Facilitating productive use of feedback in higher education. *Active Learning in Higher Education, 14*(1), 63–76. https://doi.org/10.1177/1469787412467125

Kosovich, J. J., Flake, J. K., & Hulleman, C. S. (2017). Short-term motivation trajectories: A parallel process model of expectancy-value. *Contemporary Educational Psychology, 49*, 130–139. https://doi.org/10.1016/j.cedpsych.2017.01.004

Lauermann, F., Meißner, A., & Steinmayr, R. (2020). Relative importance of intelligence and ability self-concept in predicting test performance and school grades in the math and language arts domains. *Journal of Educational Psychology, 112*(2), 364–383. https://doi.org/10.1037/edu0000377

Lauermann, F., Tsai, Y.-M., & Eccles, J. S. (2017). Math-related career aspirations and choices within Eccles et al.'s expectancy-value theory of achievement-related behaviors. *Developmental Psychology, 53*(8), 1540–1559. https://doi.org/10.1037/dev0000367

Lent, R. W., Miller, M. J., Smith, P. E., Watford, B. A., Lim, R. H., & Hui, K. (2016). Social cognitive predictors of academic persistence and performance in engineering: Applicability across gender and race/ethnicity. *Journal of Vocational Behavior, 94*, 79–88. https://doi.org/10.1016/j.jvb.2016.02.012

Linnenbrink-Garcia, L., Patall, E. A., & Pekrun, R. (2016). Adaptive motivation and emotion in education: Research and principles for instructional design. *Policy Insights from the Behavioral and Brain Sciences, 3*(2), 228–236. https://doi.org/10.1177/2372732216644450

Little, T. D. (2013). *Longitudinal structural equation modeling*. Guilford Press.

Mac Iver, D. J., Stipek, D. J., & Daniels, D. H. (1991). Explaining within-semester changes in student effort in junior high school and senior high school courses. *Journal of Educational Psychology, 83*(2), 201–211. https://doi.org/10.1037/0022-0663.83.2.201

Marsh, H. W., Hau, K.-T., & Grayson, D. (2005). Goodness of fit in structural equation models. In A. Maydeu-Olivares & J. J. McArdle (Eds.), *Contemporary psychometrics: A festschrift for Roderick P. McDonald* (pp. 275–340). Erlbaum.

Marsh, H. W., & Martin, A. J. (2011). Academic self-concept and academic achievement: Relations and causal ordering. *British Journal of Educational Psychology, 81*(1), 59–77. https://doi.org/10.1348/000709910X503501

Martin, A. J., Papworth, B., Ginns, P., Malmberg, L.-E., Collie, R. J., & Calvo, R. A. (2015). Real-time motivation and engagement during a month at school: Every moment of every day for every student matters. *Learning and Individual Differences, 38*, 26–35. https://doi.org/10.1016/j.lindif.2015.01.014

McArdle, J. J. (2009). Latent variable modeling of differences and changes with longitudinal data. *Annual Review of Psychology, 60*, 577–605. https://doi.org/10.1146/annurev.psych.60.110707.163612

Metcalfe, J. (1998). Cognitive optimism: Self-deception or memory-based processing heuristics? *Personality and Social Psychology Review, 2*(2), 100–110. https://doi.org/10.1207/s15327957pspr0202_3

Muenks, K., Canning, E. A., LaCosse, J., Green, D. J., Zirkel, S., Garcia, J. A., & Murphy, M. C. (2020). Does my professor think my ability can change? Students' perceptions of their STEM professors' mindset beliefs predict their psychological vulnerability, engagement, and performance in class. *Journal of Experimental Psychology: General, 149*(11), 2119–2144. https://doi.org/10.1037/xge0000763

Muthén, B. (2004). Latent variable analysis: Growth mixture modeling and related techniques for longitudinal data. In D. Kaplan (Ed.), *The Sage handbook of quantitative* *methodology for the social sciences* (pp. 345–369). Sage. https://doi.org/10.4135/9781412986311.n19

Nagengast, B., Marsh, H. W., Scalas, L. F., Xu, M. K., Hau, K.-T., & Trautwein, U. (2011). Who took the "×" out of expectancy-value theory? A psychological mystery, a substantive-methodological synergy, and a cross-national generalization. *Psychological Science, 22*(8), 1058–1066. https://doi.org/10.1177/0956797611415540

Nagy, G., Watt, H. M., Eccles, J. S., Trautwein, U., Lüdtke, O., & Baumert, J. (2010). The development of students' mathematics self-concept in relation to gender: Different countries, different trajectories? *Journal of Research on Adolescence, 20*(2), 482–506. https://doi.org/10.1111/j.1532-7795.2010.00644.x

Nauta, M. M. (2007). Assessing college students' satisfaction with their academic majors. *Journal of Career Assessment, 15*(4), 446–462. https://doi.org/10.1177/1069072707305762

Nowell, C., & Alston, R. M. (2007). I thought I got an A! Overconfidence across the economics curriculum. *The Journal of Economic Education, 38*(2), 131–142. https://doi.org/10.3200/JECE.38.2.131-142

Organisation for Economic Co-operation and Development [OECD]. (2019). *Education at a Glance 2019*. OECD Publishing. https://doi.org/10.1787/f8d7880d-en

Parker, P. D., Schoon, I., Tsai, Y.-M., Nagy, G., Trautwein, U., & Eccles, J. S. (2012). Achievement, agency, gender, and socioeconomic background as predictors of postschool choices: A multicontext study. *Developmental Psychology, 48*(6), 1629–1642. https://doi.org/10.1037/a0029167

Paulus, W., & Matthes, B. (2013). *Klassifikation der Berufe: Struktur, Codierung und Umsteigeschlüssel [Classification of occupations: Structure, coding, and conversion key]*. Forschungsdatenzentrum (FDZ) der Bundesagentur für Arbeit im Institut für Arbeitsmarkt- und Berufsforschung. http://doku.iab.de/fdz/reporte/2013/MR_08-13.pdf

Perez, T., Cromley, J. G., & Kaplan, A. (2014). The role of identity development, values, and costs in college STEM retention. *Journal of Educational Psychology, 106*(1), 315–329. https://doi.org/10.1037/a0034027

Perez, T., Dai, T., Kaplan, A., Cromley, J. G., Brooks, W. D., White, A. C., Mara, K. R., & Balsai, M. J. (2019). Interrelations among expectancies, task values, and perceived costs in undergraduate biology achievement. *Learning and Individual Differences, 72*, 26–38. https://doi.org/10.1016/j.lindif.2019.04.001

President's Council of Advisors on Science and Technology. (2012). *Engage to excel: Producing one million additional college graduates with degrees in science, technology, engineering, and mathematics.* Executive Office of the President. https://obamawhitehouse.archives.gov/sites/default/files/microsites/ostp/pcast-engage-to-excel-final_2-25-12.pdf

Rach, S., & Heinze, A. (2017). The transition from school to university in mathematics: Which influence do school-related variables have? *International Journal of Science* *and Mathematics Education, 15*(7), 1343–1363. https://doi.org/10.1007/s10763-016-9744-8

Rieger, S., Göllner, R., Spengler, M., Trautwein, U., Nagengast, B., & Roberts, B. W. (2017). Social cognitive constructs are just as stable as the Big Five between grades 5 and 8. *AERA Open, 3*(3), 1–9. https://doi.org/10.1177/2332858417717691

Robinson, K. A., Lee, Y.-K., Bovee, E. A., Perez, T., Walton, S. P., Briedis, D., & Linnenbrink-Garcia, L. (2019). Motivation in transition: Development and roles of expectancy, task values, and costs in early college engineering. *Journal of Educational Psychology, 111*(6), 1081–1102. https://doi.org/10.1037/edu0000331

Rosenzweig, E. Q., & Wigfield, A. (2016). STEM motivation interventions for adolescents: A promising start, but further to go. *Educational Psychologist, 51*(2), 146–163. https://doi.org/10.1080/00461520.2016.1154792

Rosenzweig, E. Q., Wigfield, A., & Hulleman, C. S. (2020). More useful or not so bad? Examining the effects of utility value and cost reduction interventions in college physics. *Journal of Educational Psychology, 112*(1), 166–182. https://doi.org/10.1037/edu0000370

Sackett, P. R., Kuncel, N. R., Arneson, J. J., Cooper, S. R., & Waters, S. D. (2009). Does socioeconomic status explain the relationship between admissions tests and post-secondary academic performance? *Psychological Bulletin, 135*(1), 1–22. https://doi.org/10.1037/a0013978

Schafer, J. L., & Graham, J. W. (2002). Missing data: Our view of the state of the art. *Psychological Methods, 7*(2), 147–177. https://doi.org/10.1037//1082-989X.7.2.147

Schneider, M., & Preckel, F. (2017). Variables associated with achievement in higher education: A systematic review of meta-analyses. *Psychological Bulletin, 143*(6), 565–600. https://doi.org/10.1037/bul0000098

Schneider, M., & Yin, L. (2011). *The high cost of low graduation rates: How much does dropping out of college really cost?* American Institutes for Research. https://www.air.org/sites/default/files/downloads/report/AIR_High_Cost_of_Low_Graduation_Aug2011_0.pdf

Schoon, I., & Polek, E. (2011). Teenage career aspirations and adult career attainment: The role of gender, social background and general cognitive ability. *International Journal of Behavioral Development, 35*(3), 210–217. https://doi.org/10.1177/0165025411398183

Seymour, E., & Hewitt, N. (1997). *Talking about leaving: Why undergraduates leave the sciences*. Westview Press.

Shute, V. J. (2008). Focus on formative feedback. *Review of Educational Research, 78*(1), 153–189. https://doi.org/10.3102/0034654307313795

Sonnert, G., Sadler, P. M., Sadler, S. M., & Bressoud, D. M. (2015). The impact of instructor pedagogy on college calculus students' attitude toward mathematics. *International Journal of Mathematical Education in Science and Technology, 46*(3), 370–387. https://doi.org/10.1080/0020739X.2014.979898

Starr, A., Betz, E. L., & Menne, J. (1972). Differences in college student satisfaction: Academic dropouts, nonacademic dropouts and nondropouts. *Journal of Counseling Psychology, 19*(4), 318–322. https://doi.org/10.1037/h0033083

Steinmayr, R., & Spinath, B. (2009). The importance of motivation as a predictor of school achievement. *Learning and Individual Differences, 19*(1), 80–90. https://doi.org/10.1016/j.lindif.2008.05.004

Tanaka, A., & Murayama, K. (2014). Within-person analyses of situational interest and boredom: Interactions between task-specific perceptions and achievement goals. *Journal of Educational Psychology, 106*(4), 1122–1134. https://doi.org/10.1037/a0036659

Tsai, Y.-M., Kunter, M., Lüdtke, O., Trautwein, U., & Ryan, R. M. (2008). What makes lessons interesting? The role of situational and individual factors in three school subjects. *Journal of Educational Psychology, 100*(2), 460–472. https://doi.org/10.1037/0022-0663.100.2.460

Vancouver, J. B., More, K. M., & Yoder, R. J. (2008). Self-efficacy and resource allocation: support for a nonmonotonic, discontinuous model. *Journal of Applied Psychology, 93*(1), 35–47. https://doi.org/10.1037/0021-9010.93.1.35

Vancouver, J. B., Thompson, C. M., Tischner, E. C., & Putka, D. J. (2002). Two studies examining the negative effect of self-efficacy on performance. *Journal of Applied Psychology, 87*(3), 506–516. https://doi.org/10.1037/0021-9010.87.3.506

Wach, F., Karbach, J., Ruffing, S., Brünken, R., & Spinath, F. M. (2016). University students' satisfaction with their academic studies: Personality and motivation matter. *Frontiers in Psychology, 7*. https://doi.org/10.3389/fpsyg.2016.00055

Walpole, M. (2003). Socioeconomic status and college: How SES affects college experiences and outcomes. *The Review of Higher Education, 27*(1), 45–73. https://doi.org/10.1353/rhe.2003.0044

Wang, M.-T. (2012). Educational and career interests in math: A longitudinal examination of the links between classroom environment, motivational beliefs, and interests. *Developmental Psychology, 48*(6), 1643–1657. https://doi.org/10.1037/a0027247

Wang, M.-T., & Degol, J. L. (2017). Gender gap in science, technology, engineering, and mathematics (STEM): Current knowledge, implications for practice, policy, and future directions. *Educational Psychology Review, 29*, 119–140. https://doi.org/10.1007/s10648-015-9355-x

Watt, H. M. (2004). Development of adolescents' self-perceptions, values, and task perceptions according to gender and domain in 7th-through 11th-grade Australian students. *Child Development, 75*(5), 1556–1574. https://doi.org/10.1111/j.1467-8624.2004.00757.x

Weidinger, A. F., Spinath, B., & Steinmayr, R. (2020). The value of valuing math: Longitudinal links between students' intrinsic, attainment, and utility values and grades in math. *Motivation Science, 6*(4), 413–422. https://doi.org/10.1037/mot0000179

Westermann, R., Elke, H., Spies, K., & Trautwein, U. (1996). Identifikation und Erfassung von Komponenten der Studienzufriedenheit [Identifying and assessing components of student satisfaction]. *Psychologie in Erziehung und Unterricht, 43*, 1–22.

Widaman, K. F., Ferrer, E., & Conger, R. D. (2010). Factorial invariance within longitudinal structural equation models: Measuring the same construct across time. *Child Development Perspectives, 4*(1), 10–18. https://doi.org/10.1111/j.1750-8606.2009.00110.x

Wigfield, A., & Cambria, J. (2010). Expectancy-value theory: Retrospective and prospective. In T. C. Urdan & S. A. Karabenick (Eds.), *Advances in motivation and achievement: Vol. 16A. The decade ahead: Theoretical perspectives on motivation and achievement* (pp. 35–70). Emerald Group Publishing Limited. https://doi.org/10.1108/S0749-7423(2010)000016A005

Wigfield, A., & Eccles, J. S. (2000). Expectancy–value theory of achievement motivation. *Contemporary Educational Psychology, 25*(1), 68–81. https://doi.org/10.1006/ceps.1999.1015

Wigfield, A., & Eccles, J. S. (2020). 35 years of research on students' subjective task values and motivation: A look back and a look forward. In A. Elliot (Ed.), *Advances in motivation science* (Vol. 7, pp. 161–198). Elsevier. https://doi.org/10.1016/bs.adms.2019.05.002

Wigfield, A., Tonks, S. M., & Klauda, S. L. (2016). Expectancy-value theory. In K. R. Wentzel & D. B. Miele (Eds.), *Handbook of motivation at school* (2 ed., pp. 55–74). Routledge. https://doi.org/10.4324/9781315773384.ch4

Zusho, A., Pintrich, P. R., & Coppola, B. (2003). Skill and will: The role of motivation and cognition in the learning of college chemistry. *International Journal of Science Education, 25*(9), 1081–1094. https://doi.org/10.1080/0950069032000052207

Supplemental Materials:

Students' Motivational Trajectories and Academic Success in Math-Intensive Study Programs: Why Short-Term Motivational Assessments Matter

Supplement S1. Full List of Self-Report Items Used in Study 1a and Study 1b
Supplement S2. Tests of Measurement Invariance Across Study Programs, Gender, SES, Participation in Preparatory Math Courses, and Time in Study 1a
Supplement S3. Plausible Values by Study Program in Study 1a and Study 1b
Supplement S4. Wald Tests of Parameter Constraints for Motivational Changes in Study 1a and Study 1b
Supplement S5. Model Fit of Latent Change Models for the Five Expectancy-Value Constructs Including Students' Study Program Satisfaction and Exam Performance in Study 1a and Study 1b
Supplement S6. Standardized Path Coefficients for Predictors of Students' Study Program Satisfaction, Exam Performance, and Course Dropout Estimated in the Latent Change Models for the Five Expectancy-Value Constructs in Study 1a and Study 1b
Supplement S7. Supplemental Analyses Concerning Missing Data in Study 1a and Study 1b

Supplement S1. Full List of Self-Report Items Used in Study 1a and Study 1b

Table S1

List of Self-Report Items Used in Study 1a and Study 1b

Construct	Instruction and items (translated from German)
Course-specific expectancy-value beliefs (Weeks 2, 8, and 15)	
Expectancy	Based on my experiences in this class, I think I will do well on the exam.[a]
	Based on my experiences in this class, I think I am good at my major.[a]
	Based on my experiences in this class, I think I will perform at a high level.[a]
Intrinsic value	Doing the coursework and the assignments for this class is something I enjoy.[a]
	Doing the coursework and the assignments for this class is interesting.[a]
Utility value	Doing the coursework and the assignments for this class is useful for my future.[a]
	Doing the coursework and the assignments for this class is important because one just needs the content.[a]
Psychological cost	Doing the coursework and the assignments for this class is stressful for me.[a]
	Doing the coursework and the assignments for this class makes me really nervous.[a]
Effort cost	Doing the coursework and the assignments for this class is exhausting for me.[a]
	Doing the coursework and the assignments for this class drains a lot of my energy.[a]
Situation-specific expectancy-value beliefs in Study 1b (Weeks 3–5)	
	Think about the current worksheet you have turned in this week:
Expectancy	If the content of the current worksheet comes up on the exam: How well do you think will you perform on the exam?[b]
Intrinsic value	Doing this week's assignments is something I enjoyed.[a]
Utility value	Doing this week's assignments was generally useful.[a]
Psychological cost	Doing this week's assignments was stressful for me.[a]
Effort cost	Doing this week's assignments drained a lot of my energy.[a]
Study program satisfaction	I am certain that my study program is the right choice for me.[c]
	I am certain that my study program is a good fit for me.[c]
	In general, I am very satisfied with my study program.[a]
	In general, I am satisfied with the type of work in my study program.[a]
	I oftentimes think about dropping out of or switching my study program.[a]

Note. [a] 6-point scale ranging from 1 = *completely disagree* to 6 = *completely agree*. [b] 6-point scale ranging from 1 = *very poorly* to 6 = *very well*. [c] 6-point scale ranging from 1 = *very uncertain* to 6 = *very certain.*

Supplement S2. Tests of Measurement Invariance Across Study Programs, Gender, SES, Participation in Preparatory Math Courses, and Time in Study 1a

In the following tables, tests of measurement invariance across students' study programs, gender, family background (SES), and participation in preparatory math courses as well as across time are reported. In the configural model, the factor structure was constrained to be equal across groups or time. The model testing weak invariance was specified by additionally constraining the factor loadings to be equal across groups or time. Finally, in the model testing strong measurement invariance, item intercepts were additionally constrained to be the same across groups or time.

Table S2.1

Multigroup Analyses by Study Program in Study 1a

Models and Time Points	χ^2	*df*	CFI	TLI	RMSEA	SRMR	ΔCFI	ΔRMSEA
T1								
Configural[a]	211.00	105	.974	.959	.058	.051	—	—
Weak[a]	217.37	117	.976	.966	.054	.056	−.002	.004
Strong (partial)[ab]	250.54	127	.970	.961	.057	.061	.006	−.003
T5								
Configural[a]	156.48	105	.988	.981	.046	.035	—	—
Weak[a]	170.73	117	.987	.982	.045	.046	.001	.001
Strong[a]	228.37	129	.977	.970	.058	.056	.010	−.013
T6								
Configural[a]	136.77	105	.989	.983	.042	.035	—	—
Weak[a]	162.50	117	.985	.979	.047	.056	.004	−.005
Strong (partial)[abc]	187.17	126	.980	.973	.053	.066	.005	−.006

Note. In all models, one factor loading per construct was fixed at 1.0 for model identification purposes. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

[a] The error variance for one of the items assessing utility value was estimated to be very close to zero and not significant, and had negative values in some of our models. This error variance was therefore fixed at zero for the multigroup analyses.

[b] The intercept of one item assessing psychological cost was freely estimated across groups.

[c] The intercept of one item assessing expectancy was freely estimated in the math teacher education group.

Table S2.2
Multigroup Analyses by Gender in Study 1a

Models and Time Points	χ^2	*df*	CFI	TLI	RMSEA	SRMR	ΔCFI	ΔRMSEA
T1								
Configural	173.87	68	.974	.958	.059	.041	—	—
Weak	184.77	74	.973	.959	.058	.046	.001	.001
Strong	199.63	80	.970	.959	.058	.047	.003	.000
T5								
Configural	119.23	68	.987	.979	.047	.030	—	—
Weak	128.17	74	.986	.979	.047	.036	.001	.000
Strong	142.88	80	.984	.978	.048	.036	.002	−.001
T6								
Configural	107.19	68	.987	.978	.048	.030		
Weak	112.13	74	.987	.981	.046	.035	.000	.002
Strong	122.45	80	.985	.980	.046	.037	.002	.000

Note. In all models, one factor loading per construct was fixed at 1.0 for model identification purposes. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

Table S2.3
Multigroup Analyses by Family Background (SES) in Study 1a

Models and Time Points	χ^2	*df*	CFI	TLI	RMSEA	SRMR	ΔCFI	ΔRMSEA
T1								
Configural	170.54	68	.970	.951	.062	.044	—	—
Weak	176.16	74	.970	.956	.059	.048	.000	.003
Strong	179.97	80	.971	.960	.056	.049	−.001	.003
T5								
Configural	122.37	68	.984	.975	.052	.031	—	—
Weak	130.55	74	.984	.976	.051	.038	.000	.001
Strong	133.23	80	.985	.979	.047	.038	−.001	.004
T6								
Configural[a]	113.33	70	.984	.974	.053	.034	—	—
Weak[a]	120.52	76	.983	.976	.051	.042	.001	.002
Strong[a]	124.25	82	.984	.979	.048	.040	−.001	.003

Note. In all models, one factor loading per construct was fixed at 1.0 for model identification purposes. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

[a] The error variance for one of the items assessing psychological cost was estimated to be very close to zero and not significant, and had negative values in some of our models. This error variance was therefore fixed at zero for the multigroup analysis at T6.

Table S2.4

Multigroup Analyses by Participation in Preparatory Math Courses in Study 1a

Models and Time Points	χ^2	*df*	CFI	TLI	RMSEA	SRMR	ΔCFI	ΔRMSEA
T1								
Configural	136.52	68	.979	.966	.052	.037	—	—
Weak	143.64	74	.979	.969	.050	.042	.000	.002
Strong	147.21	80	.980	.972	.047	.044	−.001	.003
T5								
Configural	130.77	68	.984	.975	.052	.032	—	—
Weak	135.96	74	.984	.977	.050	.036	.000	.002
Strong	144.04	80	.984	.978	.049	.037	.000	.001
T6								
Configural	88.27	68	.992	.987	.036	.032	—	—
Weak	91.77	74	.993	.989	.032	.036	−.001	.004
Strong	98.14	80	.993	.990	.031	.036	.000	.001

Note. In all models, one factor loading per construct was fixed at 1.0 for model identification purposes. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

Table S2.5

Tests of Measurement Invariance Across Time in Study 1a

Models	χ^2	*df*	CFI	TLI	RMSEA	SRMR	ΔCFI	ΔRMSEA
Freely estimated parameters (configural)[a]	534.83	358	.988	.982	.022	.032	—	—
Fixed factor loadings (weak)[a]	536.50	370	.988	.983	.022	.033	.000	.000
Fixed factor loadings and item intercepts (strong)[a]	575.71	382	.986	.981	.023	.034	−.002	.001

Note. In all models, one factor loading per construct was fixed at 1.0 for model identification purposes. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

[a] The error variances for one item assessing utility value at time points T5 and T6 were estimated to be very close to zero and not significant. Therefore, we removed the correlated residual for this item from the model.

Supplement S3. Plausible Values by Study Program in Study 1a and Study 1b

Table S3.1

Percentages of Students with Significant Motivational Changes by Math Course (Instructor) in Study 1a

Variable	ΔT5T1		ΔT6T5	
	Decrease	Increase	Decrease	Increase
Expectancy				
Physics1 [a]	27% (91%)	3% (9%)	6% (29%)	6% (71%)
Physics2 [a]	26% (89%)	2% (11%)	1% (40%)	3% (60%)
Math1	12% (61%)	7% (39%)	15% (85%)	1% (15%)
Math2	32% (83%)	2% (17%)	10% (71%)	4% (29%)
Teacher1	14% (72%)	2% (28%)	4% (62%)	4% (38%)
Teacher2	9% (67%)	7% (33%)	6% (87%)	1% (13%)
Intrinsic value				
Physics1 [a]	28% (92%)	1% (8%)	2% (33%)	4% (67%)
Physics2 [a]	21% (89%)	0% (11%)	3% (34%)	1% (66%)
Math1	5% (54%)	1% (46%)	10% (84%)	0% (16%)
Math2	22% (87%)	1% (13%)	11% (70%)	1% (30%)
Teacher1	11% (76%)	2% (24%)	2% (22%)	7% (78%)
Teacher2	9% (54%)	5% (46%)	4% (85%)	1% (15%)
Utility value				
Physics1 [a]	14% (88%)	1% (12%)	3% (42%)	4% (58%)
Physics2 [a]	14% (87%)	0% (13%)	1% (40%)	3% (60%)
Math1	5% (65%)	1% (35%)	4% (75%)	0% (24%)
Math2	12% (72%)	1% (29%)	6% (73%)	1% (26%)
Teacher1	11% (79%)	3% (21%)	2% (42%)	4% (58%)
Teacher2	2% (17%)	17% (83%)	18% (95%)	0% (5%)
Psychological cost				
Physics1 [a]	2% (9%)	33% (91%)	4% (62%)	4% (38%)
Physics2 [a]	1% (9%)	25% (91%)	2% (58%)	2% (42%)
Math1	2% (34%)	15% (66%)	6% (39%)	9% (62%)
Math2	4% (34%)	16% (66%)	5% (52%)	6% (47%)
Teacher1	11% (33%)	10% (67%)	6% (52%)	4% (48%)
Teacher2	4% (39%)	6% (61%)	2% (33%)	1% (67%)
Effort cost				
Physics1 [a]	2% (11%)	33% (90%)	6% (51%)	5% (49%)
Physics2 [a]	1% (10%)	23% (90%)	5% (57%)	4% (43%)
Math1	7% (38%)	17% (62%)	8% (53%)	9% (46%)
Math2	11% (52%)	11% (48%)	7% (60%)	4% (40%)
Teacher1	14% (47%)	10% (53%)	6% (65%)	4% (34%)
Teacher2	16% (67%)	6% (33%)	1% (42%)	2% (59%)

Note. Plausible values were generated for each latent change score using Bayesian estimation to determine the number of students experiencing significant changes in their expectancy-value beliefs. The number of students with negative and positive change scores is shown in parentheses. Physics1, Physics2, Math1, Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

[a] Both courses were taught by the same instructor.

Table S3.2

Percentages of Students with Significant Motivational Changes by Math Course (Instructor) in Study 1b

Variable	ΔT2T1		ΔT3T2		ΔT4T3	
	Decrease	Increase	Decrease	Increase	Decrease	Increase
Expectancy						
Physics1 [a]	34% (79%)	8% (18%)	13% (30%)	22% (67%)	11% (37%)	13% (59%)
Physics2 [a]	43% (86%)	5% (11%)	8% (17%)	36% (81%)	28% (70%)	10% (27%)
Math2	18% (37%)	26% (55%)	28% (66%)	12% (26%)	24% (56%)	13% (38%)
Teacher1	23% (55%)	18% (41%)	12% (37%)	23% (57%)	19% (54%)	14% (41%)
Teacher2	6% (22%)	26% (73%)	35% (90%)	5% (10%)	17% (34%)	21% (63%)
Intrinsic value						
Physics1 [a]	58% (95%)	3% (6%)	13% (35%)	22% (62%)	9% (32%)	17% (66%)
Physics2 [a]	62% (92%)	3% (5%)	12% (21%)	37% (77%)	31% (74%)	9% (23%)
Math2	38% (71%)	12% (24%)	28% (68%)	15% (30%)	22% (55%)	20% (42%)
Teacher1	40% (79%)	7% (17%)	26% (59%)	19% (38%)	20% (51%)	23% (42%)
Teacher2	32% (72%)	12% (26%)	38% (84%)	6% (15%)	11% (29%)	27% (71%)
Utility value						
Physics1 [a]	50% (86%)	3% (11%)	11% (42%)	19% (55%)	11% (39%)	14% (57%)
Physics2 [a]	52% (87%)	5% (10%)	12% (32%)	27% (67%)	27% (66%)	14% (33%)
Math2	29% (50%)	26% (46%)	31% (65%)	15% (32%)	21% (56%)	17% (39%)
Teacher1	23% (52%)	22% (38%)	21% (56%)	16% (39%)	13% (49%)	14% (46%)
Teacher2	15% (42%)	31% (54%)	29% (76%)	13% (22%)	15% (31%)	18% (65%)
Psychological cost						
Physics1 [a]	6% (13%)	49% (87%)	19% (54%)	16% (42%)	18% (66%)	13% (32%)
Physics2 [a]	4% (7%)	65% (92%)	48% (86%)	5% (11%)	8% (18%)	42% (81%)
Math2	28% (45%)	26% (50%)	20% (38%)	29% (58%)	18% (39%)	28% (58%)
Teacher1	12% (33%)	32% (60%)	32% (61%)	17% (35%)	16% (49%)	19% (47%)
Teacher2	28% (61%)	20% (37%)	18% (24%)	38% (77%)	24% (71%)	10% (24%)
Effort cost						
Physics1 [a]	7% (18%)	46% (80%)	27% (75%)	6% (24%)	19% (68%)	12% (30%)
Physics2 [a]	4% (7%)	58% (91%)	55% (94%)	5% (6%)	8% (20%)	32% (77%)
Math2	37% (68%)	14% (27%)	23% (45%)	26% (53%)	18% (42%)	29% (56%)
Teacher1	15% (34%)	28% (62%)	34% (70%)	13% (28%)	21% (40%)	24% (53%)
Teacher2	29% (71%)	12% (24%)	11% (24%)	27% (73%)	23% (72%)	11% (26%)

Note. Plausible values were generated for each latent change score using Bayesian estimation to determine the number of students experiencing significant changes in their expectancy-value beliefs. The number of students with negative and positive change scores is shown in parentheses. Physics1, Physics2, Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester.

[a] Both courses were taught by the same instructor.

Supplement S4. Wald Tests of Parameter Constraints for Motivational Changes in Study 1a and Study 1b

Table S4.1

Parameter Constraints for Latent Change Scores Within and Between the Five Expectancy-Value Constructs in Study 1a

Parameter constraints	ΔM_1	ΔM_2	Wald Test	p
Changes within constructs across time				
Expectancy: ΔM_1 (ΔT5T1) = ΔM_2 (ΔT6T5)	−0.34	−0.09	27.19***	<.001
Intrinsic value: ΔM_1 (ΔT5T1) = ΔM_2 (ΔT6T5)	−0.36	−0.08	25.02***	<.001
Utility value: ΔM_1 (ΔT5T1) = ΔM_2 (ΔT6T5)	−0.30	−0.12	7.08**	.008
Psychological cost: ΔM_1 (ΔT5T1) = ΔM_2 (ΔT6T5)	0.40	0.01	35.34***	<.001
Effort cost: ΔM_1 (ΔT5T1) = ΔM_2 (ΔT6T5)	0.26	−0.03	21.64***	<.001
Changes between constructs from T1 to T5				
ΔM_1 (Expectancy ΔT5T1) = ΔM_2 (Intrinsic value ΔT5T1)	−0.34	−0.36	0.51	.476
ΔM_1 (Expectancy ΔT5T1) = ΔM_2 (Utility value ΔT5T1)	−0.34	−0.30	0.54	.461
ΔM_1 (Expectancy ΔT5T1) = $-\Delta M_2$ (Psychological cost ΔT5T1)	−0.34	0.40	2.12	.145
ΔM_1 (Expectancy ΔT5T1) = $-\Delta M_2$ (Effort cost ΔT5T1)	−0.34	0.26	2.98†	.084
ΔM_1 (Intrinsic value ΔT5T1) = ΔM_2 (Utility value ΔT5T1)	−0.36	−0.30	1.99	.159
ΔM_1 (Intrinsic value ΔT5T1) = $-\Delta M_2$ (Psychological cost ΔT5T1)	−0.36	0.40	0.52	.471
ΔM_1 (Intrinsic value ΔT5T1) = $-\Delta M_2$ (Effort cost ΔT5T1)	−0.36	0.26	3.96*	.047
ΔM_1 (Utility value ΔT5T1) = $-\Delta M_2$ (Psychological cost ΔT5T1)	−0.30	0.40	2.92†	.088
ΔM_1 (Utility value ΔT5T1) = $-\Delta M_2$ (Effort cost ΔT5T1)	−0.30	0.26	0.57	.452
ΔM_1 (Psychological cost ΔT5T1) = ΔM_2 (Effort cost ΔT5T1)	0.40	0.26	13.41***	<.001
Changes between constructs from T5 to T6				
ΔM_1 (Expectancy ΔT6T5) = ΔM_2 (Intrinsic value ΔT6T5)	−0.09	−0.08	0.22	.639
ΔM_1 (Expectancy ΔT6T5) = ΔM_2 (Utility value ΔT6T5)	−0.09	−0.12	0.24	.623
ΔM_1 (Expectancy ΔT6T5) = $-\Delta M_2$ (Psychological cost ΔT6T5)	−0.09	0.01	3.25†	.076
ΔM_1 (Expectancy ΔT6T5) = $-\Delta M_2$ (Effort cost ΔT6T5)	−0.09	−0.03	6.94**	.008
ΔM_1 (Intrinsic value ΔT6T5) = ΔM_2 (Utility value ΔT6T5)	−0.08	−0.12	0.88	.348
ΔM_1 (Intrinsic value ΔT6T5) = $-\Delta M_2$ (Psychological cost ΔT6T5)	−0.08	0.01	1.28	.258
ΔM_1 (Intrinsic value ΔT6T5) = $-\Delta M_2$ (Effort cost ΔT6T5)	−0.08	−0.03	3.71†	.054
ΔM_1 (Utility value ΔT6T5) = $-\Delta M_2$ (Psychological cost ΔT6T5)	−0.12	0.01	3.34†	.068
ΔM_1 (Utility value ΔT6T5) = $-\Delta M_2$ (Effort cost ΔT6T5)	−0.12	−0.03	6.40*	.011
ΔM_1 (Psychological cost ΔT6T5) = ΔM_2 (Effort cost ΔT6T5)	0.01	−0.03	1.05	.305

Note. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S4.2

Parameter Constraints for Latent Change Scores Within and Between the Five Expectancy-Value Constructs in Study 1b

Parameter constraints	ΔM_1	ΔM_2	ΔM_3	Wald Test	p
Changes within constructs across time (T1 through T4)					
Expectancy: ΔM_1 (ΔT2T1) + ΔM_2 (ΔT3T2) + ΔM_3 (ΔT4T3) = 0	−0.23	0.06	−0.08	33.30***	<.001
Intrinsic value: ΔM_1 (ΔT2T1) + ΔM_2 (ΔT3T2) + ΔM_3 (ΔT4T3) = 0	−0.92	0.03	−0.03	349.89***	<.001
Utility value: ΔM_1 (ΔT2T1) + ΔM_2 (ΔT3T2) + ΔM_3 (ΔT4T3) = 0	−0.47	−0.03	−0.05	111.19***	<.001
Psych. cost: ΔM_1 (ΔT2T1) + ΔM_2 (ΔT3T2) + ΔM_3 (ΔT4T3) = 0	0.68	−0.22	0.17	105.42***	<.001
Effort cost: ΔM_1 (ΔT2T1) + ΔM_2 (ΔT3T2) + ΔM_3 (ΔT4T3) = 0	0.35	−0.39	0.07	0.52	.472
Changes between constructs from T1 to T2					
ΔM_1 (Expectancy ΔT2T1) = ΔM_2 (Intrinsic value ΔT2T1)	−0.23	−0.92	—	190.29***	<.001
ΔM_1 (Expectancy ΔT2T1) = ΔM_2 (Utility value ΔT2T1)	−0.23	−0.47	—	18.83***	<.001
ΔM_1 (Expectancy ΔT2T1) = −ΔM_2 (Psychological cost ΔT2T1)	−0.23	0.68	—	53.63***	<.001
ΔM_1 (Expectancy ΔT2T1) = −ΔM_2 (Effort cost ΔT2T1)	−0.23	0.35	—	5.10*	.024
ΔM_1 (Intrinsic value ΔT2T1) = ΔM_2 (Utility value ΔT2T1)	−0.92	−0.47	—	69.01***	<.001
ΔM_1 (Intrinsic value ΔT2T1) = −ΔM_2 (Psychological cost ΔT2T1)	−0.92	0.68	—	13.08***	<.001
ΔM_1 (Intrinsic value ΔT2T1) = −ΔM_2 (Effort cost ΔT2T1)	−0.92	0.35	—	77.74***	<.001
ΔM_1 (Utility value ΔT2T1) = −ΔM_2 (Psychological cost ΔT2T1)	−0.47	0.68	—	8.34**	.004
ΔM_1 (Utility value ΔT2T1) = −ΔM_2 (Effort cost ΔT2T1)	−0.47	0.35	—	2.77†	.096
ΔM_1 (Psychological cost ΔT2T1) = ΔM_2 (Effort cost ΔT2T1)	0.68	0.35	—	40.58***	<.001

Note. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester. Psych. cost = psychological cost.
† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Supplement S5. Model Fit of Latent Change Models for the Five Expectancy-Value Constructs Including Students' Study Program Satisfaction and Exam Performance in Study 1a and Study 1b

Table S5.1

Model Fit for Univariate Latent Change Models for the Five Expectancy-Value Constructs Including Study Program Satisfaction and Exam Performance in Study 1a

Model	χ^2	*df*	CFI	TLI	RMSEA	SRMR
Expectancy	272.27	158	.982	.974	.027	.032
Intrinsic value	261.27	97	.957	.927	.041	.034
Utility value	203.94	97	.965	.941	.033	.036
Psychological cost	256.45	97	.958	.930	.040	.041
Effort cost	178.79	97	.981	.969	.029	.031

Note. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

Table S5.2

Model Fit of the Latent Change Models for the Five Expectancy-Value Constructs Including Study Program Satisfaction and Exam Performance in Study 1b

Model	χ^2	*df*	CFI	TLI	RMSEA	SRMR
Expectancy	91.86	51	.980	.955	.032	.033
Intrinsic value	102.65	51	.970	.933	.036	.038
Utility value	103.23	51	.968	.928	.036	.037
Psychological cost	97.78	51	.974	.941	.034	.035
Effort cost	98.76	51	.973	.940	.035	.034

Note. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

Supplement S6. Standardized Path Coefficients for Predictors of Students' Study Program Satisfaction, Exam Performance, and Course Dropout Estimated in the Latent Change Models for the Five Expectancy-Value Constructs in Study 1a and Study 1b

Table S6.1

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Expectancy Model in Study 1a

Predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	.02	−.07†	−.09*	0.91
SES	−.01	.02	−.01	0.99
High school GPA	.08	.43***	−.30***	0.74
Preparatory course	.03	.02	−.19***	0.83
Math1	−.04	−.09†	−.04	0.96
Math2	−.09†	−.03	−.04	0.96
Teacher1	−.15**	.02	.13**	1.13
Teacher2	−.08†	.05	−.01	0.99
Expectancy T1	.62***	.31***	−.17***	0.84
Expectancy ΔT5T1	.39***	.27***	−.22***	0.81
Expectancy ΔT6T5	.18**	.14*	[a]	

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math1, Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

[a] Students' attrition from their math course implied that no course-specific motivational assessments were available at the end of the semester (T6). Therefore, the analyses included only the latent change score from the beginning towards the midpoint of the semester. † $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S6.2

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Intrinsic Value Model in Study 1a

Predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	−.11**	−.15***	−.05	0.95
SES	−.07	−.01	−.02	0.98
High school GPA	.11*	.48***	−.31***	0.74
Preparatory course	−.03	−.01	−.19***	0.83
Math1	−.08†	−.10†	−.01	0.99
Math2	−.09*	−.06	−.02	0.98
Teacher1	−.12**	.02	.11*	0.12
Teacher2	−.05	.06	−.01	0.99
Intrinsic value T1	.70***	.24***	−.18***	0.84
Intrinsic value ΔT5T1	.48***	.20**	−.23**	0.80
Intrinsic value ΔT6T5	.31***	.16*	[a]	

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math1, Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

[a] Students' attrition from their math course implied that no course-specific motivational assessments were available at the end of the semester (T6). Therefore, the analyses included only the latent change score from the beginning towards the midpoint of the semester. † $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S6.3

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Utility Value Model in Study 1a

Predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	−.10*	−.15***	−.05	0.96
SES	−.06	.02	−.02	0.98
High school GPA	.15*	.50***	−.38***	0.68
Preparatory course	−.01	−.01	−.19***	0.83
Math1	.02	−.09	−.04	0.96
Math2	−.02	−.06	.01	1.01
Teacher1	−.03	.06	.11**	1.12
Teacher2	.05	.07	−.01	0.99
Utility value T1	.49***	.18**	.04	1.04
Utility value ΔT5T1	.47***	.16†	−.07	0.93
Utility value ΔT6T5	.26*	.02	[a]	

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math1, Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

[a] Students' attrition from their math course implied that no course-specific motivational assessments were available at the end of the semester (T6). Therefore, the analyses included only the latent change score from the beginning towards the midpoint of the semester.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S6.4

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Psychological Cost Model in Study 1a

Predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	−.06	−.10*	−.06	0.95
SES	−.05	−.01	−.02	0.98
High school GPA	.18**	.47***	−.36***	0.70
Preparatory course	−.02	−.02	−.18***	0.84
Math1	−.09†	−.11†	−.08†	0.93
Math2	−.14**	−.08	−.03	0.97
Teacher1	−.14**	.03	.09*	1.10
Teacher2	−.07	.05	−.05	0.95
Psychological cost T1	−.58***	−.35***	.11*	1.12
Psychological cost ΔT2T1	−.35***	−.23**	.04	1.04
Psychological cost ΔT3T2	−.11†	−.03	[a]	

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math1, Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

[a] Students' attrition from their math course implied that no course-specific motivational assessments were available at the end of the semester (T6). Therefore, the analyses included only the latent change score from the beginning towards the midpoint of the semester.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S6.5

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Effort Cost Model in Study 1a

Predictors	Study satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	$-.12^{**}$	$-.12^{**}$	$-.05$	0.96
SES	$-.03$	.01	$-.02$	0.98
High school GPA	$.24^{***}$	$.50^{***}$	$-.37^{***}$	0.69
Preparatory course	.01	$-.01$	$-.18^{***}$	0.83
Math1	$-.07$	$-.08$	$-.08^{\dagger}$	0.93
Math2	$-.17^{**}$	$-.05$	$-.03$	0.97
Teacher1	$-.16^{**}$	.03	$.10^{*}$	1.10
Teacher2	$-.05$	.07	$-.05$	0.95
Effort cost T1	$-.42^{***}$	$-.39^{***}$	$.10^{*}$	1.10
Effort cost ΔT5T1	$-.22^{**}$	$-.17^{**}$	.03	1.03
Effort cost ΔT6T5	$-.14^{*}$	$-.09$	[a]	

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math1, Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

[a] Students' attrition from their math course implied that no course-specific motivational assessments were available at the end of the semester (T6). Therefore, the analyses included only the latent change score from the beginning towards the midpoint of the semester.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S6.6

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Expectancy Model in Study 1b

Predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	.01	$-.07$	$-.07$	0.93
SES	$-.06$	.04	.01	1.01
High school GPA	.08	$.43^{***}$	$-.31^{***}$	0.74
Preparatory course	.03	$-.02$	$-.18^{***}$	0.84
Math2	$-.15^{**}$	$-.13^{*}$	$-.06$	0.94
Teacher1	$-.17^{**}$	.00	$.12^{**}$	1.13
Teacher2	$-.07$	.03	$-.08^{\dagger}$	0.92
Expectancy T1	$.64^{***}$	$.33^{***}$	$-.22^{***}$	0.80
Expectancy ΔT2T1	$.40^{***}$	$.38^{***}$	$-.23^{**}$	0.80
Expectancy ΔT3T2	$.26^{**}$	$.20^{**}$	$-.29^{***}$	0.75
Expectancy ΔT4T3	.09	.02	$-.14^{*}$	0.87

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S6.7

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Intrinsic Value Model in Study 1b

Predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	$-.10^{\dagger}$	$-.12^{*}$	$-.06$	0.94
SES	$-.07$	.03	.00	1.00
High school GPA	$.11^{\dagger}$	$.49^{***}$	$-.32^{***}$	0.73
Preparatory course	.03	$-.03$	$-.17^{***}$	0.85
Math2	$-.16^{**}$	$-.10$	$-.04$	0.96
Teacher1	$-.14^{**}$	.03	$.11^{*}$	1.12
Teacher2	$-.03$	.08	$-.08^{\dagger}$	0.93
Intrinsic value T1	$.55^{***}$	$.26^{***}$	$-.22^{***}$	0.80
Intrinsic value ΔT2T1	$.37^{***}$	$.20^{\dagger}$	$-.26^{***}$	0.77
Intrinsic value ΔT3T2	$.28^{***}$	$.17^{\dagger}$	$-.29^{***}$	0.75
Intrinsic value ΔT4T3	.04	.02	$-.14^{*}$	0.87

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester.

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table S6.8

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Utility Value Model in Study 1b

Predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	$-.09^{\dagger}$	$-.12^{*}$	$-.03$	0.97
SES	$-.11^{\dagger}$	.02	.01	1.01
High school GPA	$.16^{*}$	$.51^{***}$	$-.38^{***}$	0.68
Preparatory course	.02	$-.03$	$-.19^{***}$	0.83
Math2	$-.12^{*}$	$-.09$	$-.02$	0.98
Teacher1	$-.12^{*}$	.04	$.12^{**}$	1.13
Teacher2	.02	$.10^{\dagger}$	$-.05$	0.96
Utility value T1	$.47^{***}$	$.23^{**}$	.00	1.00
Utility value ΔT2T1	$.37^{**}$	$.26^{*}$	$-.05$	0.95
Utility value ΔT3T2	$.30^{**}$	$.21^{*}$	$-.09$	0.91
Utility value ΔT4T3	.11	$-.02$	$-.14^{*}$	0.87

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester.

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table S6.9

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Psychological Cost Model in Study 1b

Predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	−.07	$-.10^{\dagger}$	−.05	0.96
SES	$-.12^{*}$	.01	.00	1.00
High school GPA	$.18^{**}$	$.50^{***}$	$-.37^{***}$	0.69
Preparatory course	.02	−.01	$-.18^{***}$	0.83
Math2	$-.20^{***}$	−.10	−.03	0.97
Teacher1	$-.14^{**}$	.04	$.11^{*}$	1.12
Teacher2	−.09	.07	−.06	0.94
Psychological cost T1	$-.58^{***}$	$-.40^{***}$	$.15^{*}$	1.16
Psychological cost ΔT2T1	$-.44^{***}$	$-.41^{***}$	.11	1.12
Psychological cost ΔT3T2	−.14	$-.29^{**}$	.09	1.09
Psychological cost ΔT4T3	.01	$-.13^{\dagger}$	.07	1.07

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester.

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table S6.10

Standardized Path Coefficients for Predictors of Study Program Satisfaction, Exam Performance, and Course Dropout in the Effort Cost Model in Study 1b

Predictors	Study program satisfaction	Exam performance	Course dropout	
			β	*OR* (β)
Female	$-.09^{\dagger}$	$-.11^{*}$	−.04	0.96
SES	−.08	.03	.00	1.00
High school GPA	$.19^{**}$	$.50^{***}$	$-.37^{***}$	0.69
Preparatory course	.05	.01	$-.18^{***}$	0.83
Math2	$-.22^{**}$	−.07	−.03	0.97
Teacher1	$-.19^{***}$	.03	$.11^{*}$	1.12
Teacher2	−.07	.08	−.06	0.95
Effort cost T1	$-.38^{***}$	$-.37^{***}$	$.09^{\dagger}$	1.10
Effort cost ΔT2T1	$-.30^{**}$	$-.28^{**}$	.02	1.02
Effort cost ΔT3T2	$-.15^{\dagger}$	$-.24^{**}$	.00	1.00
Effort cost ΔT4T3	−.03	$-.20^{**}$	.00	1.00

Note. One set of analyses focused on the prediction of students' end-of-term study program satisfaction and exam performance, and a separate set on the prediction of course dropout. *OR* = odds ratio. Math2, Teacher1, and Teacher2 = dummy variables for the respective math courses and study programs. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester.

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Supplement S7. Supplemental Analyses Concerning Missing Data in Study 1a and Study 1b

Two sets of supplemental analyses were conducted to describe the implications of missing data in both studies and to test the robustness of our findings. First, we tested the implications of including covariates as auxiliary variables in our latent change score models for the estimated change scores by estimating the models with and without auxiliary variables. The estimated latent change scores for students' expectancy and task values were similar to the original analyses, which included the covariates as auxiliary variables (see Tables S7.1 and S7.2). We also report the amount of variance in students' motivations and motivational changes that was explained by students' individual and background characteristics to show the strength of the associations between the covariates and the predicted outcomes.

Second, we replicated our latent change score analyses using only the subsample of students who were present for the end-of-term data collection (T6; Study 1a: n = 608 of 1,004; Study 1b: n = 439 of 773). Course dropout/Non-attendance at T6 was linked to lower SES ($r = -.11$, $p = .002$), lower high school GPA ($r = -.39$, $p < .001$), and non-participation in preparatory math courses ($r = -.23$, $p < .001$; see Table 1). The estimated means and variances of the latent change scores for this subsample of students versus for the full sample in our original analysis are shown in Table S7.3 for Study 1a and Table S7.4 for Study 1b. For Study 1a, motivational changes from the beginning towards the midpoint of the semester (ΔT5T1) are somewhat smaller compared to the original analysis that included all students. This pattern of results suggests that students who dropped out of their math course were at risk of experiencing somewhat greater motivational declines compared to students who did not drop out.

Table S7.1

Latent Means and Variances of Initial Motivations and Latent Change Scores With and Without Auxiliary Variables in Study 1a

Variable	T1		ΔT5T1		ΔT6T5	
	M	σ^2	M	σ^2	M	σ^2
Repeated analysis **without** auxiliary variables						
Expectancy	3.75	0.69^{***}	-0.32^{***}	0.44^{***}	-0.10^{**}	0.29^{***}
Intrinsic value	4.58	0.54^{***}	-0.34^{***}	0.51^{***}	-0.08^{*}	0.32^{***}
Utility value	4.62	0.88^{***}	-0.30^{***}	0.67^{***}	-0.08^{*}	0.37^{***}
Psychological cost	2.78	1.01^{***}	0.37^{***}	0.68^{***}	0.02	0.44^{***}
Effort cost	4.33	1.02^{***}	0.25^{***}	0.84^{***}	−0.02	0.45^{***}
Original analysis **including** all covariates as auxiliary variables						
Expectancy	3.74	0.69^{***}	-0.34^{***}	0.45^{***}	-0.09^{**}	0.30^{***}
Intrinsic value	4.57	0.54^{***}	-0.36^{***}	0.52^{***}	-0.08^{*}	0.33^{***}
Utility value	4.62	0.88^{***}	-0.30^{***}	0.67^{***}	-0.12^{**}	0.39^{***}
Psychological cost	2.75	1.01^{***}	0.40^{***}	0.69^{***}	0.01	0.44^{***}
Effort cost	4.33	1.02^{***}	0.26^{***}	0.83^{***}	−0.03	0.45^{***}
Amount of **variance explained** by covariates (gender, SES, high school GPA, preparatory math courses, course dummies)						
Expectancy	$R^2 = .089$		$R^2 = .112$		$R^2 = .059$	
Intrinsic value	$R^2 = .112$		$R^2 = .137$		$R^2 = .113$	
Utility value	$R^2 = .168$		$R^2 = .124$		$R^2 = .126$	
Psychological cost	$R^2 = .103$		$R^2 = .120$		$R^2 = .020$	
Effort cost	$R^2 = .058$		$R^2 = .126$		$R^2 = .026$	

Note. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).

$^{\dagger} p < .10$. $^{*} p < .05$. $^{**} p < .01$. $^{***} p < .001$.

Table S7.2

Latent Means and Variances of Initial Motivations and Latent Change Scores With and Without Auxiliary Variables in Study 1b

Variable	T1		ΔT2T1		ΔT3T2		ΔT4T3	
	M	σ^2	*M*	σ^2	*M*	σ^2	*M*	σ^2
Repeated analysis **without** auxiliary variables								
Expectancy	3.73	0.83^{***}	-0.21^{***}	1.01^{***}	0.06	1.05^{***}	$-0.08^{\dagger}$	0.96^{***}
Intrinsic value	4.56	0.77^{***}	-0.90^{***}	1.52^{***}	0.01	1.58^{***}	−0.02	1.38^{***}
Utility value	4.62	1.27^{***}	-0.46^{***}	1.79^{***}	−0.04	1.28^{***}	−0.05	1.03^{***}
Psychological cost	3.50	1.81^{***}	0.67^{***}	2.54^{***}	-0.22^{**}	1.99^{***}	0.19^{**}	1.87^{***}
Effort cost	4.31	1.32^{***}	0.34^{***}	1.92^{***}	-0.39^{***}	1.70^{***}	$0.09^{\dagger}$	1.62^{***}
Original analysis **including** all covariates as auxiliary variables								
Expectancy	3.73	0.83^{***}	-0.23^{***}	0.99^{***}	0.06	1.06^{***}	$-0.08^{\dagger}$	0.97^{***}
Intrinsic value	4.56	0.77^{***}	-0.92^{***}	1.52^{***}	0.03	1.58^{***}	−0.03	1.37^{***}
Utility value	4.62	1.27^{***}	-0.47^{***}	1.81^{***}	−0.03	1.28^{***}	−0.05	1.03^{***}
Psychological cost	3.49	1.82^{***}	0.68^{***}	2.49^{***}	-0.22^{***}	2.01^{***}	0.17^{**}	1.88^{***}
Effort cost	4.30	1.33^{***}	0.35^{***}	1.85^{***}	-0.39^{***}	1.71^{***}	0.07	1.63^{***}
Amount of **variance explained** by covariates (gender, SES, high school GPA, preparatory math courses, course dummies)								
Expectancy	$R^2 = .092$		$R^2 = .147$		$R^2 = .148$		$R^2 = .011$	
Intrinsic value	$R^2 = .060$		$R^2 = .157$		$R^2 = .141$		$R^2 = .031$	
Utility value	$R^2 = .160$		$R^2 = .147$		$R^2 = .066$		$R^2 = .011$	
Psychological cost	$R^2 = .119$		$R^2 = .212$		$R^2 = .143$		$R^2 = .050$	
Effort cost	$R^2 = .063$		$R^2 = .264$		$R^2 = .177$		$R^2 = .048$	

Note. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester. T6 = end-of-term (Week 15).
† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S7.3

Latent Means and Variances of Initial Motivations and Latent Change Scores Using the Full Sample or a Subsample of Students who were Present at the End of the Semester in Study 1a

Variable	T1		ΔT5T1		ΔT6T5	
	M	σ^2	*M*	σ^2	*M*	σ^2
Original analysis **with full sample** (N = 1,004)						
Expectancy	3.74	0.69^{***}	-0.34^{***}	0.45^{***}	-0.09^{**}	0.30^{***}
Intrinsic value	4.57	0.54^{***}	-0.36^{***}	0.52^{***}	-0.08^{*}	0.33^{***}
Utility value	4.62	0.88^{***}	-0.30^{***}	0.67^{***}	-0.12^{**}	0.39^{***}
Psychological cost	2.75	1.01^{***}	0.40^{***}	0.69^{***}	0.01	0.44^{***}
Effort cost	4.33	1.02^{***}	0.26^{***}	0.83^{***}	−0.03	0.45^{***}
Only including **students who were present at T6** (n = 608)						
Expectancy	3.85	0.60^{***}	-0.27^{***}	0.43^{***}	-0.12^{***}	0.29^{***}
Intrinsic value	4.70	0.41^{***}	-0.29^{***}	0.46^{***}	-0.12^{***}	0.31^{***}
Utility value	4.61	0.70^{***}	-0.24^{***}	0.60^{***}	-0.10^{*}	0.36^{***}
Psychological cost	2.59	0.90^{***}	0.37^{***}	0.62^{***}	0.02	0.43^{***}
Effort cost	4.27	1.04^{***}	0.25^{***}	0.83^{***}	−0.03	0.45^{***}

Note. T1 = beginning of the semester (Week 2), T5 = midpoint of the semester (Week 8), T6 = end of the semester (Week 15).
† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S7.4

Latent Means and Variances of Initial Motivations and Latent Change Scores Using the Full Sample or Subsample of Students Present at the End of the Semester in Study 1b

Variable	T1		ΔT2T1		ΔT3T2		ΔT4T3	
	M	σ^2	*M*	σ^2	*M*	σ^2	*M*	σ^2
Original analysis **with full sample** (*N* = 773)								
Expectancy	3.73	0.83^{***}	-0.23^{***}	0.99^{***}	0.06	1.06^{***}	$-0.08^{\dagger}$	0.97^{***}
Intrinsic value	4.56	0.77^{***}	-0.92^{***}	1.52^{***}	0.03	1.58^{***}	−0.03	1.37^{***}
Utility value	4.62	1.27^{***}	-0.47^{***}	1.81^{***}	−0.03	1.28^{***}	−0.05	1.03^{***}
Psychological cost	3.49	1.82^{***}	0.68^{***}	2.49^{***}	-0.22^{***}	2.01^{***}	0.17^{**}	1.88^{***}
Effort cost	4.30	1.33^{***}	0.35^{***}	1.85^{***}	-0.39^{***}	1.71^{***}	0.07	1.63^{***}
Only including **students who were present at T6** (*n* = 439)								
Expectancy	3.86	0.80^{***}	-0.20^{***}	0.99^{***}	0.12^{*}	1.06^{***}	$-0.09^{\dagger}$	0.91^{***}
Intrinsic value	4.68	0.61^{***}	-0.86^{***}	1.62^{***}	0.05	1.58^{***}	−0.01	1.27^{***}
Utility value	4.63	1.15^{***}	-0.44^{***}	1.68^{***}	−0.03	1.25^{***}	−0.01	1.00^{***}
Psychological cost	3.39	1.80^{***}	0.69^{***}	2.54^{***}	-0.23^{**}	1.87^{***}	0.19^{**}	1.63^{***}
Effort cost	4.24	1.41^{***}	0.36^{***}	1.91^{***}	-0.44^{***}	1.68^{***}	$0.12^{\dagger}$	1.62^{***}

Note. T1–T4 = consecutive time points from Week 2 to Week 5 of the semester. T6 = end-of-term (Week 15). † $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

2.2 Study 2: Geschlechtsunterschiede in der Variabilität situationsspezifischer Erwartungs- und Wertüberzeugungen und selbsteingeschätzter Leistung in mathematikintensiven Studienfächern: Eine Mehrebenenanalyse von motivationalen Schwankungen

Benden, D. K. & Lauermann, F. (2022). Geschlechtsunterschiede in der Variabilität situationsspezifischer Erwartungs- und Wertüberzeugungen und selbsteingeschätzter Leistung in mathematikintensiven Studienfächern. In F. Lauermann, C. Jöhren, N. McElvany, M. Becker, & H. Gaspard (Hrsg.), *Jahrbuch der Schulentwicklung (Band 22): Multiperspektivität von Unterrichtsprozessen* (S. 184–213). Beltz Juventa.

Zusammenfassung

Die Erwartungs- und Wertüberzeugungen von Lernenden spielen eine wichtige Rolle für ihre Bildungs- und Berufsentscheidungen, beispielsweise in den Bereichen Mathematik, Informatik, Naturwissenschaften und Technik (MINT), in denen Frauen weiterhin unterrepräsentiert sind. Bisherige Forschung hat sich hauptsächlich auf Mittelwertunterschiede in den motivationalen Überzeugungen von weiblichen und männlichen Lernenden fokussiert. Daher wurden in der vorliegenden Studie Geschlechtsunterschiede in der Variabilität der situationsspezifischen Erwartungs- und Wertüberzeugungen sowie der selbsteingeschätzten Leistung im Verlauf des Semesters in verpflichtenden Mathematikveranstaltungen für Studienanfängerinnen und Studienanfänger in MINT-Studiengängen untersucht. Studierende aus drei mathematikintensiven MINT-Studienfächern wurden an drei Messzeitpunkten im Semester zu ihren situationsspezifischen motivationalen Überzeugungen und Leistungen befragt (N = 927). Mehrebenenanalysen zeigten signifikante Geschlechtsunterschiede in der Variabilität der Erfolgserwartung und selbsteingeschätzten Leistung im Verlauf des Semesters sowie in der Variabilität zwischen den motivationalen Überzeugungen und der Leistungseinschätzung innerhalb von zwei der drei Messzeitpunkte im Verlauf des Semesters. Diese Unterschiede blieben auch unter Kontrolle von individuellen und familiären Merkmalen der Studierenden bestehen. Die Ergebnisse deuten darauf hin, dass weibliche Studierende in männlich-dominierten Studienfächern im MINT-Bereich anfälliger für Fluktuationen in ihren situativen motivationalen Überzeugungen sein könnten im Vergleich zu männlichen Studierenden.

Schlagworte: Erwartungs-Wert-Theorie, situationsspezifische motivationale Überzeugungen, Geschlechtsunterschiede, MINT, Studieneingangsphase

Geschlechtsunterschiede in der Variabilität situationsspezifischer Erwartungs- und Wertüberzeugungen und selbsteingeschätzter Leistung in mathematikintensiven Studienfächern: Eine Mehrebenenanalyse von motivationalen Schwankungen

Einleitung

Im internationalen Vergleich entscheidet sich in Deutschland ein überdurchschnittlich großer Anteil von Studienanfängerinnen und Studienanfängern für ein Bachelor-Studium in den Bereichen Mathematik, Informatik, Naturwissenschaften und Technik (MINT; 40% in Deutschland vs. 27% im OECD-Durchschnitt; Organisation for Economic Co-operation and Development [OECD], 2019). Allerdings liegt der Anteil an Frauen aller Studienanfängerinnen und Studienanfänger in diesem Bereich in Deutschland mit 26% unter dem OECD-Durchschnitt von 30% (OECD, 2019). Darüber hinaus zeigen verschiedene Studien, dass die Studienabbruchquoten weiblicher Studierender in mathematikintensiven MINT-Studienfächern verglichen mit männlichen Studierenden höher ausfallen (Griffith, 2010; Isphording & Qendrai, 2019). Dabei weisen solche mathematikintensiven Studienfächer wie Physik oder Mathematik mit 45% bzw. 54% besonders hohe Abbruchquoten auf (Heublein & Schmelzer, 2018). Diese geschlechtsbezogenen Disparitäten in Bildungs- und Berufsentscheidungen im MINT-Bereich bleiben auch in Studien bestehen, die für mögliche Leistungsunterschiede zwischen weiblichen und männlichen Lernenden kontrollieren (Kugler et al., 2017; Riegle-Crumb et al., 2012). Somit sind diese motivationalen Disparitäten nicht oder nur zum Teil auf Leistungsunterschiede zwischen weiblichen und männlichen Lernenden zurückzuführen. Um den zunehmenden Bedarf an Fachkräften im MINT-Bereich zu decken (Anger et al., 2020), ist es daher wichtig, die Erfahrungen insbesondere weiblicher Studierender besser zu verstehen, die zu Zweifeln am Studium, einem Studienabbruch oder einer Entscheidung gegen eine Karriere im MINT-Bereich beitragen.

Die Erwartungs-Wert-Theorie von Eccles und Kollegen (Eccles et al., 1983; Eccles & Wigfield, 2020) ist eines der einflussreichsten theoretischen Modelle zur Untersuchung der motivationalen Grundlagen von Bildungs- und Berufsentscheidungen von Lernenden. Zudem bietet die Theorie die Grundlage zur Untersuchung von Geschlechtsunterschieden in Bildungs- und Berufsentscheidungen von Lernenden, wie beispielsweise der Wahl eines Studiums im MINT-Bereich, der Entscheidung zum Studienabbruch oder der Entscheidung gegen eine Karriere im MINT-Bereich (z. B. Guo et al., 2015; Lauermann et al., 2017; Perez et al., 2014). Zahlreiche Studien belegen, dass die Erfolgserwartung („*Kann ich die Aufgabe schaffen?*“)

sowie die subjektiven Werte („*Will ich die Aufgabe schaffen?*“) von Studierenden zentrale Prädiktoren von leistungsbezogenen Entscheidungen und Verhalten im Lernkontext darstellen, selbst wenn für kognitive Fähigkeiten kontrolliert wird (z. B. Perez et al., 2014; siehe Überblick in Wigfield & Cambria, 2010). Eine zentrale Annahme der Theorie ist, dass Geschlechtsunterschiede in Bildungs- und Berufsentscheidungen von Lernenden (z. B. die Entscheidung für ein MINT-Studium oder den Abbruch eines MINT-Studiums) mit Unterschieden in der Erfolgserwartung für ein Studium im MINT-Bereich oder den subjektiven Werten, die diesem Studium beigemessen werden (z. B. Interesse, die wahrgenommene Nützlichkeit und persönliche Wichtigkeit der Studieninhalte), zusammenhängen (Eccles, 2011; Eccles et al., 1983).

Bisherige Forschung auf Basis der Erwartungs-Wert-Theorie mit dem Fokus auf Geschlechtsunterschiede in Bildungs- und Berufsentscheidungen hat relativ konsistente Mittelwertunterschiede in den motivationalen Überzeugungen zwischen weiblichen und männlichen Lernenden im mathematischen Bereich zum Vorteil männlicher Lernender dokumentiert (Gaspard et al., 2015; Wigfield & Cambria, 2010). Dabei zeigt sich, dass die Erwartungs- und Wertüberzeugungen der Lernenden vergleichbare prädiktive Effekte auf die Bildungs- und Berufsentscheidungen von weiblichen im Vergleich zu männlichen Lernenden haben (Guo et al., 2015; Nagengast et al., 2011; Wang, 2012); diese motivationalen Überzeugungen sind also für beide Geschlechter von großer Bedeutung. Im Gegensatz dazu gibt es nur wenige Studien, die Geschlechtsunterschiede in der Variabilität in diesen motivationalen Überzeugungen – d. h. geschlechtsspezifische motivationale Schwankungen – untersucht haben, beispielsweise über verschiedene Lernsituationen hinweg (z. B. Tsai, Kunter, Lüdtke, Trautwein, & Ryan, 2008).

Motivationale Schwankungen, erfasst durch eine vergleichsmäßig größere Variabilität der Erwartungs- und Wertüberzeugungen von einzelnen Studierenden oder Studierendengruppen, sowohl über mehrere Lernsituationen als auch zwischen den verschiedenen Erwartungs- und Wertüberzeugungen, könnten dabei ein frühes Anzeichen für eine nachlassende Identifizierung mit dem Studium sein (vgl. Eccles, 2009). Beispielsweise zeigt die Studie von Lazarides et al. (2020), dass sich Lernende, die inkonsistente Motivationsprofile aufweisen – d. h. Profile bestehend aus sowohl positiven als auch negativen Ausprägungen der Erwartungs- und Wertüberzeugungen (z. B. hohe wahrgenommene Nützlichkeit und Wichtigkeit sowie geringes intrinsisches Interesse an den Lerninhalten) – seltener für ein Studium im MINT-Bereich entscheiden im Vergleich zu Lernenden, die konsistente positive Motivationsprofile aufweisen. Motivationale Veränderungen über die Zeit spielen ebenfalls eine wichtige Rolle bei der Vorhersage des späteren Studienerfolgs (Robinson et al., 2019). Es mangelt jedoch an Studien, die geschlechtsspezifische Unterschiede bezüglich solcher motivationaler Schwankungen und situativer Motivationsprofile als eine mögliche Erklärung für Geschlechtsdisparitäten im MINT-Bereich untersucht haben.

In der vorliegenden Studie werden daher nicht nur Mittelwertunterschiede, sondern auch mögliche Geschlechtsunterschiede in der Variabilität der motivationalen Überzeugungen von Studierenden in mathematikintensiven Studienfächern im ersten Semester an der Universität untersucht. Es werden sowohl zeitliche Schwankungen im Laufe eines Semesters als auch der Übereinstimmungsgrad beziehungsweise mögliche Diskrepanzen in den motivationalen Überzeugungen von männlichen und weiblichen Studierenden untersucht (d. h. sind verschiedene Facetten ihrer motivationalen Überzeugungen im Einklang?). Wir fokussieren uns dabei auf verpflichtende Mathematikveranstaltungen in der Studieneingangsphase, weil Studienabbrüche in dieser Phase besonders wahrscheinlich sind und solche Mathematikveranstaltungen oft eine Hürde darstellen, an der viele Studierende scheitern (Heublein et al., 2017; Seymour & Hewitt, 1997).

Erwartungs-Wert-Theorie und geschlechtsspezifische motivationale Prozesse: Mittelwertunterschiede, Interaktionsprozesse und Variabilität

Die Erwartungs-Wert-Theorie von Eccles und Kolleg*innen (Eccles et al., 1983) nimmt an, dass die Erfolgserwartung sowie die subjektiven Werte von Lernenden, beispielsweise im MINT-Bereich, proximale Prädiktoren bedeutsamer leistungsbezogener Entscheidungen sowie Verhaltensweisen darstellen, wie etwa der Entscheidung für ein MINT-Studium oder dem Engagement im Studium. Demnach sind Lernende dann für eine Aufgabe motiviert (z. B. ein Studium im MINT-Bereich absolvieren), wenn die Aufgabe sowohl als erreichbar als auch als subjektiv wertvoll wahrgenommen wird. Die Erfolgserwartung beschreibt dabei die vom Lernenden subjektiv wahrgenommene Wahrscheinlichkeit, die Aufgabe erfolgreich zu absolvieren (z. B. erfolgreich das Studium absolvieren zu können). Dagegen wird der subjektive Wert in verschiedene Facetten differenziert: den intrinsischen Wert, die persönliche Wichtigkeit, die Nützlichkeit sowie die wahrgenommenen Kosten (Eccles et al., 1983; Eccles & Wigfield, 2020). Die Aufgabe ist dabei von intrinsischem Wert, wenn die Aufgabe Spaß macht oder die Lerninhalte subjektiv als interessant wahrgenommen werden (z. B. Interesse am Studienfach, Freude beim Lernen der Studieninhalte). Die persönliche Wichtigkeit beschreibt dagegen die Bedeutung der Aufgabe für die eigene Identität (z. B. erfolgreich ein Mathestudium zu absolvieren, weil man sich als Mathematiker definiert), während die

Nützlichkeit sich auf den wahrgenommenen Nutzen der Aufgabe für zukünftige Ziele bezieht (z. B. günstige Berufsaussichten oder hohes Einkommen durch das Studium im MINT-Bereich). Diesen positiven Facetten des subjektiven Wertes stehen die Kosten gegenüber, die mit der Aufgabe verbunden sind. Diese umfassen den nötigen Aufwand, der investiert werden muss, um erfolgreich zu sein (Anstrengungskosten, z. B. Anstrengung, die Lerninhalte im Studium zu meistern), die negativen Emotionen, die mit der Aufgabe einhergehen, beispielsweise mit Blick auf einen möglichen Misserfolg im Studium (psychologische Kosten) sowie die verpassten Gelegenheiten, anderen subjektiv wertvollen Aktivitäten nachzugehen (Opportunitätskosten, z. B. für eine Klausur lernen anstatt etwas mit Freunden zu unternehmen).

Eine zentrale Annahme der Erwartungs-Wert-Theorie ist, dass die Erfolgserwartung und die subjektiven Werte von Lernenden bezüglich einer Aufgabe (z. B. eine Mathematikveranstaltung erfolgreich zu absolvieren) an die spezifische Leistungssituation gebunden sind, in der die Lernenden sich befinden (Eccles & Wigfield, 2020). Das bedeutet, dass situative Faktoren wie beispielsweise die wahrgenommene Schwierigkeit einer Aufgabe nicht nur den erwarteten Erfolg und die subjektiven Werte bezüglich dieser Aufgabe beeinflussen, sondern dass die verschiedenen motivationalen Überzeugungen in unterschiedlichen Situationen auch unterschiedlich stark gewichtet werden können. Beispielsweise könnte das intrinsische Interesse eines Studierenden ein zentraler Faktor für die Wahl eines Studiums im MINT-Bereich darstellen, während die wahrgenommenen Kosten zunehmend relevant bei der Gewichtung der verschiedenen Wertkomponenten werden könnten, sobald die Studierenden mit anspruchsvollen Lerninhalten oder schwierigen Prüfungen konfrontiert werden. Darüber hinaus wird angenommen, dass diese relative Gewichtung der verschiedenen Wertfacetten auch von individuellen Voraussetzungen der Lernenden sowie Interaktionsprozessen zwischen situativen und persönlichen Merkmalen beeinflusst wird (Eccles & Wigfield, 2020). So könnten weibliche Lernende in einem männlich-dominierten Studienfach im MINT-Bereich beispielsweise die wahrgenommenen Kosten, anspruchsvolle Lerninhalte zu meistern oder eine wichtige Klausur zu bestehen, aufgrund von negativen Stereotypen über Frauen in mathematikintensiven Studienfächern als höher einschätzen: sie könnten befürchten, dass sie im Vergleich zu anderen Studierenden mehr Zeit und Aufwand investieren müssten, um erfolgreich zu sein, oder Sorge haben, diese negativen Stereotype zu bestätigen (vgl. Murphy et al., 2007).

Bisherige Forschung auf Basis der Erwartungs-Wert-Theorie im Schulkontext hat im Allgemeinen eher konsistente Geschlechtsunterschiede in den motivationalen Überzeugungen von Lernenden bezüglich Mathematik dokumentiert (Gaspard et al., 2015; Nagy et al., 2010; Watt, 2004). Demnach geben weibliche Lernende im mathematischen Bereich geringere Erfolgserwartungen, intrinsische Werte und Nützlichkeit bezüglich der Lerninhalte sowie höhere wahrgenommene Kosten im Vergleich zu männlichen Lernenden an. Studien im Hochschulkontext deuten dagegen auf eher geringe Geschlechtsunterschiede in den motivationalen Überzeugungen männlicher und weiblicher Studierender hin, die sich bereits für ein Studium im MINT-Bereich entschieden haben (Benden & Lauermann, 2021; Robinson et al., 2019). Falls Geschlechtsunterschiede gefunden wurden, fallen diese in Übereinstimmung mit der Forschung im Schulkontext zum Vorteil männlicher Studierender aus (Benden & Lauermann, 2021).

Darüber hinaus weisen bisherige Studien auf ähnliche Zusammenhänge zwischen den Erwartungs- und Wertüberzeugungen und den Bildungs- und Berufsentscheidungen bei weiblichen und männlichen Lernenden hin (z. B. Guo et al., 2015; Nagengast et al., 2011; für eine Ausnahme, siehe Watt et al., 2012). Beispielsweise fanden Guo et al. (2015) keine signifikanten Geschlechtsunterschiede in den Zusammenhängen zwischen den motivationalen Überzeugungen der Lernenden in Mathematik (mathematisches Selbstkonzept, intrinsischer Wert und Nützlichkeit der Lerninhalte) und der Wahl von Mathematikkursen in der Sekundarstufe sowie der Wahl eines MINT-Studienfachs (siehe auch Wang, 2012). Folglich können die bisher untersuchten geschlechtsspezifischen motivationalen Prozesse die Geschlechtsunterschiede in den Bildungs- und Berufsentscheidungen weiblicher und männlicher Lernender im MINT-Bereich nicht vollständig erklären.

Ein Faktor, der in der bisherigen Forschung dagegen kaum untersucht wurde, sind Geschlechtsunterschiede in der Variabilität der motivationalen Überzeugungen von Lernenden über verschiedene Lernsituationen hinweg (siehe z. B. Tsai, Kunter, Lüdtke, & Trautwein, 2008; Tsai, Kunter, Lüdtke, Trautwein, & Ryan, 2008). Beispielsweise zeigten sich in einzelnen Studien signifikante Fluktuationen im Interesse an den Lerninhalten sowie in den Kompetenzüberzeugungen (d. h. wie gut man sich in Mathe in einer Situation einschätzt) in einem dreiwöchigen Zeitraum bei Siebtklässlerinnen und Siebtklässlern im Mathematik-unterricht, obwohl in diesen Studien keine signifikanten Geschlechtsunterschiede beobachtet wurden (36% bzw. 48% Varianz auf within-person-Ebene; Tsai, Kunter, Lüdtke, & Trautwein, 2008; Tsai, Kunter, Lüdtke, Trautwein, & Ryan, 2008). Allerdings ist der Beobachtungszeitraum in diesen Studien relativ kurz und es ist unklar, ob die Befunde auf andere Kontexte übertragbar sind. Insbesondere bleibt unklar, ob sich diese Befunde auf den Hochschulkontext in mathematikintensiven Studienfächern im MINT-Bereich übertragen lassen, in denen weibliche Studierende typischerweise in der Minderheit sind und negativen Stereotypen ausgesetzt sein können (Murphy et al., 2007; OECD, 2019). Keine Studie bisher hat geschlechtsspezifische Unterschiede in der zeitlichen Variabilität von Erfolgserwartungen und Werten wie Interesse, Nützlichkeit oder den wahrgenommenen psychologischen und Anstrengungskosten in einem MINT-Studium untersucht.

Zuletzt könnten Geschlechtsunterschiede auch in der Variabilität *zwischen* den verschiedenen Erwartungs- und Wertüberzeugungen auftreten, also in dem Übereinstimmungsgrad zwischen verschiedenen motivationalen Facetten (z. B. hoher wahrgenommener Nutzen von Lerninhalten, aber geringe Erfolgserwartungen). So deuten einige Studien, in denen Motivationsprofile von Lernenden im MINT-Bereich untersucht wurden, darauf hin, dass weibliche im Vergleich zu männlichen Lernenden öfter Motivationsprofile aufweisen, die sowohl von positiven als auch negativen motivationalen Überzeugungen geprägt sind (Kegel et al., 2021; Lazarides et al., 2016). Beispielsweise zeigt die Studie von Kegel et al. (2021), dass weibliche Studierende häufiger Motivationsprofile bestehend aus moderater Studienwahlmotivation (d. h. den Gründen für die Wahl ihres Studienfaches wie intrinsisches Interesse oder spätere Berufsaussichten) in Kombination mit geringen Fähigkeitsüberzeugungen aufwiesen, während männliche Studierende signifikant häufiger in einem Profil mit hoher Studienwahlmotivation sowie hohen Fähigkeitsüberzeugungen vertreten waren. Solche divergenten Motivationsprofile können im Vergleich zu ausschließlich positiven Profilen Indikatoren für spätere Leistungsprobleme, geringeres Engagement, und höhere Studienabbruchintentionen sein (Kegel et al., 2021; Perez et al., 2019; Tuominen-Soini & Salmela-Aro, 2014). Der Großteil der dargestellten Studien bezieht sich dabei allerdings auf eher globale, domänenspezifische Einschätzungen der verschiedenen motivationalen Überzeugungen, sodass unklar ist, ob bisherige Befunde zur Variabilität in motivationalen Überzeugungen auf situationsspezifische Wahrnehmungen weiblicher und männlicher Lernender übertragbar sind. Folglich bleibt auch offen, inwiefern mögliche Geschlechtsunterschiede in situationsspezifischen motivationalen Überzeugungen von Lernenden im mathematischen Bereich durch relativ stabile trait-Unterschiede zwischen den Lernenden oder durch unterschiedliche situative Erfahrungen weiblicher und männlicher Lernender bestimmt werden. Die vorliegende Studie untersucht daher Geschlechtsunterschiede in der Variabilität der Erwartungs- und Wertüberzeugungen von Studierenden in Mathematikveranstaltungen im Laufe des ersten Semesters in MINT-Studienfächern. Diese Zeit nach dem Übergang in die Hochschulbildung stellt eine besonders kritische Phase des

Studiums dar, in der viele Studierende ein MINT-Studium bereits abbrechen (Heublein et al., 2017).

Zusätzlich zu den Erwartungs- und Wertüberzeugungen von weiblichen und männlichen Studiereden im MINT-Bereich wird außerdem die Variabilität in der selbsteingeschätzten Leistung der Studierenden im Laufe des Semesters untersucht. Die subjektive Interpretation früherer Leistungen von Lernenden ist gemäß der Erwartungs-Wert-Theorie eine zentrale Determinante der Erfolgserwartungen und subjektiven Werte von Lernenden (Eccles & Wigfield, 2020). Darüber hinaus stellt die subjektive Wahrnehmung, die Leistungsanforderungen im Studium nicht bewältigen zu können, einen der häufigsten Gründe für einen Studienabbruch dar (Heublein et al., 2017). Eine vergleichsweise größere Variabilität der selbsteingeschätzten Leistungen im Verlauf eines Semesters könnte daher ein Anzeichen einer Anfälligkeit für Studienabbruchsintentionen darstellen.

Die vorliegende Studie

Die vorliegende Untersuchung knüpft an bisherige Befunde zu Geschlechtsunterschieden in motivationalen Überzeugungen an, indem mögliche Geschlechtsunterschiede in der Variabilität von Erwartungs- und Wertüberzeugungen und selbsteingeschätzter Leistung der Studierenden in Mathematikveranstaltungen im ersten Semester von MINT-Studiengängen untersucht werden. Die folgenden Forschungsfragen werden analysiert: Gibt es Geschlechtsunterschiede im Anteil der Varianz auf „within-person“- bzw. „between-person“-Ebene in Erfolgserwartung, subjektivem Wert und selbsteingeschätzter Leistung von Studierenden innerhalb eines Semesters in Mathematikveranstaltungen der Studieneingangsphase (*F1*)? Die „within-person“-Ebene beinhaltet dabei situationsspezifische Schwankungen und die „between-person“-Ebene beinhaltet personenspezifische Stabilität über die Zeit.

Gibt es Geschlechtsunterschiede im Anteil der Varianz zwischen den verschiedenen situationsspezifischen motivationalen Überzeugungen und selbsteingeschätzter Leistung auf within-person bzw. between-person-Ebene jeweils zu Beginn, zur Mitte und am Ende des Semesters (*F2*)?

Zur Beantwortung dieser Fragen werden jeweils zunächst Modelle ohne Kontrollvariablen berechnet (*F1a* und *F2a*). In einem zweiten Schritt werden dann der sozioökonomische Status, die Abiturnote, die jeweilige Mathematikveranstaltung und eine mögliche Teilnahme am Vorkurs der Studierenden als Kontrollvariablen auf between-person-Ebene in die Modelle aufgenommen, um für stabile interindividuelle Unterschiede sowie

Unterschiede zwischen den Mathematikveranstaltungen in den motivationalen Überzeugungen und der selbsteingeschätzten Leistung zu kontrollieren (*F1b* und *F2b*). Bisherige Forschung hat gezeigt, dass ein vergleichsweise geringerer sozioökonomischer Status, schlechtere schulische Leistungen sowie eine schlechtere inhaltliche Vorbereitung auf das Studium mit einem erhöhten Studienabbruchrisiko verbunden sein können (Heublein et al., 2017; Isleib, 2019).

Methode

Studiendesign und Stichprobe

Die Stichprobe der Studie setzt sich zusammen aus N = 927 Studierenden (n = 318 weibliche Studierende) der Fächer Physik (n = 338), Mathematik (n = 413) oder Mathematik auf Lehramt (n = 176), die jeweils eine verpflichtende Mathematikveranstaltung des ersten Semesters in ihrem Studiengang besuchten. Pro Studiengang wurden zwei aufeinanderfolgende Kohorten Studierender in derselben Mathematikveranstaltung des entsprechenden Studienfachs zu Studienbeginn im Wintersemester rekrutiert (Wintersemester 2017/2018 und 2018/2019). Die Mehrheit der Studierenden mit gültigen Angaben befand sich im ersten Semester ihres Studiengangs (90%), war in Deutschland geboren (91%) und gab Deutsch als die Sprache an, die sie zuhause am häufigsten sprechen (86%). Aus der ursprünglichen Stichprobe (N = 1038) wurden für die Analysen 77 Fälle ausgeschlossen, in denen das Geschlecht der Studierenden nicht bekannt war. Zudem wurden 27 Fälle für die Analysen entfernt, in denen die Studierenden keinen anonymisierten, persönlichen Code zur Verlinkung der longitudinalen Daten angegeben hatten. Zuletzt wurden sieben Fälle ausgeschlossen, in denen Studierende unbrauchbare Angaben machten (z. B. gleiche Antworten bei allen Items).

Die Studierenden wurden über ein ganzes Semester in ihrer verpflichtenden Mathematikvorlesung des ersten Semesters begleitet, wobei die Daten jeweils zu Beginn des Semesters (Woche 2), zur Mitte des Semesters (Woche 8) und am Ende des Semesters (Woche 15) mittels Paper-and-Pencil-Fragebögen erfasst wurden. Die Datenerhebungen fanden in den Mathevorlesungen statt, in denen die Studierenden verpflichtende Übungsblätter einreichen mussten. Nahezu alle Studierende, die während der Datenerhebungen in der Vorlesung anwesend waren, nahmen an der Studie teil (Rücklaufquote zwischen 98% und 100% an jedem Messzeitpunkt). Die Studierenden erhielten Leistungsfeedback zu den Übungsblättern in ihrer jeweiligen Übungsgruppe. Die Übungsblätter konnten von den Studierenden in Kleingruppen von zwei bis drei Personen eingereicht werden und mussten bestanden werden, um zur Klausur am Semesterende zugelassen zu werden. Die Leistung der Studierenden auf den Übungsblättern hatte allerdings keinen Einfluss auf die Note am Ende der Veranstaltung.

Instrumente

Die Studierenden beantworteten Fragen zu ihrer Erfolgserwartung, ihren subjektiven Werten und ihrer selbsteingeschätzten Leistung an allen drei Messzeitpunkten (T1–T3).

Erfolgserwartung, subjektive Werte und selbsteingeschätzte Leistung

Die *Erfolgserwartung* der Studierenden wurde mit drei Items adaptiert nach Eccles und Wigfield (1995) und Tanaka und Murayama (2014) erfasst (z. B. „Aufgrund meiner bisherigen Erfahrungen in dieser Veranstaltung denke ich, dass ich bei der Prüfung gut abschneiden werde.“). Zur Erfassung der *subjektiven Werte* der Studierenden wurden Items adaptiert nach Gaspard et al. (2015) eingesetzt, wobei aufgrund der begrenzten Zeit für die Datenerhebungen in den Vorlesungen nicht alle Facetten des Erwartungs-Wert-Modells berücksichtigt werden konnten Der *intrinsische Wert* (z. B. „Die Beschäftigung mit den Inhalten und Aufgaben in dieser Veranstaltung macht mir Spaß.“), die *Nützlichkeit* (z. B. „Die Beschäftigung mit den Inhalten und Aufgaben in dieser Veranstaltung ist nützlich für meine Zukunft.“) sowie die wahrgenommenen *psychologischen Kosten* (z. B. „Die Beschäftigung mit den Inhalten und Aufgaben in dieser Veranstaltung finde ich stressig.“) und *Anstrengungskosten* (z. B. „Die Beschäftigung mit den Inhalten und Aufgaben in dieser Veranstaltung kostet mich eine Menge Energie.“) wurden mit jeweils zwei Items erfasst. Die persönliche Wichtigkeit wurde in der vorliegenden Studie nicht berücksichtigt, da vorherige Studien gezeigt haben, dass diese Wertfacette stabiler ist im Vergleich zum intrinsischen Wert und zur Nützlichkeit (z. B. Robinson et al., 2019). Alle Erwartungs- und Wertüberzeugungen wurden auf einer 6-Punkte-Skala von 1 = *stimme überhaupt nicht zu* bis 6 = *stimme voll und ganz zu* erhoben. Die interne Konsistenz der Skalen lag bei $\alpha = .67–.92$. Zuletzt wurde die *selbsteingeschätzte Leistung* der Studierenden auf dem aktuellen Übungsblatt mit einem Item auf einer 10-Punkte-Skala von 1 = *0%–10%* bis 10 = *91%–100%* erfasst.

Individuelle Voraussetzungen und familiärer Hintergrund

Die teilnehmenden Studierenden gaben ihr Geschlecht (34% weiblich) und ihre Abiturnote ($M = 1.87$, $SD = 0.65$) zu Beginn des Semesters an und teilten mit ob sie vor Studienbeginn am Mathematikvorkurs teilgenommen hatten (65% Teilnahme). Der familiäre Hintergrund der Studierenden wurde mit einer offenen Frage nach den Berufen der Eltern erfasst. Die Berufe wurden dann anhand der Klassifikation der Berufe der Bundesagentur für Arbeit kodiert (KldB; Paulus & Matthes, 2013), wobei das Klassifizierungssystem zwischen vier Anforderungsniveaus für Berufe differenziert (1 = *benötigt keine/geringe Ausbildung* bis 4 = *benötigt einen Hochschulabschluss*). Die Mehrheit der Studierenden (61%) hatte mindestens ein Elternteil mit einem Hochschulabschluss und weniger als 1% der Studiereden hatten Elternteile, deren Beruf keinen schulischen oder berufsqualifizierenden Abschluss voraussetzte. Daher wurde eine binäre Variable als Maß für den sozioökonomischen Status (SES) der Studierenden gebildet (0 = *geringer SES/Anforderungsniveau 1–3*, 1 = *hoher SES/Anforderungsniveau 4*). Zur Kontrolle möglicher Unterschiede zwischen den Mathematikkursen wurden außerdem Dummyvariablen für die jeweiligen Mathematikveranstaltungen in die Analysen aufgenommen.

Statistische Analysen

Zur Analyse der Forschungsfragen wurden Mehrebenanalysen mit M*plus* 8.5 durchgeführt, um die genestete Datenstruktur zu berücksichtigen (d. h. Messzeitpunkte bzw. Konstrukte genestet in Studierenden). Maximum-Likelihood-Schätzverfahren mit robusten Standardfehlern wurde für alle Modelle verwendet, die robust gegenüber Abweichungen der beobachteten Variablen von einer Normalverteilung sind. Mehrebenanalysen erlauben es, die Gesamtvarianz in zwei Anteile aufzuteilen: Variabilität zwischen den Studierenden (between-level) und intraindividuelle Variabilität (within-level). Mit Blick auf die erste Forschungsfrage wurde somit der Anteil der Varianz in den Erwartungs- und Wertüberzeugungen sowie der selbsteingeschätzten Leistung der Studierenden berechnet, der auf Unterschiede zwischen den Studierenden im Gegensatz zu intraindividuellen Unterschieden zwischen den drei Messzeitpunkten innerhalb des Semesters zurückzuführen ist. Für Forschungsfrage 2 wurden dann die Erwartungs- und Wertüberzeugungen sowie die selbsteingeschätzte Leistung der Studierenden als genestet innerhalb eines Messzeitpunktes (zu Beginn, zur Mitte oder zum Ende des Semesters) betrachtet und somit der Anteil der Varianz berechnet, der auf Unterschieden zwischen den Studierenden versus intraindividuellen Unterschieden zwischen den Konstrukten innerhalb einer Situation basiert. Für beide Forschungsfragen wurden somit Intraklassenkorrelationen (ICC) berechnet, die das Verhältnis der Varianz zwischen den Studierenden (between-level) zur Gesamtvarianz angeben und ein Maß für stabile trait-Unterschiede in den Erwartungs- und Wertüberzeugungen und der selbsteingeschätzten Leistung über die drei Messzeitpunkte beziehungsweise die Konsistenz dieser Maße innerhalb einer Situation darstellen.

Zur Beantwortung der Forschungsfragen wurden die Mehrebenenmodelle als Mehrgruppenmodelle spezifiziert (d. h. separate Modelle für männliche und weibliche Studierende), sodass getrennte ICCs für weibliche und männliche Studierende vorliegen. Geschlechtsunterschiede in den ICCs wurden dann durch Bildung der Differenz der beiden ICCs getestet und 95%-Konfidenzintervalle für diese Differenz und die jeweiligen ICCs geschätzt (Dowling et al., 2019; Raykov, 2011). Für Forschungsfragen 1a und 2a wurden Nullmodelle geschätzt, während für Forschungsfragen 1b und 2b die Abiturnote, der sozioökonomische Status, eine Teilnahme am Vorkurs und die Dummyvariablen für die Mathematikveranstaltungen als Prädiktoren auf dem between-level aufgenommen wurden. Alle getesteten Modelle waren vollständig saturiert ($df = 0$).

Aus den Items der Erwartungs- und Wertüberzeugungen wurden für die Analysen jeweils Summenscores gebildet. Für Forschungsfrage 2 wurden außerdem die wahrgenommenen Kosten umgepolt und die selbsteingeschätzte Leistung auf eine 6-Punkte-Skala umskaliert, sodass alle Variablen auf derselben Intervallskala vorlagen und die Konstrukte als Messwiederholungen innerhalb einer Person aufgefasst werden konnten.

Für den Umgang mit fehlenden Werten wurde das Full-Information-Maximum-Likelihood-Verfahren genutzt. Studierende, die an mindestens einem der drei Messzeitpunkte abwesend waren, hatten einen geringeren sozioökonomischen Status ($r = -.11$, $p = .003$), schlechtere Abiturnoten ($r = .39$, $p < .001$) und hatten weniger oft am Vorkurs teilgenommen ($r = -.24$, $p < .001$) im Vergleich zu Studierenden, die an allen drei Messzeitpunkten an der Studie teilgenommen haben. Diese Variablen wurden jeweils im zweiten Schritt der Analysen als Prädiktoren der Erwartungs- und Wertüberzeugungen und der selbsteingeschätzten Leistung auf der between-Ebene aufgenommen.

Ergebnisse

Vorbereitende Analysen

Deskriptive Statistiken aller Variablen sind in Tabelle 1 dargestellt. Männliche und weibliche Studierende unterschieden sich nicht signifikant in ihren individuellen und familiären Hintergrundmerkmalen. Signifikante Mittelwertunterschiede zwischen männlichen und weiblichen Studierenden zeigten sich hingegen in der Erfolgserwartung und den psychologischen Kosten an allen drei Messzeitpunkten sowie zwischen der selbsteingeschätzten Leistung (mit Ausnahme von T3). Weibliche Studierende berichteten geringere Erfolgserwartungen, höhere psychologische Kosten und schätzten ihre Leistung schlechter ein im Vergleich zu männlichen Studierenden. Darüber hinaus ist zu erkennen, dass die Erwartungs- und Wertüberzeugungen sowie die selbsteingeschätzte Leistung im Verlauf des Semesters sowohl für männliche als auch weibliche Studierende abnahmen (siehe Tabelle 1).

Variabilität der motivationalen Überzeugungen im Verlauf des Semesters

Zur Beantwortung der ersten Forschungsfrage wurde zunächst ein Nullmodell geschätzt, in dem die Varianz in within-person und between-person-Anteile zerlegt wird (*F1a*), bevor im zweiten Schritt auf Level 2 die Kontrollvariablen als Prädiktoren der Erwartungs- und Wertüberzeugungen sowie der selbsteingeschätzten Leistung der Studierenden hinzugefügt wurden (*F1b*). Vorbereitende Analysen zeigten keine signifikanten Unterschiede in der Gesamtvarianz der motivationalen Überzeugungen sowie der selbsteingeschätzten Leistung bei weiblichen und männlichen Studierenden im Verlauf des Semesters ($\chi^2(1) \leq 2.272$, $p \geq .132$), mit Ausnahme einer signifikant größeren Gesamtvarianz in den wahrgenommenen Anstrengungskosten bei männlichen Studierenden ($\chi^2(1) = 6.727$, $p = .010$).

In Tabelle 2 sind die ICCs aller Variablen für weibliche und männliche Studierende sowie die Differenz der ICCs zwischen weiblichen und männlichen Studierenden dargestellt. Es zeigte sich, dass zwischen 42% und 74% der Varianz in der Erfolgserwartung, den subjektiven Werten und der selbsteingeschätzten Leistung der Studierenden auf Variabilität zwischen den Studierenden zurückzuführen war. Entsprechend betrug der Anteil situationsspezifischer Variabilität zwischen 26% und 58% der Gesamtvarianz.

Darüber hinaus zeigten sich signifikante Unterschiede in den ICCs der Erfolgserwartung und selbsteingeschätzter Leistung zwischen weiblichen und männlichen Studierenden (siehe Tabelle 2). Die ICCs der Erfolgserwartung und selbsteingeschätzten Leistung von weiblichen Studierenden waren 11 bzw. 14 Prozentpunkte kleiner verglichen mit den ICCs der männlichen Studierenden. Das bedeutet, dass bei weiblichen im Vergleich zu männlichen Studierenden ein kleinerer Anteil der Gesamtvarianz in der Erfolgserwartung und der selbsteingeschätzten Leistung auf konstante trait-Faktoren beziehungsweise Unterschiede zwischen den Studierenden zurückzuführen war. Mit Blick auf die subjektiven Werte zeigten sich keine signifikanten Geschlechtsunterschiede in den ICCs der männlichen und weiblichen Studierenden ($p \geq .085$), obwohl mit Ausnahme der psychologischen Kosten alle Vorzeichen negativ waren (d. h. die männlichen Studierenden hatten leicht höhere ICC-Werte, vgl. Tabelle 2).

Tabelle 1

Korrelationen und deskriptive Statistiken aller Variablen für weibliche und männliche Studierende sowie Gruppenunterschiede zwischen weiblichen und männlichen Studierenden

Variable		1	2	3	4	5	6	7	8	9	10	11
1. Sozioökononom. Status		—	−.23**	.18**	−.04	.04	−.05	.06	.08	.21**	−.01	.04
2. Abiturnote		−.17**	—	−.25**	−.11	−.20**	−.13	−.15*	−.20**	−.11	−.07	−.14*
3. Vorkursteilnahme		.07	−.19**	—	.01	−.01	−.05	.11	.00	.10	.08	.01
4. Erfolgserwartung T1		.10*	−.19**	−.04	—	.62**	.51**	.41**	.32**	.19**	.29**	.25**
5. Erfolgserwartung T2		.05	−.26**	.01	.66**	—	.73**	.26**	.52**	.40**	.14*	.35**
6. Erfolgserwartung T3		.03	−.22**	−.04	.66**	.80**	—	.20**	.36**	.44**	.18**	.29**
7. Interesse T1		.04	−.23**	.12**	.44**	.35**	.38**	—	.41**	.34**	.43**	.28**
8. Interesse T2		.01	−.29**	.10*	.36**	.54**	.42**	.54**	—	.69**	.19**	.50**
9. Interesse T3		.05	−.18**	.04	.32**	.46**	.56**	.45**	.61**	—	.13	.20*
10. Nützlichkeit T1		.02	−.05	.07	.32**	.19**	.25**	.37**	.23**	.26**	—	.51**
11. Nützlichkeit T2		.02	−.10*	.04	.27**	.32**	.29**	.29**	.41**	.42**	.57**	—
12. Nützlichkeit T3		.03	−.15**	.04	.23**	.33**	.30**	.28**	.36**	.52**	.51**	.68**
13. Psych. Kosten T1 [a]		.12**	−.08	.06	.51**	.46**	.42**	.38**	.33**	.35**	.27**	.25**
14. Psych. Kosten T2 [a]		.11**	−.25**	.09	.31**	.50**	.45**	.20**	.38**	.36**	.09	.16**
15. Psych. Kosten T3 [a]		.14**	−.16**	.05	.37**	.50**	.53**	.30**	.35**	.37**	.19**	.20**
16. Anstrengungskosten T1 [a]		.05	−.01	−.06	.45**	.42**	.41**	.18**	.20**	.19**	.13**	.20**
17. Anstrengungskosten T2 [a]		.06	−.13**	.01	.33**	.43**	.39**	.15**	.18**	.19**	.05	.10*
18. Anstrengungskosten T3 [a]		.04	−.09	−.03	.36**	.46**	.44**	.22**	.18**	.24**	.08	.11
19. Selbst. Leistung T1 [b]		.11*	−.32**	.10*	.53**	.56**	.55**	.40**	.34**	.40**	.24**	.27**
20. Selbst. Leistung T2 [b]		.03	−.35**	.10*	.41**	.64**	.54**	.33**	.53**	.46**	.16**	.29**
21. Selbst. Leistung T3 [b]		−.01	−.23**	.04	.42**	.47**	.55**	.29**	.45**	.43**	.17**	.19**
Weibliche Studierende:	*M*	.64	1.83	.67	3.50	3.18	3.20	4.71	4.38	4.41	4.52	4.20
	SD		0.64		0.79	0.80	0.92	0.82	0.91	0.91	1.02	1.09
Männliche Studierende:	*M*	.59	1.89	.64	3.82	3.56	3.57	4.76	4.46	4.47	4.56	4.32
	SD		0.65		0.75	0.91	1.01	0.80	0.91	0.91	0.99	1.03
Cohen's *d*			0.10		0.38	0.42	0.38	0.06	0.09	0.06	0.04	0.11
p			.174		<.001	<.001	<.001	.429	.257	.490	.611	.182

Variable		12	13	14	15	16	17	18	19	20	21
1. Sozioökononom. Status		.18**	.00	−.01	.06	.00	−.03	.00	.04	.04	−.06
2. Abiturnote		−.23**	−.14*	−.13*	−.04	−.06	−.07	−.03	−.34**	−.35**	.03
3. Vorkursteilnahme		.00	.12	.03	.03	.07	.04	−.05	.05	.03	−.05
4. Erfolgserwartung T1		.26**	.44**	.32**	.30**	.40**	.24**	.24**	.42**	.32**	.36**
5. Erfolgserwartung T2		.38**	.31**	.45**	.35**	.32**	.35**	.36**	.35**	.44**	.37**
6. Erfolgserwartung T3		.28**	.28**	.40**	.39**	.33**	.34**	.37**	.42**	.44**	.54**
7. Interesse T1		.26**	.32**	.25**	.25**	.21**	.07	.07	.19**	.14*	.22*
8. Interesse T2		.30**	.16*	.28**	.28**	.03	.10	.14	.28**	.35**	.31**
9. Interesse T3		.38**	.13	.24**	.29**	.04	.16*	.15*	.17*	.25**	.31**
10. Nützlichkeit T1		.51**	.11	.00	.03	.14*	−.08	−.02	.17**	.06	.16
11. Nützlichkeit T2		.66**	.09	.02	−.02	.05	−.09	−.02	.25**	.22**	.14
12. Nützlichkeit T3		—	.17*	.22**	.13	.12	.09	.00	.12	.26**	.18*
13. Psych. Kosten T1 [a]		.27**	—	.60**	.61**	.68**	.38**	.38**	.34**	−.28**	.22**
14. Psych. Kosten T2 [a]		.23**	.56**	—	.65**	.44**	.70**	.46**	.20**	.36**	.27**
15. Psych. Kosten T3 [a]		.22**	.56**	.70**	—	.42**	.53**	.64**	.18*	.19*	.24**
16. Anstrengungskosten T1 [a]		.17**	.60**	.41**	.37**	—	.47**	.51**	.33**	.23**	.30**
17. Anstrengungskosten T2 [a]		.10	.42**	.67**	.52**	.55**	—	.59**	.11	.37**	.27**
18. Anstrengungskosten T3 [a]		.09	.42**	.51**	.65**	.50**	.73**	—	.30**	.20**	.26**
19. Selbst. Leistung T1 [b]		.25**	.42**	.33**	.34**	.35**	.27**	.30**	—	.41**	.37**
20. Selbst. Leistung T2 [b]		.23**	.34**	.48**	.43**	.34**	.37**	.39**	.63**	—	.48**
21. Selbst. Leistung T3 [b]		.28**	.33**	.36**	.39**	.28**	.31**	.32**	.49**	.59**	—
Weibliche Studierende:	*M*	4.19	3.60	3.30	3.37	2.62	2.35	2.49	4.08	3.63	3.37
	SD	0.98	1.23	1.22	1.18	1.05	0.95	0.89	1.30	1.36	1.54
Männliche Studierende:	*M*	4.28	4.01	3.64	3.68	2.73	2.52	2.56	4.57	4.11	3.57
	SD	1.00	1.23	1.16	1.24	1.11	1.08	1.07	1.27	1.38	1.77
Cohen's *d*		0.09	0.34	0.29	0.26	0.10	0.16	0.08	0.38	0.35	0.11
p		.346	<.001	<.001	.006	.157	.044	.420	<.001	<.001	.299

Anmerkung. $N = 927$. Korrelationen für weibliche Studierende über der Diagonalen, für männliche Studierende unterhalb der Diagonalen. T1 = Beginn des Semesters, T2 = Mitte des Semesters, T3 = Ende des Semesters; Psych. Kosten = Psychologische Kosten; Selbst. Leistung = Selbsteingeschätzte Leistung.

[a] Psychologische Kosten und Anstrengungskosten wurden für die Analysen umgepolt, sodass niedrigere Werte höheren wahrgenommenen Kosten entsprechen.

[b] Die selbsteingeschätzte Leistung wurde für die Analysen von der ursprünglichen 10-Punkte-Skala auf eine 6-Punkte-Skala umskaliert.

$^{*}p < .05$. $^{**}p < .01$.

Tabelle 2

Intraklassenkorrelationen (ICCs) und zugehörige Konfidenzintervalle von Erfolgserwartung, subjektiven Werten und selbsteingeschätzter Leistung für weibliche und männliche Studierende

	ICC_w	95% KI ICC_w	ICC_m	95% KI ICC_m	ΔICC	95% KI ΔICC
Erfolgserwartung	$.55^{***}$	[.49, .62]	$.67^{***}$	[.62, .72]	$-.11^{**}$	[−.20, −.03]
Intrinsischer Wert	$.42^{***}$	[.33, .50]	$.51^{***}$	[.44, .58]	$-.10^{\dagger}$	[−.20, .01]
Nützlichkeit	$.55^{***}$	[.46, .64]	$.59^{***}$	[.52, .65]	−.04	[−.15, .08]
Psychologische Kosten	$.59^{***}$	[.51, .65]	$.58^{***}$	[.52, .64]	.00	[−.09, .10]
Anstrengungskosten	$.50^{***}$	[.41, .58]	$.57^{***}$	[.51, .63]	−.07	[−.18, .03]
Selbsteingeschätzte Leistung	$.60^{***}$	[.52, .67]	$.74^{***}$	[.69, .79]	$-.14^{**}$	[−.23, −.05]

Anmerkung. ΔICC = Differenz von ICC_w und ICC_m; 95% KI ICC = 95%-Konfidenzintervall für ICC, 95% KI ΔICC = 95%-Konfidenzintervall für ΔICC.
$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

In weiterführenden Analysen wurde anschließend getestet, ob die gefundenen Geschlechtsunterschiede auf Unterschiede in der within-person Variabilität oder der between-person Variabilität zwischen weiblichen und männlichen Studierenden zurückzuführen waren. Mit diesen Analysen lässt sich prüfen, ob die identifizierten Geschlechtsunterschiede auf größere intraindividuelle Fluktuationen bei weiblichen vs. männlichen Studierenden im Laufe des Semesters oder größere Variabilität in der Gruppe der männlichen im Vergleich zur Gruppe der weiblichen Studierenden zurückzuführen waren (vgl. Dowling et al., 2019). Die Ergebnisse deuten darauf hin, dass sowohl Geschlechtsunterschiede in der Variabilität der selbsteingeschätzten Leistung im Verlauf des Semesters (within-person) als auch in der Varianz zwischen den Studierenden (between-person) vorlagen: Bei weiblichen Studierenden war die situationsspezifische Variabilität in der selbsteingeschätzten Leistung im Verlauf des Semesters signifikant größer als bei männlichen Studierenden ($\Delta\sigma_w^2 = 0.86$, $\chi^2(1) = 9.77$, $p = .002$), während bei männlichen Studierenden die Varianz zwischen den Studierenden signifikant größer war, verglichen mit weiblichen Studierenden ($\Delta\sigma_b^2 = -0.90$, $\chi^2(1) = 3.96$, $p = .047$). Weiterhin zeigten sich mit Blick auf die Variabilität in der Erfolgserwartung der Studierenden signifikante Geschlechtsunterschiede in der Varianz zwischen den Studierenden, die bei männlichen Studierenden größer war als bei weiblichen Studierenden ($\Delta\sigma_b^2 = -0.16$, $\chi^2(1) = 5.56$, $p = .018$). Demgegenüber waren keine signifikanten Geschlechtsunterschiede in der situationsspezifischen Variabilität der Erfolgserwartung zu finden, obwohl die Tendenz auch hier in Richtung einer größeren Variabilität der Erfolgserwartung im Verlauf des Semesters bei weiblichen Studierenden ging ($\Delta\sigma_w^2 = 0.05$, $\chi^2(1) = 2.40$, $p = .121$).

Im zweiten Schritt wurden der sozioökonomischer Status, die Abiturnote, die Teilnahme am Vorkurs und die Dummyvariablen für die Mathematikkurse als between-level-

Prädiktoren in das Modell aufgenommen (*F1b*). Die Schätzungen der ICCs für weibliche und männliche Studierende sowie zugehörige Konfidenzintervalle sind in Tabelle 3 dargestellt. Nach Kontrolle für individuelle und familiäre Hintergrundmerkmale sowie die Mathematikkurse der Studierenden zeigten sich vergleichbare Ergebnisse wie bei Forschungsfrage 1a: Die Differenz der ICCs weiblicher und männlicher Studierender war signifikant für die Erfolgserwartung und die selbsteingeschätzte Leistung (11 bzw. 16 Prozentpunkte geringer für weibliche Studierende), wohingegen sich keine signifikanten Geschlechtsunterschiede in den ICCs der subjektiven Werte zeigten (2–8 Prozentpunkte Differenz).

Tabelle 3

Intraklassenkorrelationen (ICCs) und zugehörige Konfidenzintervalle von Erfolgserwartung, subjektiven Werten und selbsteingeschätzter Leistung für weibliche und männliche Studierende unter Kontrolle von SES, Abiturnote, Vorkursteilnahme und der Mathematikkurse

	ICC_w	95% KI ICC_w	ICC_m	95% KI ICC_m	ΔICC	95% KI ΔICC
Erfolgserwartung	$.53^{***}$	[.46, .60]	$.64^{***}$	[.59, .69]	$-.11^{*}$	[−.20, −.02]
Intrinsischer Wert	$.39^{***}$	[.30, .48]	$.47^{***}$	[.40, .55]	−.08	[−.20, .03]
Nützlichkeit	$.49^{***}$	[.39, .59]	$.55^{***}$	[.48, .61]	−.06	[−.18, .07]
Psychologische Kosten	$.58^{***}$	[.50, .65]	$.56^{***}$	[.50, .62]	.02	[−.08, .11]
Anstrengungskosten	$.49^{***}$	[.40, .57]	$.56^{***}$	[.49, .62]	−.07	[−.18, .04]
Selbsteingeschätzte Leistung	$.54^{***}$	[.45, .62]	$.70^{***}$	[.64, .75]	$-.16^{**}$	[−.27, −.06]

Anmerkung. ΔICC = Differenz von ICC_w und ICC_m; 95% KI ICC = 95%-Konfidenzintervall für ICC, 95% KI ΔICC = 95%-Konfidenzintervall für ΔICC.

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Im Vergleich zu männlichen Studierenden war bei weiblichen Studierenden somit auch unter Kontrolle individueller Merkmale und der Mathematikkurse ein kleinerer Anteil der Varianz in der Erfolgserwartung und in der selbsteingeschätzten Leistung auf Unterschiede zwischen den Studierenden zurückzuführen. Das bedeutet, dass bei Betrachtung einer weiblichen und eines männlichen Studierenden mit vergleichbarem sozioökonomischem Status, vergleichbarer Abiturnote sowie Vorkursteilnahme und die die gleiche Mathematikveranstaltung besuchten, bei der weiblichen Studierenden ein kleinerer Anteil der Gesamtvarianz in der Erfolgserwartung und in der selbsteingeschätzten Leistung im Verlauf des Semesters auf konstante Anteile über alle Messzeitpunkte zurückzuführen war.

Variabilität zwischen den motivationalen Überzeugungen

In der zweiten Forschungsfrage wurde die Kohärenz der Erwartungs- und Wertüberzeugungen und der selbsteingeschätzten Leistung innerhalb der einzelnen

Messzeitpunkte untersucht, wobei analog zu Forschungsfrage 1 zunächst ein unkonditionelles Modell geschätzt wurde (*F2a*) und im Anschluss individuelle und familiäre Merkmale auf der between-Ebene kontrolliert wurden (*F2b*). Vorbereitende Analysen zeigten keine signifikanten Unterschiede in der Gesamtvarianz zwischen den motivationalen Überzeugungen sowie der selbsteingeschätzten Leistung bei weiblichen und männlichen Studierenden jeweils innerhalb der drei Messzeitpunkte ($\chi^2(1) \leq 0.015$, $p \geq .903$), mit Ausnahme einer signifikant größeren Gesamtvarianz zwischen den motivationalen Überzeugungen und der Leistungseinschätzung am Ende des Semesters bei männlichen Studierenden ($\chi^2(1) = 8.631$, $p = .003$).

In Tabelle 4 sind die geschätzten ICCs der untersuchten Konstrukte genestet innerhalb des jeweiligen Messzeitpunktes zu Beginn (T1), zur Mitte (T2) und zum Ende des Semesters (T3) inklusive der 95%-Konfidenzintervalle sowie die ICC-Differenz zwischen weiblichen und männlichen Studierenden dargestellt. Zwischen 15% und 27% der Variabilität zwischen Erfolgserwartung, subjektiven Werten und selbsteingeschätzter Leistung innerhalb einer Situation waren Unterschiede zwischen den Studierenden, während 63% bis 85% der Varianz auf within-person Variabilität zwischen den motivationalen Überzeugungen und Leistungseinschätzung zurückzuführen war.

Tabelle 4

Intraklassenkorrelationen (ICCs) und Konfidenzintervalle der Konstrukte für weibliche und männliche Studierende

	ICC_w	95% KI ICC_w	ICC_m	95% KI ICC_m	ΔICC	95% KI ΔICC
Motivationale Überzeugungen und Leistungseinschätzung T1	$.15^{***}$	[.11, .20]	$.20^{***}$	[.16, .23]	−.05	[−.10, .01]
Motivationale Überzeugungen und Leistungseinschätzung T2	$.17^{***}$	[.12, .23]	$.26^{***}$	[.22, .30]	$-.09^{*}$	[−.15, −.02]
Motivationale Überzeugungen und Leistungseinschätzung T3	$.17^{***}$	[.12, .24]	$.27^{***}$	[.23, .32]	$-.10^{**}$	[−.18, −.03]

Anmerkung. T1 = Beginn des Semesters, T2 = Mitte des Semesters, T3 = Ende des Semesters; ΔICC = Differenz von ICC_w und ICC_m; 95% KI ICC = 95%-Konfidenzintervall für ICC, 95% KI ΔICC = 95%-Konfidenzintervall für ΔICC.

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Darüber hinaus zeigten sich signifikante Geschlechtsunterschiede in den ICCs der motivationalen Überzeugungen an zwei der drei Messzeitpunkten (siehe Tabelle 4). Die geschlechtsspezifischen Diskrepanzen in der Kohärenz der motivationalen Überzeugungen sowie der Leistungseinschätzung stiegen von ΔICC = −.05 (p = .120) zu Messzeitpunkt T1 (Anfang des Semesters) bis ΔICC = −.10 (p < .012) zu Messzeitpunkt T3 (Ende des Semesters) an. Weiterführende Analysen deuten auch hier auf signifikante Geschlechtsunterschiede in der within-person-Varianz (Kohärenz der Überzeugungen innerhalb einer Situation) sowie der Varianz zwischen den Studierenden hin: An beiden Messzeitpunkten zur Mitte und zum Ende des Semesters zeigte sich eine größere Varianz in den motivationalen Überzeugungen und Leistungseinschätzung in der Gruppe der männlichen im Vergleich zur Gruppe der weiblichen Studierenden ($\Delta\sigma_b^2 = -0.15$ bzw. -0.24, $\chi^2(1) = 4.76$ bzw. 8.82, $ps \leq .030$). Darüber hinaus war am Messzeitpunkt T2 zur Mitte des Semesters die Variabilität zwischen den Konstrukten innerhalb der weiblichen Studierenden größer als innerhalb der männlichen Studierenden ($\Delta\sigma_w^2 = 0.14$, $\chi^2(1) = 4.63$, $p = .032$). Das bedeutet, dass die motivationalen und leistungsbezogenen Überzeugungen von männlichen im Vergleich zu weiblichen Studierenden eine höhere Konsistenz innerhalb einer Situation aufwiesen.

Im nächsten Schritt wurden individuelle und familiäre Hintergrundvariablen als Level 2-Prädiktoren in das Modell aufgenommen (*F2b*). Tabelle 5 zeigt die ICCs der motivationalen Überzeugungen und Leistungseinschätzung innerhalb der drei Messzeitpunkte für weibliche und männliche Studierende.

Tabelle 5

Intraklassenkorrelationen (ICCs) und Konfidenzintervalle der Konstrukte für weibliche und männliche Studierende unter Kontrolle von SES, Abiturnote, Vorkursteilnahme und der Mathekurse

	ICC_w	95% KI ICC_w	ICC_m	95% KI ICC_m	ΔICC	95% KI ΔICC
Motivationale Überzeugungen und Leistungseinschätzung T1	$.11^{***}$	[.07, .16]	$.16^{***}$	[.13, .20]	$-.05^{\dagger}$	[−.11, .00]
Motivationale Überzeugungen und Leistungseinschätzung T2	$.13^{***}$	[.09, .18]	$.21^{***}$	[.17, .26]	$-.08^{*}$	[−.15, −.02]
Motivationale Überzeugungen und Leistungseinschätzung T3	$.15^{***}$	[.10, .21]	$.23^{***}$	[.18, .28]	$-.08^{*}$	[−.16, −.01]

Anmerkung. T1 = Beginn des Semesters, T2 = Mitte des Semesters, T3 = Ende des Semesters; ΔICC = Differenz von ICC_w und ICC_m; 95% KI ICC = 95%-Konfidenzintervall für ICC, 95% KI ΔICC = 95%-Konfidenzintervall für ΔICC.

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Analog zum Modell ohne Kontrollvariablen fanden sich signifikante Geschlechtsunterschiede in den ICCs zur Mitte und zum Ende des Semesters (je 8 Prozentpunkte), während die ICC-Differenz zu Beginn des Semesters nicht signifikant war (5 Prozentpunkte, p = .064; Tabelle 5). Demensprechend lag auch unter Kontrolle des sozioökonomischen Status, der Abiturnote, einer Vorkursteilnahme sowie den Mathematikkursen bei männlichen Studierenden ein größerer Anteil der Varianz zwischen den Konstrukten innerhalb einer Situation zwischen den Studierenden, während bei weiblichen Studierenden ein größerer Anteil der Varianz auf situationsspezifische Variabilität zwischen Erfolgserwartung, subjektiven Werten und selbsteingeschätzter Leistung zurückzuführen war.

Diskussion

Ziel der vorliegenden Studie war es, Geschlechtsunterschiede in der Variabilität der situationsspezifischen Erwartungs- und Wertüberzeugungen sowie der selbsteingeschätzten Leistung von Studierenden in Mathematikveranstaltungen im ersten Semester von MINT-Studienfächern zu untersuchen. In Übereinstimmung mit der situativen Erwartungs-Wert-Theorie (Eccles & Wigfield, 2020) zeigte sich, dass wesentliche Anteile der Variabilität der motivationalen Überzeugungen sowie der selbsteingeschätzten Leistung auf situations-spezifische Faktoren zurückzuführen waren. Die Analysen offenbarten dabei Geschlechts-unterschiede in der Variabilität der Erfolgserwartung und der selbsteingeschätzten Leistung von Studierenden im Laufe des Semesters, während keine signifikanten Unterschiede zwischen weiblichen und männlichen Studierenden in der Variabilität der subjektiven Werte zu finden waren. Darüber hinaus zeigte sich, dass bei weiblichen Studierenden ein größerer Anteil der Gesamtvarianz zwischen den verschiedenen motivationalen Überzeugungen und der selbsteingeschätzten Leistung auf Variabilität zwischen diesen Konstrukten innerhalb einer Situation anstatt von Varianz zwischen den Studierenden zurückzuführen war als bei männlichen Studierenden. Die gefundenen Geschlechtsunterschiede blieben signifikant auch unter Kontrolle des sozioökonomischen Status, vorheriger akademischer Leistungen, einer Teilnahme am Mathematikvorkurs sowie den Mathematikveranstaltungen, die die Studierenden besuchten. Unsere Analysen deuten folglich darauf hin, dass situations-spezifische Erfolgserwartungen, subjektive Werte und Leistungseinschätzungen zumindest teilweise durch stabile trait-Unterschiede zwischen den Studierenden geprägt werden und dass diese trait-Unterschiede bei männlichen Studierenden einen größeren Anteil der Variabilität in der Erfolgserwartung und den selbsteingeschätzten Leistungen sowie der Variabilität zwischen den Konstrukten erklären als bei weiblichen Studierenden.

Variabilität der motivationalen Überzeugungen im Verlauf des Semesters

Im Gegensatz zu Tsai, Kunter, Lüdtke und Trautwein (2008), die keine signifikanten Geschlechtsunterschiede in der Variabilität der Kompetenzüberzeugungen von Schülerinnen und Schülern im Mathematikunterricht gefunden haben, zeigten unsere Analysen signifikante Geschlechtsunterschiede in der Variabilität der Erfolgserwartung der Studierenden im Verlauf eines Semesters in mathematikintensiven MINT-Studiengängen. Der unterschiedliche Untersuchungszeitraum (ein Semester vs. 3 Wochen) könnte zu diesen Ergebnissen beigetragen haben, allerdings könnten die abweichenden Ergebnisse auch durch den Kontext der vorliegenden Studie bedingt sein. Die Fachkultur in mathematikintensiven Studienfächern könnte die identifizierten Geschlechtsunterschiede in der Variabilität von motivationalen und leistungsbezogenen Einschätzungen verstärken. Typische Elemente mathematikintensiver MINT-Studienfächer sind hoher Arbeitsaufwand und Leistungsdruck (Heublein et al., 2017; Seymour & Hewitt, 1997), beispielsweise durch verpflichtende wöchentliche Übungsblätter. Dabei stellt das erste Studienjahr eine besonders wichtige Zeit für die Anpassung der Studierenden an den neuen Bildungskontext dar (Heublein et al., 2017) und könnte für weibliche Studierende in männlich-dominierten MINT-Studienfächern mit zusätzlichen Herausforderungen einhergehen, wie beispielsweise Sorgen negative Stereotype über Frauen im MINT-Bereich zu bestätigen (vgl. Murphy et al., 2007).

Unsere Analysen zeigten darüber hinaus, dass signifikante Geschlechtsunterschiede im Anteil der Varianz in der Erfolgserwartung sowie der selbsteingeschätzten Leistung im Verlauf des Semesters auch nach Kontrolle der individuellen Voraussetzungen sowie der Mathematikveranstaltungen der Studierenden in der gleichen Größenordnung lagen. Dies deutet darauf hin, dass die Diskrepanzen in der Variabilität der Erfolgserwartung und selbsteingeschätzten Leistung weiblicher und männlicher Studierender eher nicht durch tatsächliche Unterschiede in den akademischen Leistungen zwischen weiblichen und männlichen Studierenden erklärbar sind. Stattdessen könnten situative Faktoren die Erfolgserwartung und Leistungseinschätzung weiblicher Studierender stärker beeinflussen als jene Einschätzungen männlicher Studierender. Beispielsweise könnten weibliche Studierende aufgrund unterschiedlicher Attributionsprozesse von Erfolgs- und Misserfolgserlebnissen anfälliger für Schwankungen in ihrem erwarteten Erfolg in der Klausur am Semesterende sein als männliche Studierende (Beyer, 1998; Ryckman & Peckham, 1987). Verschiedene Studien deuten darauf hin, dass weibliche Lernende Erfolgserlebnisse in Mathematik eher mit der investierten Anstrengung erklären und Misserfolge eher auf mangelnde Fähigkeiten zurückführen, während männliche Lernende Erfolge und Misserfolge eher ähnlich interpretieren (Ryckman & Peckham, 1987). Bisherige Studien im mathematischen Bereich zeigen zudem auch, dass männliche im Vergleich zu weiblichen Lernenden Erfolge häufiger durch ihre Fähigkeiten erklären (Beyer, 1998; Ryckman & Peckham, 1987). Dementsprechend könnten weibliche Studierende aufgrund dieser weniger adaptiven Attributionsmuster anfälliger für Schwankungen in ihrem erwarteten Erfolg sein, wenn sie in einer Situation mit schwierigen Lerninhalten konfrontiert sind. Diese Ergebnisse deuten darauf hin, dass Anpassungen der Lernprozesse nötig sind, um insbesondere weibliche Studierende in der Studieneingangsphase zu unterstützen. Beispielsweise könnten eine Reduzierung des Leistungsdrucks durch die verpflichtenden Übungsblätter oder motivationsförderliches Feedback zu den Übungsblättern, in welchem Möglichkeiten zur Verbesserung aufgezeigt werden, insbesondere für weibliche Studierende zu positiveren Erfolgsaussichten und Leistungseinschätzungen beitragen. Zudem könnten gerade weibliche Studierende von Interventionsmaßnahmen wie Reattributionstrainings (Ziegler & Heller, 1998) oder Social-Belonging-Interventionen (Walton et al., 2015) profitieren, in denen Schwierigkeiten in der Studieneingangsphase in mathematikintensiven Studienfächern nicht auf mangelnde Fähigkeiten, sondern einen temporären Anpassungsprozess an schwierige Lerninhalte und den neuen Bildungskontext zurückgeführt werden.

Darüber hinaus könnten die selbsteingeschätzten Leistungen sowie der erwartete Erfolg weiblicher Studierender stärker durch situative Wahrnehmungen von (impliziten) Stereotypen über Frauen in mathematikintensiven MINT-Studienfächern geprägt sein als jene Einschätzungen männlicher Studierender (Murphy et al., 2007; Ramsey & Sekaquaptewa, 2011). Beispielsweise zeigten Ramsey und Sekaquaptewa (2011), dass implizite Stereotype über mathematische Fähigkeiten von Frauen situationsspezifisch sind: Die impliziten Stereotype nahmen innerhalb eines Semesters in Mathematikkursen im College im Durchschnitt zu, allerdings zeigten sich auch intraindividuelle Unterschiede in den Wahrnehmungen weiblicher Studierender. Zudem fanden sich signifikante Zusammenhänge mit den Klausurergebnissen von weiblichen Studierenden am Semesterende: Frauen, deren implizite Stereotype über das Semester hinweg zunahmen, schnitten signifikant schlechter ab als Frauen, deren implizite Stereotype im Laufe des Semesters abnahmen. Folglich könnte die Disposition weiblicher Studierender bezüglich solcher Stereotype in Kombination mit situativen Faktoren, die solche Geschlechtsstereotypen aktivieren, weibliche Lernende in männlich-dominierten Kontexten anfälliger für Fluktuationen in ihrem erwarteten Erfolg und ihren Leistungseinschätzungen machen (vgl. Eccles & Wigfield, 2020).

Hinsichtlich der Variabilität in den subjektiven Werten der Studierenden im Verlauf des Semesters fanden sich keine signifikanten Unterschiede zwischen weiblichen und männlichen Studierenden. Dieser Befund deckt sich mit einer früheren Studie, in der keine Geschlechtsunterschiede in der Variabilität des situationalen Interesses am Mathematikunterricht bei Siebtklässlerinnen und Siebtklässlern über einen dreiwöchigen Zeitraum gefunden wurden (Tsai, Kunter, Lüdtke, Trautwein, & Ryan, 2008). Dies deutet darauf hin, dass vergleichbare situative Prozesse und Faktoren die subjektiven Werte bezüglich der Lerninhalte von weiblichen und männlichen Studierenden in Mathematikveranstaltungen in der Studieneingangsphase im MINT-Bereich prägen.

Variabilität zwischen den motivationalen Überzeugungen

Weitere Evidenz für die Relevanz situationsspezifischer Faktoren für die motivationalen Überzeugungen der Studierenden zeigte sich in der Analyse zur Variabilität zwischen Erfolgserwartung, subjektiven Werten und selbsteingeschätzter Leistung innerhalb der jeweiligen Situation zu Beginn, zur Mitte und zum Ende des Semesters. Auch hier befand sich bei weiblichen Studierenden ein signifikant größerer Anteil der Gesamtvarianz zwischen den Konstrukten in einer Situation auf within-person- statt between-person-Ebene verglichen mit männlichen Studierenden. Dies deutet darauf hin, dass Erfolgserwartung, subjektive Werte und selbsteingeschätzte Leistung weiblicher Studierender innerhalb einer Situation weniger eng miteinander verzahnt sind als bei männlichen Studierenden. Dies stünde im Einklang mit Befunden zu globalen (d. h. situationsunspezifischen) Motivationsprofilen von Lernenden im mathematischen Bereich, wonach weibliche Lernende häufiger Profile bestehend aus positiven sowie negativen Ausprägungen verschiedener Motivationsfacetten aufweisen (z. B. geringes Selbstkonzept und moderate Nützlichkeit bzw. Wichtigkeit in Mathe), während männliche Lernende signifikant häufiger in positiven bzw. hoch motivierten Profilen vertreten sind (Kegel et al., 2021; Lazarides et al., 2016).

Diese größere Diskrepanz zwischen den motivationalen Überzeugungen sowie der selbsteingeschätzten Leistung bei weiblichen Studierenden kann ein Zeichen für nachlassendes Engagement bzw. Identifizierung mit dem Studium sein. Eccles (2009) betont, dass eine psychologisch adaptive Art mit herausfordernden Lerninhalten und Aufgaben umzugehen darin besteht, die Erwartungs- und Wertüberzeugungen in Einklang zu bringen. Die eigenen Erfolgserwartungen zu erhöhen, um diese an eher hohe Niveaus der subjektiven Werte anzupassen, könnte allerdings in Leistungskontexten mit anspruchsvollen Lerninhalten wie in der vorliegenden Studie nicht immer möglich sein. Stattdessen könnten Studierende ihre motivationalen Überzeugungen eher angleichen, indem sie die subjektiven Werte reduzieren, die sie den Lerninhalten bzw. dem Studium beimessen (Eccles, 2009). Dies würde im weiteren Verlauf zu vergleichsweise niedrigeren Erwartungs- und Wertüberzeugungen hinsichtlich des Studiums führen und könnte mit einem Anstieg der Studienabbruchstendenzen einhergehen (vgl. Benden & Lauermann, 2021; Perez et al., 2014). In der aktuellen Studie bleibt allerdings unklar, ob diese geschlechtsspezifischen Unterschiede in der Kohärenz der Erwartungs- und Wertüberzeugungen von Lernenden primär durch eine größere Trennung zwischen der Erfolgserwartung und den subjektiven Werten oder auch durch Diskrepanzen in der situativen Wahrnehmung der verschiedenen Wertfacetten geprägt sind, sodass weitere Studien nötig sind, um diese Zusammenhänge besser zu verstehen (vgl. Denissen et al., 2007).

Limitationen und Ausblick

Bei der Interpretation der Ergebnisse der vorliegenden Studie müssen verschiedene Einschränkungen berücksichtigt werden. Erstens war die Stichprobe der vorliegenden Studie mit Blick auf den familiären Hintergrund und die schulische Vorbereitung auf das Studium insgesamt eher homogen. Dennoch lässt nicht ausschließen, dass weitere individuelle Merkmale und Überzeugungen der Studierenden zu den Geschlechtsunterschieden in der Variabilität von Erfolgserwartung und Leistungseinschätzung sowie der Variabilität zwischen den motivationalen Konstrukten beitragen können. Dazu zählen beispielweise wie bereits angesprochen Überzeugungen über (implizite) Stereotype im MINT-Bereich (Ramsey & Sekaquaptewa, 2011). Zudem wurde in der vorliegenden Studie lediglich für vorherige Leistungsunterschiede in der Abiturnote kontrolliert und nicht für mögliche Unterschiede im mathematischen Bereich in der Schule (z. B. Leistungen, Lerngelegenheiten).

Zweitens bleibt auch offen, ob die identifizierten Geschlechtsunterschiede in der Variabilität der situationsspezifischen motivationalen Überzeugungen der Studierenden durch unterschiedliche situative Wahrnehmungen geprägt sind oder durch unterschiedlich große trait-Anteile in den situativen motivationalen Überzeugungen bei weiblichen im Vergleich zu männlichen Studierenden bestimmt werden. Um interindividuelle Unterschiede in situationsspezifischen motivationalen Überzeugungen von Lernenden besser zu verstehen, ist daher weitere Forschung notwendig, in der die Anteile der Variabilität, die auf individuelle situative Wahrnehmungen beziehungsweise trait-Faktoren der Lernenden zurückzuführen sind, separiert werden (vgl. Geiser et al., 2017). Bedeutsame situationsspezifische Faktoren, die die motivationalen Überzeugungen von Lernenden beeinflussen, könnten im Vergleich zu eher stabilen trait-Unterschieden zwischen Studierenden leichter verändert werden (z. B. durch

Anpassungen der Unterrichtsgestaltung, motivationsförderliche Feedbackgebung), um negativen Motivationsprofilen und Fluktuationen in den motivationalen Überzeugungen entgegenzuwirken (vgl. Rosenzweig & Wigfield, 2016). In diesem Zusammenhang ist zudem auch anzumerken, dass die tatsächliche Leistung der Studierenden auf den Übungsblättern in den Analysen nicht berücksichtigt wurde, u. a. da die Übungsblätter nicht unter kontrollierten Bedingungen bearbeitet wurden. Daher bleibt offen, ob die größere situationsspezifische Variabilität in der selbsteingeschätzten Leistung sowie die geringere Kohärenz der motivationalen und leistungsbezogenen Einstellungen von weiblichen im Vergleich zu männlichen Studierenden mit Geschlechtsunterschieden in der Leistung auf den Übungsblättern zusammenhängen. Da die Studierenden die Übungsblätter in Kleingruppen abgegeben haben, lagen allerdings keine objektiven Informationen über Geschlechtsunterschiede in der Leistung auf den Übungsblättern vor, sodass in den vorliegenden Analysen der Anteil der selbstständig gelösten Aufgaben durch die Studierenden als Maß für die (selbsteingeschätzte) Leistung verwendet wurde. Falls die größere Variabilität der selbsteingeschätzten Leistung nicht auf objektive Leistungsunterschiede zurückzuführen ist, wäre dies ein Indiz für geschlechtsspezifische Bewertungsprozesse der eigenen Leistung (vgl. Ryckman & Peckham, 1987).

Zuletzt bleiben die Konsequenzen der größeren Variabilität der Erfolgserwartung und selbsteingeschätzten Leistung sowie der motivationalen Konstrukte untereinander bei weiblichen im Vergleich zu männlichen Studierenden unklar. Erhöhte Variabilität der situationsspezifischen Erwartungs- und Wertüberzeugungen sowohl im Verlauf eines Semesters als auch zwischen den motivationalen Konstrukten könnte ein Zeichen für einen maladaptiven Umgang mit den hohen Anforderungen in MINT-Studienfächern darstellen (vgl. Eccles, 2009). Diese Variabilität in den motivationalen Überzeugungen könnte andererseits auch Teil des Anpassungsprozesses an den neuen Bildungskontext im MINT-Bereich sein. Weitere Studien sind daher nötig, um die Bedeutung von Variabilität in den situationsspezifischen Erwartungsüberzeugungen und subjektiven Werten von Studierenden für spätere Bildungs- und Berufsentscheidungen, insbesondere mit Blick auf höhere Studienabbruchquoten bei weiblichen Studierenden in MINT-Studiengängen, zu untersuchen.

Fazit

Die Gründe für geschlechtsspezifische Unterschiede in den Bildungs- und Berufsentscheidungen von weiblichen und männlichen Lernenden im MINT-Bereich besser zu verstehen ist ein wichtiges gesellschaftliches Anliegen, um den Bedarf an hochqualifizierten Arbeitskräften zu decken und eine vielfältigere Zusammensetzung der Erwerbsbevölkerung in MINT-Berufen zu erreichen. Die vorliegende Studie untersuchte Geschlechtsunterschiede in der Variabilität der situationsspezifischen Erwartungs- und Wertüberzeugungen sowie der selbsteingeschätzten Leistung von Studierenden in verpflichtenden Mathematik-veranstaltungen nach dem Übergang in den Hochschulkontext im MINT-Bereich. Die Analysen zeigten signifikante Geschlechtsunterschiede im Anteil der Variabilität der Erfolgserwartung und selbsteingeschätzten Leistung der Studierenden im Verlauf des Semesters. Bei weiblichen Studierenden war ein größerer Anteil der Varianz in der Erfolgserwartung und selbsteingeschätzten Leistung auf situationsspezifische Faktoren anstelle von stabilen Unterschieden zwischen den weiblichen Studierenden zurückzuführen, während sich bei männlichen Studierenden vergleichsweise größere Unterschiede zwischen den Studierenden zeigten. Darüber hinaus zeigte sich, dass die Verzahnung der motivationalen Überzeugungen und selbsteingeschätzten Leistung innerhalb einer Situation bei weiblichen Studierenden stärker von situativen Faktoren geprägt zu sein scheint als bei männlichen Studierenden. Weibliche Studierende in männlich-dominierten Studienfächern im MINT-Bereich könnten folglich anfälliger für Fluktuationen in ihren situativen motivationalen Überzeugungen sein, was eine Vorstufe für nachlassende Identifizierung mit dem Studium und Studienabbruchtendenzen darstellen kann. Analysen geschlechtsspezifischer Bildungs- und Berufswahlprozesse sollten daher die Bedeutung solcher situationsspezifischen Schwankungen in den motivationalen Überzeugungen für Entscheidungen im MINT-Bereich untersuchen.

Literatur

Anger, C., Kohlisch, E., Koppel, O., & Plünnecke, A. (2020). *MINT-Herbstreport 2020: MINT-Engpässe und Corona-Pandemie: kurzfristige Effekte und langfristige Herausforderungen*. Institut der deutschen Wirtschaft. https://www.iwkoeln.de/fileadmin/user_upload/Studien/Gutachten/PDF/2020/MINT-Herbstreport_2020.pdf

Benden, D. K., & Lauermann, F. (2021). Students' motivational trajectories and academic success in math-intensive study programs: Why short-term motivational assessments matter. *Journal of Educational Psychology*. Advance online publication. https://doi.org/10.1037/edu0000708

Beyer, S. (1998). Gender differences in causal attributions by college students of performance on course examinations. *Current Psychology, 17*(4), 346–358.

Denissen, J. J., Zarrett, N. R., & Eccles, J. S. (2007). I like to do it, I'm able, and I know I am: Longitudinal couplings between domain-specific achievement, self-concept, and interest. *Child Development, 78*(2), 430–447. https://doi.org/10.1111/j.1467-8624.2007.01007.x

Dowling, N. M., Raykov, T., & Marcoulides, G. A. (2019). Examining population differences in within-person variability in longitudinal designs using latent variable modeling: An application to the study of cognitive functioning of older adults. *Educational and Psychological Measurement, 79*(3), 598–609. https://doi.org/10.1177/0013164418758834

Eccles, J. S. (2009). Who am I and what am I going to do with my life? Personal and collective identities as motivators of action. *Educational Psychologist, 44*(2), 78–89. https://doi.org/10.1080/00461520902832368

Eccles, J. S. (2011). Gendered educational and occupational choices: Applying the Eccles et al. model of achievement-related choices. *International Journal of Behavioral Development, 35*(3), 195–201. https://doi.org/10.1177/0165025411398185

Eccles, J. S., Adler, T., Futterman, R., Goff, S., Kaczala, C., Meece, J., & Midgley, C. (1983). Expectancies, values, and academic behaviors. In J. T. Spence (Ed.), *Achievement and achievement motives* (pp. 75–146). Freeman.

Eccles, J. S., & Wigfield, A. (1995). In the mind of the actor: The structure of adolescents' achievement task values and expectancy-related beliefs. *Personality and Social Psychology Bulletin, 21*(3), 215–225. https://doi.org/10.1177/0146167295213003

Eccles, J. S., & Wigfield, A. (2020). From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation. *Contemporary Educational Psychology, 61*. https://doi.org/10.1016/j.cedpsych.2020.101859

Gaspard, H., Dicke, A.-L., Flunger, B., Schreier, B., Häfner, I., Trautwein, U., & Nagengast, B. (2015). More value through greater differentiation: Gender differences in value beliefs about math. *Journal of Educational Psychology, 107*(3), 663–677. https://doi.org/10.1037/edu0000003

Geiser, C., Götz, T., Preckel, F., & Freund, P. A. (2017). States and traits: Theories, models, and assessment. *European Journal of Psychological Assessment, 33*(4), 219–223. https://doi.org/10.1027/1015-5759/a000413

Griffith, A. L. (2010). Persistence of women and minorities in STEM field majors: Is it the school that matters? *Economics of Education Review, 29*(6), 911–922. https://doi.org/10.1016/j.econedurev.2010.06.010

Guo, J., Parker, P. D., Marsh, H. W., & Morin, A. J. (2015). Achievement, motivation, and educational choices: A longitudinal study of expectancy and value using a multiplicative perspective. *Developmental Psychology, 51*(8), 1163–1176. https://doi.org/10.1037/a0039440

Heublein, U., Ebert, J., Hutzsch, C., Isleib, S., König, R., Richter, J., & Woisch, A. (2017). *Zwischen Studienerwartungen und Studienwirklichkeit: Ursachen des Studienabbruchs, beruflicher Verbleib der Studienabbrecherinnen und Studienabbrecher und Entwicklung der Studienabbruchquote an deutschen Hochschulen*. Deutsches Zentrum für Hochschul-und Wissenschaftsforschung (DZHW). https://www.dzhw.eu/pdf/pub_fh/fh-201701.pdf

Heublein, U., & Schmelzer, R. (2018). *Die Entwicklung der Studienabbruchquoten an den deutschen*. Deutsches Zentrum für Hochschul- und Wissenschaftsforschung (DZHW). https://www.dzhw.eu/pdf/21/studienabbruchquoten_absolventen_2016.pdf

Isleib, S. (2019). Soziale Herkunft und Studienabbruch im Bachelor- und Masterstudium. In M. Lörz & H. Quast (Eds.), *Bildungs- und Berufsverläufe mit Bachelor und Master* (pp. 307–337). Springer. https://doi.org/10.1007/978-3-658-22394-6_10

Isphording, I., & Qendrai, P. (2019). *Gender differences in student dropout in STEM (IZA research report no. 87)*. Institute of Labor Economics (IZA). http://ftp.iza.org/report_pdfs/iza_report_87.pdf

Kegel, L. S., Schnettler, T., Scheunemann, A., Bäulke, L., Thies, D. O., Dresel, M., Fries, S., Leutner, D., Wirth, J., & Grunschel, C. (2021). Unterschiedlich motiviert für das Studium: Motivationale Profile von Studierenden und ihre Zusammenhänge mit demografischen Merkmalen, Lernverhalten und Befinden. *Zeitschrift für Empirische Hochschulforschung, 4*(1), 81–105. https://doi.org/10.3224/zehf.v4i1.0

Kugler, A. D., Tinsley, C. H., & Ukhaneva, O. (2017). *Choice of majors: Are women really different from men?* (NBER Working Paper No. 23735). National Bureau of Economic Research. http://www.nber.org/papers/w23735

Lauermann, F., Tsai, Y.-M., & Eccles, J. S. (2017). Math-related career aspirations and choices within Eccles et al.'s expectancy-value theory of achievement-related behaviors. *Developmental Psychology, 53*(8), 1540–1559. https://doi.org/10.1037/dev0000367

Lazarides, R., Dicke, A.-L., Rubach, C., & Eccles, J. S. (2020). Profiles of motivational beliefs in math: Exploring their development, relations to student-perceived classroom characteristics, and impact on future career aspirations and choices. *Journal of Educational Psychology, 112*(1), 70–92. https://doi.org/10.1037/edu0000368

Lazarides, R., Rubach, C., & Ittel, A. (2016). Motivational profiles in mathematics: What role do gender, age and parents' valuing of mathematics play? *International Journal of Gender, Science and Technology, 8*(1), 124–143.

Murphy, M. C., Steele, C. M., & Gross, J. J. (2007). Signaling threat: How situational cues affect women in math, science, and engineering settings. *Psychological Science, 18*(10), 879–885. https://doi.org/10.1111/j.1467-9280.2007.01995.x

Nagengast, B., Marsh, H. W., Scalas, L. F., Xu, M. K., Hau, K.-T., & Trautwein, U. (2011). Who took the "×" out of expectancy-value theory? A psychological mystery, a substantive-methodological synergy, and a cross-national generalization. *Psychological Science, 22*(8), 1058–1066. https://doi.org/10.1177/0956797611415540

Nagy, G., Watt, H. M., Eccles, J. S., Trautwein, U., Lüdtke, O., & Baumert, J. (2010). The development of students' mathematics self-concept in relation to gender: Different countries, different trajectories? *Journal of Research on Adolescence, 20*(2), 482–506. https://doi.org/10.1111/j.1532-7795.2010.00644.x

Organisation for Economic Co-operation and Development [OECD]. (2019). *Education at a Glance 2019*. OECD Publishing. https://doi.org/10.1787/f8d7880d-en

Paulus, W., & Matthes, B. (2013). *Klassifikation der Berufe: Struktur, Codierung und Umsteigeschlüssel*. Forschungsdatenzentrum (FDZ) der Bundesagentur für Arbeit im Institut für Arbeitsmarkt- und Berufsforschung. http://doku.iab.de/fdz/reporte/2013/MR_08-13.pdf

Perez, T., Cromley, J. G., & Kaplan, A. (2014). The role of identity development, values, and costs in college STEM retention. *Journal of Educational Psychology, 106*(1), 315–329. https://doi.org/10.1037/a0034027

Perez, T., Wormington, S. V., Barger, M. M., Schwartz-Bloom, R. D., Lee, Y.-K., & Linnenbrink-Garcia, L. (2019). Science expectancy, value, and cost profiles and their proximal and distal relations to undergraduate science, technology, engineering, and math persistence. *Science Education, 103*(2), 264–286. https://doi.org/10.1002/sce.21490

Ramsey, L. R., & Sekaquaptewa, D. (2011). Changing stereotypes, changing grades: A longitudinal study of stereotyping during a college math course. *Social Psychology of Education, 14*(3), 377–387. https://doi.org/10.1007/s11218-010-9150-y

Raykov, T. (2011). Intraclass correlation coefficients in hierarchical designs: Evaluation using latent variable modeling. *Structural Equation Modeling, 18*(1), 73–90. https://doi.org/10.1080/10705511.2011.534319

Riegle-Crumb, C., King, B., Grodsky, E., & Muller, C. (2012). The more things change, the more they stay the same? Prior achievement fails to explain gender inequality in entry into STEM college majors over time. *American Educational Research Journal, 49*(6), 1048–1073. https://doi.org/10.3102/0002831211435229

Robinson, K. A., Lee, Y.-K., Bovee, E. A., Perez, T., Walton, S. P., Briedis, D., & Linnenbrink-Garcia, L. (2019). Motivation in transition: Development and roles of expectancy, task values, and costs in early college engineering. *Journal of Educational Psychology, 111*(6), 1081–1102. https://doi.org/10.1037/edu0000331

Rosenzweig, E. Q., & Wigfield, A. (2016). STEM motivation interventions for adolescents: A promising start, but further to go. *Educational Psychologist, 51*(2), 146–163. https://doi.org/10.1080/00461520.2016.1154792

Ryckman, D. B., & Peckham, P. (1987). Gender differences in attributions for success and failure situations across/subject areas. *The Journal of Educational Research, 81*(2), 120–125. https://doi.org/10.1080/00220671.1987.10885808

Seymour, E., & Hewitt, N. (1997). *Talking about leaving: Why undergraduates leave the sciences*. Westview Press.

Tanaka, A., & Murayama, K. (2014). Within-person analyses of situational interest and boredom: Interactions between task-specific perceptions and achievement goals. *Journal of Educational Psychology, 106*(4), 1122–1134. https://doi.org/10.1037/a0036659

Tsai, Y.-M., Kunter, M., Lüdtke, O., & Trautwein, U. (2008). Day-to-day variation in competence beliefs: How autonomy support predicts young adolescents' felt competence. In H. W. Marsh, R. G. Craven, & D. M. McInerney (Eds.), *Self-processes, learning, and enabling human potential: Dynamic new approaches* (pp. 119–143). Information Age Publishing.

Tsai, Y.-M., Kunter, M., Lüdtke, O., Trautwein, U., & Ryan, R. M. (2008). What makes lessons interesting? The role of situational and individual factors in three school subjects. *Journal of Educational Psychology, 100*(2), 460–472. https://doi.org/10.1037/0022-0663.100.2.460

Tuominen-Soini, H., & Salmela-Aro, K. (2014). Schoolwork engagement and burnout among Finnish high school students and young adults: Profiles, progressions, and educational outcomes. *Developmental Psychology, 50*(3), 649–662. https://doi.org/10.1037/a0033898

Walton, G. M., Logel, C., Peach, J. M., Spencer, S. J., & Zanna, M. P. (2015). Two brief interventions to mitigate a "chilly climate" transform women's experience, relationships, and achievement in engineering. *Journal of Educational Psychology, 107*(2), 468–485. https://doi.org/10.1037/a0037461

Wang, M.-T. (2012). Educational and career interests in math: A longitudinal examination of the links between classroom environment, motivational beliefs, and interests. *Developmental Psychology, 48*(6), 1643–1657. https://doi.org/10.1037/a0027247

Watt, H. M. (2004). Development of adolescents' self-perceptions, values, and task perceptions according to gender and domain in 7th-through 11th-grade Australian students. *Child Development, 75*(5), 1556–1574. https://doi.org/10.1111/j.1467-8624.2004.00757.x

Watt, H. M., Shapka, J. D., Morris, Z. A., Durik, A. M., Keating, D. P., & Eccles, J. S. (2012). Gendered motivational processes affecting high school mathematics participation, educational aspirations, and career plans: a comparison of samples from Australia, Canada, and the United States. *Developmental Psychology, 48*(6), 1594–1611. https://doi.org/10.1037/a0027838

Wigfield, A., & Cambria, J. (2010). Expectancy-value theory: Retrospective and prospective. In T. C. Urdan & S. A. Karabenick (Eds.), *Advances in motivation and achievement: Vol. 16A. The decade ahead: Theoretical perspectives on motivation and achievement* (pp. 35–70). Emerald Group Publishing Limited. https://doi.org/10.1108/S0749-7423(2010)000016A005

Ziegler, A., & Heller, K. A. (1998). Motivationsförderung mit Hilfe eines Reattributionstrainings. *Psychologie in Erziehung und Unterricht, 44*, 216–229.

3 General Discussion

Students' math- or science-related expectancy-value beliefs are important predictors of their decisions to persist in or drop out of math-intensive study programs (Fleischer et al., 2019; Perez et al., 2014; K. A. Robinson et al., 2019). Longitudinal studies over several years have identified declines in these motivational beliefs as a precursor to low levels of achievement and drop out from educational and occupational STEM fields (Gaspard et al., 2020; K. A. Robinson et al., 2019). In contrast, only a handful of studies have examined the developmental processes of students' expectancies and task values over shorter periods of time shortly after the transition to postsecondary education (e.g., one semester). This is an important gap in the literature because the first year after the transition is a particularly critical time in students' postsecondary education (Heublein et al., 2017; Seymour & Hewitt, 1997). Highly demanding, mandatory math courses in the first year of higher education often serve as gatekeepers to further engagement and academic success in STEM fields (Chen, 2013; Gasiewski et al., 2012; Seymour & Hewitt, 1997). Examining the developmental processes of students' situation-specific expectancy-value beliefs in gateway math courses is thus important to better understand the situational experiences that contribute to students' academic struggles and dropout tendencies shortly after the transition to math-intensive STEM programs. Motivational declines in the early stage of students' study programs may be linked to the adaptation to the new educational context and only temporary, or could be a warning sign of later academic difficulties and dropout tendencies, particularly for underrepresented groups in math-intensive STEM fields (e.g., female students, first generation students).

Thus, the present dissertation examined (a) how students' expectancies of success and subjective task values developed in the first semester in math-intensive study programs, (b) whether the developmental processes of students' expectancy-value beliefs differed as a function of students' personal characteristics, and (c) whether potential motivational changes were linked to students' academic success at the end of their first semester in math-intensive STEM programs. In the following section, further analyses (Study 3) on the within-person developmental processes of students' expectancies and task values will be presented. Following the presentation of these analyses, the main results of the three empirical studies will be summarized and discussed with respect to the three central research questions outlined in the introduction of this dissertation, followed by a discussion of strengths and limitations of the present dissertation. The dissertation will conclude with implications for future research and educational practice.

3.1 Further Analyses (Study 3): Searching for Short-Term Motivational Spillover Effects: A Random Intercept Cross-Lagged Panel Analysis of Students' Expectancies and Task Values in Math-Intensive Study Programs

Benden, D. K., & Lauermann, F. (2022). *Searching for Short-Term Motivational Spillover Effects: A Random Intercept Cross-Lagged Panel Analysis of Students' Expectancies and Task Values in Math-Intensive Study Programs* [Manuscript submitted for publication]. Center for Research on Education and School Development, TU Dortmund University.
For a preprint, see: https://doi.org/10.31234/osf.io/buv9a

Abstract

Students' math-related expectancy-value beliefs shape their educational choices and success in math-intensive study programs. Informed by *situated* expectancy-value theory, this study examined within-person changes in the associations among students' course-specific (summative) or week-specific (situated) expectancies and task values in gateway math courses ($N = 773$). Random intercept cross-lagged panel analyses revealed an increasing within-person alignment of students' course-specific expectancy for success and their intrinsic and utility values (but not costs) over one semester. Similarly, within-person motivational spillover effects emerged for course-specific motivational beliefs: students' expectancy to do well in their math course predicted subsequent within-person changes in intrinsic and utility values. In contrast, no significant motivational alignment processes and within-person reciprocal links emerged for students' week-specific expectancy-value beliefs. Students' gender and prior achievement functioned as "trait-like" predictors of their expectancy-value beliefs. These findings underscore the importance of differentiating between-person and within-person motivational processes and indicate that summative versus situation-specific assessments of motivational beliefs are likely to reveal different developmental processes.

Keywords: situated expectancy-value theory, situation-specific assessments, summative assessments, random intercept cross-lagged panel model, motivation, STEM

Searching for Short-Term Motivational Spillover Effects: A Random Intercept Cross-Lagged Analysis of Students' Expectancies and Task Values in Math-Intensive Study Programs

Eccles and colleagues' situated expectancy-value theory (SEVT; Eccles et al., 1983; Eccles & Wigfield, 2020) is one of the most prominent theoretical frameworks used to explain students' achievement-related choices and behaviors such as their educational and career decisions. According to SEVT, students engage in tasks or domains at which they expect to do well (i.e., high subjective expectancy for success) and that have a high value to them (i.e., high subjective task values). Students' expectancies and task values are potent predictors of their career aspirations, academic achievement, planned persistence, retention, and career attainment in different fields such as science, technology, engineering, and mathematics (STEM; e.g., Lauermann et al., 2017; Nagengast et al., 2011; Perez et al., 2014; K. A. Robinson et al., 2019). Furthermore, declines in students' expectancy-value beliefs over long (e.g., many years; Gaspard et al., 2020; Jacobs et al., 2002) or short (e.g., a semester in college; Benden & Lauermann, 2022; Zusho et al., 2003) periods are a precursor to academic difficulties such as low academic achievement, dropout, and disengagement from school, college, or STEM fields in general.

It is therefore important to understand *how* students' expectancy-value beliefs develop and potentially influence each other over time. A basic premise of SEVT is that students typically value tasks and domains in which they expect to do well and vice versa; that is, students' expectancies and task values are positively related (Eccles et al., 1983; Eccles & Wigfield, 2020; Wigfield et al., 1997). Eccles and colleagues proposed that the emergence of a positive association between students' expectancies and task values is an important developmental process and that these motivational beliefs should become increasingly well aligned over time (Eccles, 2009; Wigfield & Eccles, 1992; Wigfield et al., 1997). They further proposed that high levels of expectancy and subjective task values that are well aligned should be linked to sustained engagement, positive learning experiences, long-term educational choices, and well-being (Eccles, 2009; Wigfield & Eccles, 1992; see also Harter, 1990). A greater alignment of students' expectancy and task value beliefs may result, for instance, from their mutual reciprocal links (e.g., Marsh, Trautwein, et al., 2005). If students' expectancy and task value beliefs influence each other over time, increases or declines in one type of belief (e.g., expectancy) should trigger corresponding increases or declines in the other (e.g., task values).

However, research on the longitudinal, reciprocal links and corresponding alignment processes between students' expectancy and task value beliefs is limited in several important ways. First, most studies to date have examined the longitudinal relations between students' expectancy-value beliefs over many years, typically using annual measurement points and rather general and stable, albeit subject-specific, motivational assessments (e.g., Arens et al., 2019; Denissen et al., 2007; Marsh, Trautwein, et al., 2005; Wigfield et al., 1997). This is a limitation because important developmental processes often unfold over shorter periods of time and may thus be overlooked. For instance, postsecondary students' expectancy-value beliefs can decline dramatically over the course of just one semester, which is a precursor to later academic struggles and dropout intentions (Benden & Lauermann, 2022; Dresel & Grassinger, 2013; Kosovich et al., 2017). Second, the available studies have failed to distinguish *between-person* differences and *within-person* variability in students' expectancy-value beliefs when examining the longitudinal links between these two types of beliefs (e.g., Arens et al., 2019; Marsh, Trautwein, et al., 2005). Failing to do so can lead to severely biased estimates of reciprocal associations (Berry & Willoughby, 2017; Hamaker et al., 2015). Finally, whereas a substantial amount of research has examined interindividual differences in students' domain-specific motivational beliefs (e.g., as a function of gender or prior achievement), comparatively less is known about analogous differences in more situation-specific expectancies and task values (e.g., whether gender differences vary across situations or are relatively time-invariant; Eccles & Wigfield, 2020).

Accordingly, the present study had the following research objectives. First, we examined the degree of (within-person) alignment of students' expectancy-value beliefs at different time points during their first semester in math-intensive study programs, as well as, second, so-called "spill-over" effects (Mulder & Hamaker, 2021, p. 640) between different expectancy-value constructs (i.e., within-person reciprocal associations). We used the random intercept cross-lagged panel approach to separate within-person motivational changes over time from relatively stable between-person differences (Hamaker et al., 2015). We focused on three different time points spanning the entire semester (beginning, midpoint, and end-of-term) using *course-specific and summative* assessments of students' expectancy-value beliefs that asked students to evaluate their experiences in their math course up until that point. In addition, over three consecutive weeks at the beginning of the semester, we used *weekly and situation-specific assessments* to capture students' situated expectancy-value beliefs about the content taught each week. We focused on consecutive weeks at the beginning of the semester because this is often a sensitive period of adaptation (Coertjens et al., 2017; Gale & Parker, 2014). This study design allowed us to examine the development of motivational alignment and spillover effects using different types of motivational assessments (i.e., course-specific/summative vs. week-specific/situated) and time lags (weekly vs. half-semester intervals). Finally, third, we examined possible group differences in the codevelopment of students' summative or situated expectancy-value beliefs (i.e., degree of within-person alignment and reciprocal links) as a function of students' gender, prior achievement, socioeconomic status, and participation in preparatory math courses.

In a previous study using the same data (Benden & Lauermann, 2022), we found significant declines in first-semester students' expectancy-value beliefs in challenging, gateway math courses in math-intensive STEM programs. Controlling for differences in students' prior achievement, socioeconomic status, and gender, students who experienced greater motivational declines, particularly at the beginning of the semester, had lower end-of-term exam performance, lower study program satisfaction, and substantially higher likelihood of course dropout. Thus, motivational declines can be an important warning sign of later academic difficulties, but we know little about the within-person developmental processes that may contribute to such changes over time. The present study expands upon these findings by conducting theory-driven analyses of within-person motivational alignment and spillover effects among different facets of students' math-related expectancy-value beliefs shortly after the transition to higher education. These alignment processes have been proposed in SEVT (Eccles, 2009; Wigfield et al., 1997) but have not yet been empirically tested on the within-person level, controlling for stable, between-person differences.

Students' Situated Expectancy and Task Value Beliefs and Short-Term Developmental Processes

Eccles and colleagues' (Eccles et al., 1983; Eccles & Wigfield, 2020) situated expectancy-value theory posits that students' domain- and task-specific expectancy of success and their subjective task values are proximal predictors of students' achievement-related choices and behaviors (e.g., effort and persistence in STEM). Students' expectancy reflects their subjective probability of success on a given task or domain (e.g., solving a math worksheet, succeeding in a math course, or generally succeeding in the math domain; Eccles et al., 1983; Eccles & Wigfield, 2020). Students' subjective task values reflect possible reasons for engaging in a given task or domain, as well as the perceived relative cost, which refers to what the individual has to give up or suffer if they were to engage in the task or domain (Eccles et al., 1983; Eccles & Wigfield, 2020; Wigfield & Eccles, 2020). Important task value components include, for instance, students' interest in or enjoyment of the task or domain at hand (*intrinsic value*), as well as its perceived usefulness for current or future goals (*utility value*). In addition, several cost components have been proposed in the literature (Eccles et al., 1983; Flake et al., 2015; Perez et al., 2014; Wigfield et al., 2017). The most frequently studied cost components are the perceived amount of effort required to be successful (*effort cost*) and the anticipated or experienced stress and negative emotions in achievement situations (*psychological cost*).

Recently, Eccles and Wigfield (2020) renamed their theory as *situated* expectancy-value theory and thus underscored the importance of studying not only developmental but also situational influences shaping students' expectancies and subjective task values. Such influences are comparatively underresearched, even though the number of studies using (a) short-term repeated-measures designs and (b) situation-specific motivational assessments is growing (e.g., Benden & Lauermann, 2022; Dietrich et al., 2017; Parrisius et al., 2022). This research shows that the developmental trajectories of students' generalized versus situation-specific motivational beliefs can differ. For instance, research focusing on domain-specific but relatively general expectancies and task values (e.g., "How much do you like math?"; Eccles & Wigfield, 1995) suggests that adolescents' expectancy-value beliefs are quite stable, both over long (e.g., years; Rieger et al., 2017) and short periods (e.g., weeks or months; Spinath & Steinmayr, 2008). By comparison, studies using situation-specific assessments (e.g., "I like these contents"; Dietrich et al., 2017) reveal substantial variability in these beliefs across different lessons and topics (Dietrich et al., 2017; Tanaka & Murayama, 2014; Tsai, Kunter, Lüdtke, Trautwein, & Ryan, 2008). Furthermore, as noted previously, not only long-term but also short-term changes in students' (situated) motivational beliefs can predict important educational outcomes and therefore warrant attention. For instance, several studies identified significant declines in students' expectancy-value beliefs shortly after the transition to higher education, which predicted later academic difficulties such as poor achievement, low study program satisfaction, and dropout tendencies in college (Benden & Lauermann, 2022; Dresel & Grassinger, 2013; Kosovich et al., 2017).

What developmental processes shape students' expectancy-value beliefs in the short- or long-term? Eccles and Wigfield proposed that students' expectancy-value beliefs should become increasingly well-aligned over time because students likely come to value the tasks and domains for which they have high expectancies for success and vice versa (Eccles, 2009; Wigfield & Eccles, 1992). Moreover, if students have low expectancies of success for a given task or domain, they may devalue it to protect their self-worth (Eccles, 2009; Wigfield &

Eccles, 1992; Wigfield & Eccles, 2020; see also Harter, 1990). These reciprocal processes should lead to greater consistency of students' expectancy-value beliefs over time (i.e., a greater motivational alignment). A few studies have examined potential changes in the alignment of students' expectancy (or more global competence-related beliefs) and their valuing of academic tasks or domains using relatively general motivational assessments (Denissen et al., 2007; Fredricks & Eccles, 2002; Wigfield et al., 1997). For instance, Denissen et al. (2007) observed that the intraindividual correlations between students' domain-specific self-concepts of ability and their interests in math, science, and English increased across Grades 1 through 12. However, similar analyses have not been conducted over shorter time periods (e.g., one semester) and using situationally-sensitive motivational assessments (i.e., assessments asking students to describe their motivations in a specific situation). Thus, we know little about the potential alignment of students' *situated* motivational beliefs (and their reciprocal links).

Notably, more than 15 years ago Eccles (2005) pointed out that analyses of the reciprocal links among students' expectancy and task values must carefully consider (a) which time lags and (b) which types of assessments are best suited to capture such links (see also Dormann & Griffin, 2015). First, Eccles (2005) proposed that the optimal time lag likely depends on the underlying developmental processes of the respective constructs. Some processes may unfold over many years (e.g., a long-term motivational decline across school years; Gaspard et al., 2020), others over a short period (e.g., short-term motivational declines after the transition to postsecondary education; Benden & Lauermann, 2022; Dresel & Grassinger, 2013; Kosovich et al., 2017). As mentioned previously, however, most of the available evidence has focused on long-term reciprocal associations using annual assessments (e.g., Arens et al., 2019; Lee & Seo, 2021; Viljaranta et al., 2014). With some exceptions (e.g., Lee & Seo, 2021; Marsh, Trautwein, et al., 2005; Pinxten et al., 2014), these studies point to significant cross-lagged effects of students' expectancy (or competence-related beliefs) on their subjective task values but do not support reciprocal links (Arens et al., 2019; Du et al., 2021; Lauermann et al., 2017; Lent et al., 2008; Sewasew et al., 2018; Viljaranta et al., 2014). Only a few studies have examined reciprocal links over shorter periods of time (Moeller et al., 2022; Perez et al., 2019; Spinath & Steinmayr, 2008). These studies show mixed results, potentially due to their different contexts and motivational assessments (e.g., situation-/task-specific, Moeller et al., 2022; vs. course-/domain-specific, Perez et al., 2019; Spinath & Steinmayr, 2008).

Indeed, second, Eccles (2005) argued that researchers must identify what types of assessments are best suited to capture the reciprocal links between (or alignment of) students' expectancy-value beliefs. In postsecondary settings, which are most relevant for the present study, either domain-specific or course-specific assessments have been used to examine motivational changes and reciprocal links (e.g., "I expect to do well in this class"; Kosovich et al., 2017). We believe that most of these assessments can be described as *summative* because students are likely to aggregate their self-evaluations across multiple situations and tasks to judge their experiences and motivational beliefs in a given "class" or "domain" (e.g., for self-concept measures, see Marsh et al., 2019). In contrast, situation-specific items explicitly reference a particular task and situation (Moeller et al., 2022). No study to date has examined motivational alignment processes or reciprocal links using both summative and situation-specific assessments of students' expectancy-value beliefs in the same sample.

A Random Intercept Cross-Lagged Panel Approach for Analyses of Motivational Spillover Effects

In addition to choosing suitable time lags and types of assessment, analyses of the potential reciprocal links between students' expectancy-value beliefs require careful consideration of the most appropriate analytical approach. To date, such analyses have generally relied on traditional cross-lagged panel models (CLPM) to examine whether students' expectancy predicts subsequent changes in their task values and vice versa (e.g., Arens et al., 2019; Lee & Seo, 2021; Marsh, Trautwein, et al., 2005; Spinath & Steinmayr, 2008). This methodological approach has recently been criticized because it fails to differentiate between- versus within-person variability in constructs of interest (e.g., students' motivational beliefs), thus rendering the estimated cross-lagged effects uninterpretable (Berry & Willoughby, 2017; Lucas, 2022). Hamaker et al. (2015) introduced the random intercept cross-lagged panel model (RI-CLPM) as an alternative to the traditional CLPM and as a means to differentiate within-person developmental processes from stable between-person differences. It is important to note, however, that there is an ongoing debate over whether the traditional CLPM or the RI-CLPM (or yet other alternatives) is most appropriate for analyses of reciprocal effects (Lucas, 2022; Lüdtke & Robitzsch, 2021; Orth et al., 2021). Here, we outline the key points of debate and their relevance for our research objectives.

The RI-CLPM has gained popularity in educational research as a means to examine the reciprocal links between psychological constructs such as students' academic achievement and their self-concept of ability in reading (Ehm et al., 2019), students' self-concepts of ability and achievement emotions in math and literacy (Clem et al., 2021), and students' classroom perceptions and their motivation in secondary school (Ruzek & Schenke, 2019). The RI-CLPM expands upon the traditional CLPM by including random intercepts that capture trait-like, time-invariant, between-person differences for the observation period (e.g., students' average levels of expectancy and task values across all time points) and thus differentiates between-person versus within-person variability in constructs of interest (Hamaker et al., 2015). The RI-CLPM is thus better suited for research questions concerning within-person developmental processes such as motivational alignment.

A central point of the ongoing methodological debate is the interpretation of cross-lagged effects. In the traditional CLPM, these effects are typically interpreted as prospective between-person effects (Orth et al., 2021). Having higher expectancies than other students in the sample may predict a subsequent rank-order increase in intrinsic value relative to other students (but see recent critique by Hamaker et al., 2015; Lucas, 2022, who argue that these coefficients are essentially uninterpretable due to the mixture of within- and between-person effects). By comparison, the corresponding cross-lagged effects in the RI-CLPM test whether students who report higher expectancies than usual (i.e., a within-person deviation from their expectancy baseline) may experience a subsequent increase in intrinsic value, relative to their usual levels of intrinsic value (i.e., a within-person deviation from their intrinsic value baseline). Accordingly, Lüdtke and Robitzsch (2021) proposed that the RI-CLPM is appropriate for analyses of within-person dynamics over comparatively short periods of time (i.e., fluctuations around a personal mean), but has limited utility for developmental analyses of between-person differences over longer periods (see also Orth et al., 2021).

Given our focus on short-term motivational shifts from week to week and over one semester, we used the RI-CLPM approach in the present study. This approach allowed us to examine potential within-person motivational spillover effects from one learning situation to the next. Importantly, the motivational alignment processes described in the previous section are fundamentally within-person effects (see, e.g., Denissen et al., 2007), and thus disentangling within-person and between-person differences is necessary for answering our main research questions.

Interindividual Differences in Students' Expectancy-Value Beliefs: The Role of Gender, Prior Achievement, and Socioeconomic Status

A substantial amount of research grounded in SEVT has examined interindividual differences in students' expectancies and subjective task values, including the effects of students' gender, prior achievement, and socioeconomic status (SES; e.g., Gaspard, Dicke, Flunger, Schreier, et al., 2015; Guo, Marsh, et al., 2015; Guo, Parker, et al., 2015; Perez et al., 2014; K. A. Robinson et al., 2019; Watt, 2004). However, much of this research has focused on students' relatively general expectancy (or competence-related) beliefs and valuing of academic domains such as math or science. For the math domain, this research suggests that, first, gender differences in students' expectancy-value beliefs—when such differences exist—tend to be in favor of male over female students (e.g., Gaspard, Dicke, Flunger, Schreier, et al., 2015; Guo, Marsh, et al., 2015; Watt, 2004). Second, students' prior achievement is a consistent positive predictor of their expectancy-value beliefs for both genders (e.g., Guo, Parker, et al., 2015; Perez et al., 2014; K. A. Robinson et al., 2019). Third, there are no or only small mean-level differences in students' expectancy-value beliefs for students from less versus more advantageous socioeconomic backgrounds (e.g., Guo, Marsh, et al., 2015; Guo, Parker, et al., 2015; K. A. Robinson et al., 2019).

However, comparatively less is known about potential interindividual differences in students' situation-specific motivations (see also Eccles & Wigfield, 2020). On the one hand, male (relative to female), high-achieving, and high-SES students may be comparatively better equipped to handle situational challenges successfully so that similar results should emerge for domain-specific and situation- or task-specific motivational assessments. On the other hand, evidence suggests that situation-specific (state-like) and generalized (trait-like) assessments of psychological constructs such as human emotions (M. D. Robinson & Clore, 2002), and possibly motivations, can elicit different cognitive processes and thus reveal different group effects. For instance, Goetz et al. (2013) found that situation-specific measures of high school students' math anxiety (i.e., the anxiety experienced in a specific situation in math class) revealed smaller gender differences compared to a more global assessment of math anxiety. Similarly, Tsai and colleagues (Tsai, Kunter, Lüdtke, & Trautwein, 2008; Tsai, Kunter, Lüdtke, Trautwein, & Ryan, 2008) found no gender differences in students' perceived competence and interest in math using lesson-specific measures, whereas more general assessments of these constructs in similar samples typically reveal mean level differences favoring male over female students (e.g., Gaspard, Dicke, Flunger, Schreier, et al., 2015; Guo, Marsh, et al., 2015). These measurement-specific effects have been attributed to different cognitive processes. State-like measures capture an individual's momentary experiences (e.g., experienced anxiety), whereas trait-like measures also capture more general beliefs and attitudes such as stereotypes (e.g., female students being viewed as more emotional than male students; Goetz et al., 2013; M. D. Robinson & Clore, 2002; see also Eccles et al., 1983 and Frieze et al., 1978). Accordingly, group-specific differences in students' motivational beliefs, for instance, by gender, might depend on the type of motivational assessment used and whether this assessment is situation-specific or generalized across different situations.

The Present Study

Drawing on SEVT (Eccles & Wigfield, 2020), we specified RI-CLPMs to examine the level of alignment and reciprocal links between students' expectancy and value beliefs in gateway math courses at the beginning of higher education in math-intensive study programs. We used two types of assessments. Course-specific, summative assessments of students' expectancy of success and task values at the beginning, midpoint, and end of the semester captured students' experiences in the course up until that point. Week- and situation-specific assessments during three consecutive weeks at the beginning of the semester captured students' expectancy-value beliefs about the content taught that particular week. We focused on consecutive weeks at the beginning of the semester because we expected that this may be a sensitive period of adaptation after the transition to higher education, as has been shown in prior research (Coertjens et al., 2017; Gale & Parker, 2014; Kosovich et al., 2017; Zusho et al., 2003).

The following research questions guided our analyses: First, *does the within-person alignment of students' expectancy of success and task values increase over time for different types of assessments and at different time points during the semester*? Based on Eccles and colleagues' (Eccles, 2009; Wigfield & Eccles, 1992) theoretical assumptions and the few prior studies in the school context (Denissen et al., 2007; Wigfield et al., 1997), we expected to find an increasing alignment of students' course-specific, summative expectancy-value beliefs. We did not formulate specific predictions about the alignment of students' week-specific, situated expectancies and task values because it is unclear to what extent these experiences may be contained within a given situation or become increasingly consistent from week to week due to students' cumulative experiences. In both cases, we controlled for stable between-person differences in our analyses of within-person associations.

Second, *are there significant within-person reciprocal associations between students' expectancies and task values over time (i.e., so-called motivational spillover effects)*? These reciprocal links were examined for students' course-specific/summative and week-specific/situated expectancy-value beliefs and controlling for stable between-person differences. Consistent with prior research and predictions by Eccles and colleagues (Eccles, 2005, 2009; Perez et al., 2019; Sewasew et al., 2018), we expected to find some evidence for students' expectancy beliefs as a driving force behind changes in their subjective task values. However, we did not pose specific hypotheses about reciprocal effects due to the scarcity of prior research on short-term motivational changes, and because no study to date has used a RI-CLPM that controls for stable between-person motivational differences in the analyses of within-person motivational spillover effects.

Third, *are there significant interindividual differences in students' expectancy-value beliefs and the degree of alignment of these beliefs as a function of students' gender, prior achievement, and SES, and are these differences consistent across different types of assessments and time points*? If motivational differences exist, we expected them to favor male, high-achieving, and high-SES students. In a set of exploratory analyses, we examined whether the predictive effects of students' gender, prior achievement, and SES on their motivational experiences were invariant across time, as well as whether the degree of alignment of students' expectancy-value beliefs within a given time point differed by group. Some students had participated in preparatory math courses over the summer so we examined possible group differences for this variable as well.

Method

Participants and Procedure

The sample of the study included five cohorts of students enrolled in demanding math courses for beginning students in their respective study programs at a German university ($N = 773$, 36% female). The students were enrolled in physics ($n = 366$; two cohorts), math ($n = 214$; one cohort), or math teacher education study programs ($n = 193$; two cohorts). As is typical in Germany, students in this study had declared their major prior to enrollment and were admitted only for this major based on their high school GPA. The data were collected in the winter terms of 2017 and 2018. Most students were in the first year of their respective study program (90%), were born in Germany (92%), and had at least one parent with a university degree (60%).

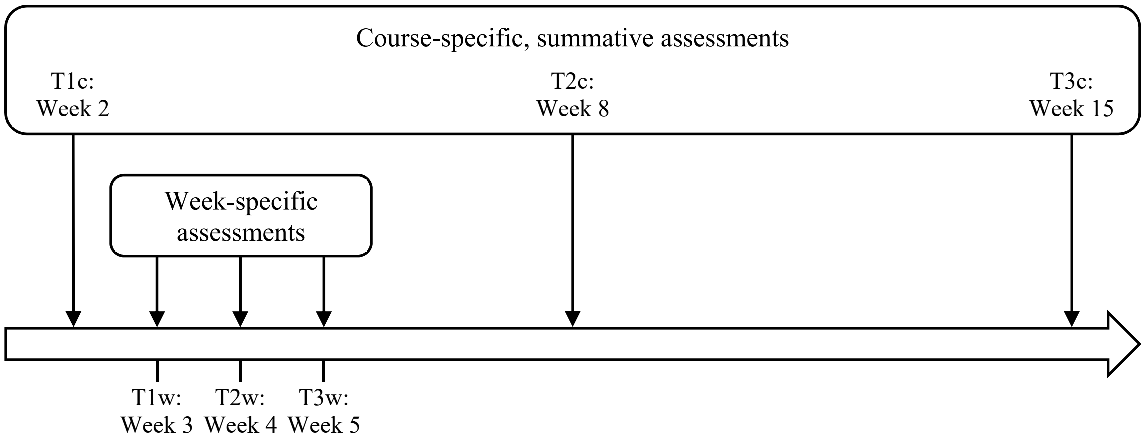
The students completed paper-and-pencil questionnaires in math lectures that were required for their respective study programs and functioned as gateway math courses. There were six data collections during the semester. Three data collections were scheduled at the beginning (Week 2, T1c), midpoint (Week 8, T2c), and end of the semester (Week 15, T3c) and focused on students' motivational beliefs about their math course.[1] Three additional data collections in Weeks 3 to 5 of the semester (T1w–T3w) focused on students' week-specific experiences with their current coursework shortly after the transition to higher education. The students were required to submit weekly math worksheets to qualify for their final exam. Solutions to the worksheets were discussed in separate tutoring sections but new content was covered solely in the lectures. All data collections took place during the lecture in which students had to submit their weekly worksheets. Nearly all students who were present in the lecture participated in the study (98%–100% at each time point).

Measures

The students answered questions about their expectancy-value beliefs at each of the six data collections during the semester (see Figure 1).

Figure 1

Time Points and Types of Assessments of Students' Expectancy and Subjective Task Values in the Present Study



Note. T = time point, T1c–T3c = course-specific summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet.

Course-Specific Expectancies and Task Values (Summative Judgments)

Students' course-specific, summative expectancy-value beliefs were assessed at the beginning (T1c), midpoint (T2c), and end of the semester (T3c). All items are reported in the online supplemental materials. Students' summative *expectancy beliefs* were assessed with three items adapted from Eccles and Wigfield (1995) and Tanaka and Murayama (2014), for

[1] Lectures in Week 1 were mostly used for organizational purposes. The students received their first mandatory worksheet in Week 2 and their first feedback regarding the solutions in Week 3.

instance: "Based on my experiences in this class so far, I think I will do well on the exam" (α = .90 to .92 across time points). Subjective task values were assessed using scales adapted from Gaspard, Dicke, Flunger, Schreier, et al. (2015). Two-item scales were used for students' *intrinsic value* (e.g., "Doing the coursework and the assignments for this class is something I enjoy," α = .79 to .85), *utility value* (e.g., "Doing the coursework and the assignments for this class is useful for my future," α = .66 to .76), *psychological cost* (e.g., "Doing the coursework and the assignments for this class is stressful for me," α = .80 to .83), and *effort cost* (e.g., "Doing the coursework and the assignments for this class drains a lot of my energy," α = .88 to .91). All items were assessed on a 6-point scale ranging from 1 = *completely disagree* to 6 = *completely agree*. Note that the items referenced students' overall experiences in the course and did not refer to a specific situation or content.

Week-Specific Expectancies and Task Values (Situated Judgments)

Week-specific motivational assessments were used in Weeks 3 to 5 of the semester (T1w–T3w). These assessments referenced students' experiences with the content that was covered each week and that was assessed on their mandatory weekly worksheets. Single items were used to reduce survey fatigue due to the repeated exposure to the same items. The items were preceded by the statement: "Think about the current worksheet you turned in this week." As noted previously, the students had to turn in their worksheets in the same lecture in which the data were collected; i.e., they were asked to answer questions about the worksheet they had just turned in. Students' expectancy was measured with the item "If the content of the current worksheet comes up on the exam: How well do you think will you perform on the exam?" (1 = *very poorly* to 6 = *very well*). Intrinsic and utility values and perceived psychological and effort costs were assessed with the following items: "Doing this week's assignments is something I enjoyed/…was generally useful/…was stressful for me/…drained a lot of my energy." (1 = *completely disagree* to 6 = *completely agree*).

Students' Personal Characteristics

In the first data collection, the students reported their gender (36% female; 0 = *male*, 1 = *female*), their parents' current or most recent occupation, high school GPA, and whether they had participated in math preparatory courses prior to enrollment (63% participation). In Germany, lower scores indicate higher achievement. We recoded students' high school GPA so that higher scores indicate higher achievement to facilitate the interpretation of the results ($M = 3.1$, $SD = 0.65$, range from 1 = *sufficient* to 4 = *very good*). The students' SES was coded based on their reported parental occupations according to the German Classification of Occupations (KldB; Paulus & Matthes, 2013). Occupations were matched to one of four job skill levels (1 = *requiring little or no education* to 4 = *requiring an advanced degree*). Since most students (60%) had at least one parent with an advanced degree and only a few students had parents whose education required little or no education, we used a dichotomous variable for students' SES (0 = *low SES/job skill levels 1–3*, 1 = *high SES/job skill level 4*).

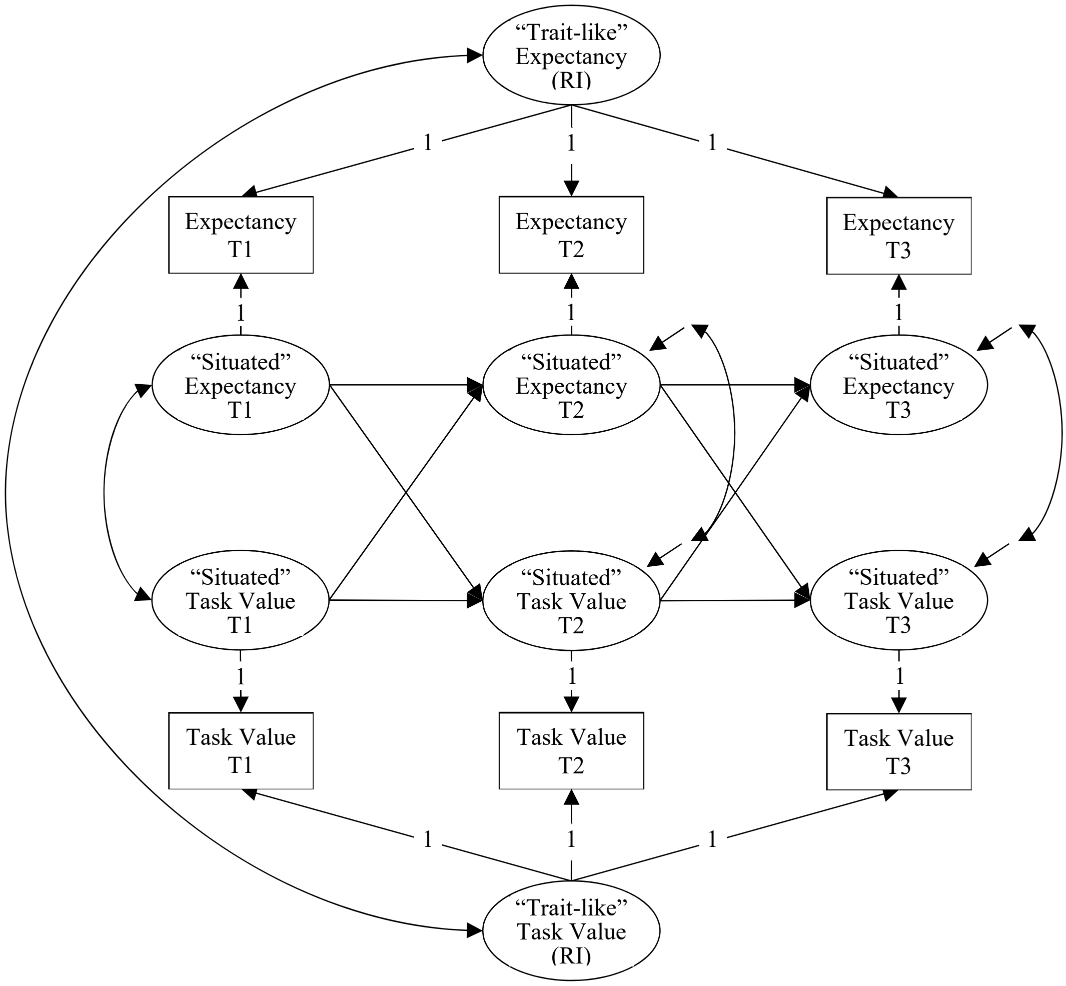
Statistical Analyses

We examined bivariate correlations and missing data patterns in a set of preliminary analyses. Confirmatory factor analyses (CFA) tested the assumption of measurement invariance across time points and study programs for all multi-item scales (i.e., for students' course-specific expectancy and task value beliefs). To answer our main research questions, we specified RI-CLPMs (Hamaker et al., 2015; see Figure 2) using Mplus 8.6. These models estimated the associations between two random intercepts (i.e., stable between-person motivational differences for expectancy and different task values), concurrent within-person associations (i.e., within-person correlations between students' expectancy and values within a given time point), and the hypothesized reciprocal effects (i.e., within-person motivational spillover effects between students' expectancy and each task value facet). We tested four RI-CLPMs including students' expectancy in combination with intrinsic value, utility value, psychological cost, or effort cost, respectively. One set of RI-CLPMs focused on students' course-specific, summative expectancy and task values across the entire semester (T1c–T3c). The second set of RI-CLPMs focused on students' week-specific expectancy-value beliefs (T1w–T3w). Dummy variables representing the different math courses were included as predictors of students' motivational beliefs to control for mean-level differences between these courses (Mulder & Hamaker, 2021). The same instructor taught both courses in the physics program so that only one dummy variable was included in this case. Students' gender, prior achievement, and SES were included in the final models to test possible group-specific differences. Some students had participated in math preparatory courses prior to enrollment, which may affect students' motivations at the beginning of the semester due to a period of adaptation to the new learning environment. Therefore, we included students' participation in such courses as a control variable.

For our first research question regarding the degree of within-person alignment of students' motivational beliefs, we specified a correlational model within the RI-CLPM framework. That is, we modeled bivariate associations instead of autoregressive and cross-lagged associations between students' expectancy and task values, which allowed us to examine whether these within-person correlations increased over time (i.e., the degree of motivational alignment). To address our second research question regarding motivational spillover effects, we examined within-person cross-lagged effects between students' expectancy and value beliefs with a set of RI-CLPMs and using either course- or week-specific assessments.

Figure 2

Random Intercept Cross-Lagged Panel Model for Students' Expectancy and Subjective Task Values



Note. Analogous models were specified for each task value construct (intrinsic value, utility value, psychological cost, effort cost). Two sets of models were specified focusing on students' course-specific, summative expectancies and task values across the entire semester (T1c/Week 2, T2c/Week 8, T3c/Week 15) and week-specific expectancy-value beliefs across three weeks at the beginning of the semester (T1w/Week 3, T2w/Week 4, T3w/Week 5). RI = random intercept, T1 = time point 1, T2 = time point 2, T3 = time point 3. For course-specific assessments, expectancy and task values were modeled as latent variables (see multiple-indicator RI-CLPM in Mulder & Hamaker, 2021).

Finally, for our third research question regarding interindividual differences, we included students' gender, prior achievement, SES, and participation in preparatory math courses as predictors of students' motivational beliefs in the RI-CLPMs (Mulder & Hamaker, 2021). There are two possibilities for these analyses. One can either test group differences in students' random intercepts or students' motivational beliefs at each time point. We chose the second option because it allowed us to test whether these interindividual differences are time-invariant. Time-invariance would suggest that mean-level differences in students' expectancy-value beliefs are constant over time and thus "trait-like" (Mulder & Hamaker, 2021). We further specified multigroup models in the RI-CLPM framework (Mulder & Hamaker, 2021) to examine if there are interindividual differences in the degree of alignment of students' expectancy-value beliefs. For this multigroup analysis, we split the sample by (a) gender, (b) prior achievement, (c) SES, and (d) having participated in a preparatory math class or not. For prior achievement, we split the sample into high-achieving (GPA greater than 3.3, which is the cut-off for "very good" grades in Germany) and lower-achieving students (GPA smaller or equal to 3.3, corresponding to "sufficient" to "good" grades). This split resulted in two groups of roughly equal size (43% of the students had "very good" grades).

Full information maximum likelihood estimation (FIML) was used to account for missing data. Multiple indicator RI-CLPMs (Mulder & Hamaker, 2021) were modeled for students' course-specific (summative) expectancy and task value beliefs. Students' motivational beliefs were modeled as latent constructs, which were then decomposed into a time-invariant between-person part and time-specific within-person factors. Analogous models were tested for students' week-specific, situated motivational beliefs, but these analyses relied on single-item scales for each week. Across all models, we used maximum likelihood estimation with robust standard errors (MLR) and evaluated model fit based on the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). Good model fit is generally indicated by a CFI value of .95 or higher and RMSEA and SRMR values of .06 or lower (Marsh, Hau, et al., 2005). For model comparisons, a CFI difference between two models of less than .01 and an RMSEA difference of less than .015 generally indicate a negligible change in overall model fit and support the more parsimonious model (Chen, 2007; Cheung & Rensvold, 2002). We additionally compared nested models using Satorra-Bentler scaling-corrected chi-square difference tests, the Akaike information criterion (AIC), and the Bayesian information criterion (BIC).

Results

Preliminary Analyses

Descriptive statistics and bivariate correlations are shown in Table 1 for all variables and time points. All correlations between the expectancy-value constructs were consistent with our expectations, confirming positive associations among expectancy, intrinsic value, and utility value, and negative associations among expectancy and psychological and effort costs, as well as among intrinsic and utility values and perceived costs, within each time point. The only exception was a nonsignificant correlation between utility value and effort cost.

Mean values of students' expectancies and task values reported in Table 1 suggest that the students experienced a motivational decline in the first half of the semester and perceived relatively high levels of psychological and effort cots. This pattern likely results from the high workload students were expecting and experiencing in their respective math courses.

Table 1 further shows the number of students with available data for each variable and time point. Missing data were generally due to course dropout or nonattendance, as almost all students who were present in a given week to turn in their mandatory worksheets participated in our surveys (98%–100% participation at each time point). The course dropout rate of 43% by the end of the semester is comparable to prior research in demanding math courses (36% in Geisler, 2021; 38% in Rach & Heinze, 2017). Missing data were linked to lower SES ($r = -.10$, $p = .011$), lower high school GPA ($r = -.35$, $p < .001$), and a lower likelihood of participation in preparatory math courses prior to enrollment ($r = -.23$, $p < .001$). These student characteristics were included as auxiliary variables or as covariates in all analyses (Graham, 2003; Schafer & Graham, 2002). Importantly, our findings concerning motivational alignment and cross-lagged effects were consistent when we limited our analyses to students who did not drop out.

For students' course-specific motivational beliefs, multigroup CFAs including expectancy and the four task value facets confirmed the same factor structure across the different study programs (i.e., physics, math, and math teacher education) at the beginning, midpoint, and end of the semester (T1c, T2c, and T3c). The CFA supported strong measurement invariance, which is a prerequisite for our subsequent analyses (Mulder & Hamaker, 2021). We specified correlated residuals between repeated assessments of the same indicator at different time points to account for indicator-specific covariances (Little, 2013). The invariance analyses are reported in the online supplemental materials.

Table 1

Descriptive Statistics and Observed Bivariate Correlations for Course-Specific (Above the Diagonal) and Week-Specific (Below the Diagonal) Expectancy-Value Beliefs

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Female	—	.08	.06	.07	−.17**	−.03	−.03	.18**	.04	−.20**	−.03	−.08	.13**	.05	−.17**	−.01	−.07	.08	.02
2. Socioeconomic status	.08	—	.18**	.12**	.01	.03	.03	−.07	.00	.02	.04	.04	−.06	.00	−.06	.08	.08	−.11*	−.03
3. High school GPA	.06	.18**	—	.20**	.15**	.15**	.06	−.07	−.03	.22**	.20**	.09*	−.17**	−.10**	.16**	.11*	.14**	−.10	−.06
4. Preparatory course	.07	.12**	.20**	—	−.05	.09*	.08	−.07	.01	−.01	.03	.02	−.06	.00	−.02	.06	.04	−.04	.03
5. Expectancy Time T1c/T1w	−.15**	.04	.20**	.02	—	.44**	.30**	−.51**	−.44**	.65**	.36**	.27**	−.33**	−.31**	.61**	.28**	.24**	−.38**	−.35**
6. Intrinsic value T1c/T1w	−.07	.13**	.21**	.09*	.48**	—	.39**	−.37**	−.22**	.30**	.47**	.29**	−.21**	−.10*	.24**	.39**	.26**	−.26**	−.12*
7. Utility value T1c/T1w	−.06	.13**	.14**	.08	.31**	.53**	—	−.21**	−.12**	.16**	.20**	.54**	−.08	−.02	.23**	.21**	.49**	−.17**	−.07
8. Psychological cost T1c/T1w	.02	−.05	−.02	−.02	−.43**	−.30**	−.12**	—	.63**	−.40**	−.24**	−.20**	.57**	.40**	−.39**	−.27**	−.25**	.58**	.42**
9. Effort cost T1c/T1w	.02	.00	−.01	.05	−.42**	−.21**	−.03	.74**	—	−.39**	−.15**	−.16**	.43**	.52**	−.38**	−.17**	−.16**	.39**	.52**
10. Expectancy T2c/T2w	−.11*	.05	.25**	.05	.55**	.24**	.13**	−.28**	−.27**	—	.56**	.35**	−.50**	−.44**	.79**	.46**	.35**	−.49**	−.47**
11. Intrinsic value T2c/T2w	−.10*	.01	.19**	.07	.33**	.40**	.28**	−.18**	−.11*	.54**	—	.49**	−.33**	−.18**	.40**	.65**	.39**	−.34**	−.18**
12. Utility value T2c/T2w	−.08	.09*	.15**	.07	.19**	.22**	.42**	−.08	.01	.34**	.58**	—	−.15**	−.05	.32**	.34**	.65**	−.17**	−.09
13. Psychological cost T2c/T2w	.10*	−.04	−.09*	−.07	−.34**	−.16**	−.08	.47**	.38**	−.53**	−.38**	−.22**	—	.72**	−.45**	−.33**	−.26**	.70**	.55**
14. Effort cost T2c/T2w	.08	−.04	−.07	−.05	−.31**	−.09*	.02	.40**	.46**	−.45**	−.25**	−.07	.77**	—	−.40**	−.23**	−.11*	.54**	.73**
15. Expectancy T3c/T3w	−.13*	.03	.21**	.01	.52**	.27**	.19**	−.27**	−.25**	.57**	.35**	.26**	−.36**	−.31**	—	.55**	.35**	−.49**	−.41**
16. Intrinsic value T3c/T3w	−.08	.06	.22**	.07	.34**	.48**	.34**	−.14**	−.06	.30**	.45**	.29**	−.14**	.00	.56**	—	.48**	−.36**	−.23**
17. Utility value T3c/T3w	−.05	.11*	.13**	.05	.23**	.29**	.47**	−.03	.05	.29**	.38**	.52**	−.12**	−.01	.39**	.56**	—	−.23**	−.08
18. Psychological cost T3c/T3w	.05	.04	−.05	.06	−.28**	−.15**	−.10*	.46**	.34**	−.27**	−.19**	−.12**	.48**	.40**	−.43**	−.34**	−.16**	—	.64**
19. Effort cost T3c/T3w	.00	.03	.01	.08	−.26**	−.06	.00	.39**	.40**	−.25**	−.14**	−.04	.43**	.46**	−.36**	−.13**	.01	.73**	—
Course-specific assessments							T1c					T2c					T3c		
M	.36	.60	3.06	.63	3.71	4.74	4.55	3.15	4.27	3.36	4.32	4.26	3.55	4.53	3.44	4.42	4.28	3.46	4.46
SD	.48	.49	.65	.48	.85	.80	1.01	1.25	1.08	.94	.91	1.06	1.22	1.05	1.02	.91	1.01	1.24	1.02
N	715	622	688	630	686	693	688	693	693	523	524	522	523	524	366	368	366	368	368
Skewness			−.33		−.04	−.68	−.83	.31	−.34	−.12	−.66	−.61	.06	−.69	−.12	−.83	−.54	.26	−.46
Kurtosis			−.75		.52	.97	.71	−.62	−.25	.26	.76	.30	−.56	.20	.12	.73	.12	−.42	−.11
Cronbach's α					.90	.79	.66	.81	.88	.92	.82	.76	.80	.91	.92	.85	.69	.83	.91
Week-specific assessments							T1w					T2w					T3w		
M					3.56	3.70	4.17	4.13	4.62	3.60	3.72	4.13	3.92	4.25	3.55	3.71	4.09	4.11	4.34
SD					1.08	1.20	1.07	1.33	1.24	1.10	1.10	1.03	1.39	1.25	1.03	1.14	1.03	1.25	1.18
N					617	619	615	621	620	582	585	583	584	585	557	557	554	553	555
Skewness					−.11	−.38	−.70	−.43	−.80	−.39	−.56	−.57	−.20	−.36	−.30	−.47	−.71	−.27	−.52
Kurtosis					−.19	−.34	.42	−.61	.00	.05	.02	.34	−.85	−.54	−.05	−.16	.61	−.64	−.24

Note. $N = 773$, T1c–T3c = course-specific, summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet.

$^{*}p < .05$. $^{**}p < .01$.

Within-Person Alignment of Students' Course-Specific and Week-Specific Expectancies and Task Values Over Time

To address our first research question about motivational alignment, we decomposed the observed scores into between-person and within-person factors using the RI-CLPM framework but specified bivariate associations instead of autoregressive and cross-lagged effects for all within-person factors. The resulting within-person associations between students' expectancy and the different task value facets are reported in Table 2. As expected, the correlation between students' course-specific expectancy and their intrinsic and utility values increased significantly from the beginning to the midpoint of the semester (T1c: *r*s = .18/.13, T2c: *r*s = .71/.42, *p*s < .001) suggesting an increased alignment of these motivational beliefs. This alignment remained at a moderate-to-high level towards the end of the semester (T3c: *r*s = .69/.47, *p*s ≥ .288). In contrast, the analogous correlations between students' expectancy and psychological and effort costs were somewhat weaker and not statistically different across the three time points (T1c: *r*s = −.26/−.12, T2c: *r*s = −.43/−.25, T3c: *r*s = −.38/−.24; *p*s ≥ .063). Thus, the alignment of students' positively valenced motivational beliefs increased towards the midpoint of the semester and then stabilized at a moderate-to-high level, whereas no significant increase occurred in the alignment between students' expectancy and cost.

Table 2

Within-Person Correlations Between Students' Expectancy and Task Values in the Correlational Models

	Intrinsic value model	Utility value model	Psychological cost model	Effort cost model
	r	*r*	*r*	*r*
Course-specific assessments				
Within-person correlation T1c	.18	.13	−.26	−.12
Within-person correlation T2c	$.71^{***}$	$.42^{***}$	$-.43^{***}$	$-.25^{*}$
Within-person correlation T3c	$.69^{***}$	$.47^{***}$	$-.38^{***}$	$-.24^{*}$
Week-specific assessments				
Within-person correlation T1w	$.16^{***}$	$.23^{**}$	$-.24^{***}$	$-.18^{**}$
Within-person correlation T2w	$.25^{***}$	$.26^{**}$	$-.49^{***}$	$-.36^{***}$
Within-person correlation T3w	$.27^{***}$	$.36^{***}$	$-.26^{***}$	$-.18^{*}$

Note. T1c–T3c = course-specific, summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Analogous analyses were conducted for students' week-specific, situated motivational beliefs. However, we found no statistically significant differences in the correlations between students' week-specific expectancy beliefs and their intrinsic and utility values (*p*s ≥ .184;

Table 2) and the estimated coefficients were generally lower than those for summative assessments. The correlations between students' week-specific expectancy and their psychological and effort costs were greater at T2w compared to the remaining two time points (T2w: $rs = -.49/-.36$, T1w: $rs = -.24/-.18$, T3w: $rs = -.26/-.18$; $ps < .027$). Overall, in contrast to our findings for summative assessments, we found no evidence of an increasing alignment of students' week-specific expectancy-value beliefs during the first weeks of the semester (in Weeks 3–5).

Between-Person Associations of Students' Expectancies and Task Values and Within-Person Motivational Spillover Effects

To address our second research question regarding motivational spillover effects, we specified RI-CLPMs for students' expectancies and the different task value facets. Controlling for stable between-person motivational differences, we tested whether there are significant within-person autoregressive and cross-lagged effects and whether these effects were invariant over time. We report the results separately for students' course- and week-specific motivational beliefs.

Course-Specific Expectancies and Task Values Across the Entire Semester

The RI-CLPMs showed a satisfactory model fit for all expectancy and task value facets (i.e., expectancy in combination with intrinsic value, utility value, psychological cost, or effort cost). The random intercepts for intrinsic value and utility value did not have significant variance, indicating that, after controlling for mean-level differences between students' math courses, very little of the observed variance was due to stable between-person motivational differences. As recommended by Mulder and Hamaker (2021), we fixed the variance of these random intercepts and their covariances with the random intercept of students' expectancy to zero.[2] All other random intercepts had significant variances. Next, we tested if the autoregressive and cross-lagged parameters were invariant across time. Chi-square difference tests and the evaluation of overall model fit supported time-invariant effects for the models

[2] These constrained models had comparable model fit to the unconstrained models and were therefore retained. The loglikelihood difference of the two models does not follow a regular chi-square distribution because two (co)variances are fixed to zero (Hamaker et al., 2015; Mulder & Hamaker, 2021). Therefore, a nonsignificant test does not imply that the variance of the random intercept is indeed not statistically different from zero. However, the model with constrained variance and covariance showed better model fit in terms of lower AIC and BIC values and was thus retained. We additionally repeated our main analyses with models including a random intercept for intrinsic/utility values. The results are consistent with the results presented below and are reported in the online supplemental materials.

including expectancy and intrinsic and utility values. However, the chi-square difference tests did not support invariant autoregressive and cross-lagged effects for students' expectancy and perceived psychological and effort costs. These effects were freely estimated in subsequent models.[3] Model fit information and comparisons are reported in the online supplemental materials.

The random intercepts of students' course-specific expectancy and psychological and effort costs were significantly negatively correlated (rs = −.65 and −.63, ps ≤ .001; Table 3). That is, students who, on average, had higher expectancies about being successful in their math course relative to their peers reported lower levels of psychological and effort costs. Furthermore, significant within-person contemporaneous associations emerged in all models. These associations were positive for students' expectancy and intrinsic and utility values (rs = .30 to .67, ps ≤ .005) and negative for students' expectancy and perceived costs (rs = −.56 to −.20, ps ≤ .030; Table 3). Thus, within a given time point, students who reported higher than usual expectancy beliefs (relative to their personal baseline across all time points) also reported higher than usual intrinsic and utility values as well as lower than usual psychological and effort costs. Students' course-specific motivational beliefs thus seemed to shift "in synchrony" within a given time point.

Table 3

Correlations Between Random Intercepts of Students' Expectancy and Each Task Value Facets and Within-Time Point (Residual) Correlations Between Expectancy and Task Values

	Intrinsic value model	Utility value model	Psychological cost model	Effort cost model
	r	*r*	*r*	*r*
Course-specific assessments				
Random intercepts	[a]	[a]	$-.65^{***}$	$-.63^{***}$
Within-person correlation T1c	$.67^{***}$	$.49^{***}$	−.36	−.21
Within-person residual correlation T2c	$.62^{***}$	$.39^{***}$	$-.56^{**}$	$-.31^{*}$
Within-person residual correlation T3c	$.53^{***}$	$.30^{**}$	$-.28^{**}$	$-.20^{*}$
Week-specific assessments				
Random intercepts	$.63^{***}$	$.39^{***}$	$-.58^{***}$	$-.58^{***}$
Within-person correlation T1w	$.28^{***}$	$.27^{***}$	$-.21^{**}$	$-.14^{*}$
Within-person residual correlation T2w	$.42^{***}$	$.24^{*}$	$-.44^{***}$	$-.31^{***}$
Within-person residual correlation T3w	$.48^{***}$	$.31^{***}$	$-.27^{***}$	$-.21^{**}$

Note. T1c–T3c = course-specific, summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet.

[a] The variance of the random intercept for intrinsic/utility value was nonsignificant; it was fixed at zero in subsequent analyses to obtain a more parsimonious model (Mulder & Hamaker, 2021).

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

[3] The constrained models showed similar model fit in terms of RMSEA, CFI, and TLI values and had lower BIC values compared to the unconstrained models. We report the autoregressive and cross-lagged parameter estimates for the constrained models in the online supplemental materials.

Analyses of within-person autoregressive and cross-lagged effects across the semester revealed significant autoregressive (i.e., carryover) effects for students' course-specific expectancy, intrinsic value, and utility value (βs = .47 to .77, *p*s $\leq$ .001; Table 4), whereas the autoregressive effects in the models including perceived costs were significant only from the midpoint towards the end of the semester and marginally significant for students' psychological cost (expectancy: β = .77, effort cost: β = .46, *p*s $\leq$ .002; psychological cost: β = .27, *p* = .062). Accordingly, a positive intraindividual deviation from students' personal baseline in expectancy and intrinsic and utility values at one time point was linked to a positive intraindividual deviation in the same construct at the next time point. Furthermore, we found significant cross-lagged (i.e., spillover) effects for students' expectancy beliefs on later intrinsic and utility values, indicating that if a student felt more confident to be successful in their math course relative to their personal baseline, the student also reported higher than usual intrinsic and utility values at the next time point (βs = .15 to .30, *p*s $\leq$ .014). In contrast, no significant spillover effects emerged for students' intraindividual fluctuations in expectancy and subsequent changes in perceived costs, nor for intraindividual fluctuations in task values and subsequent changes in expectancy (βs = −.23 to .18, *p*s $\geq$ .115). The observed within-person motivational spillover effects were thus unidirectional (from expectancy to intrinsic/ utility values) and they were limited to the positively valenced task values.

Week-Specific Expectancies and Task Values at the Beginning of the Semester

Analogous to the models including students' course-specific motivational beliefs, we tested RI-CLPMs for students' week-specific expectancy and different task value facets. The overall model fit was satisfactory across all analyses, and model fit comparisons supported time-invariant autoregressive and cross-lagged effects (see the online supplemental materials for model fit and model comparisons). The random intercepts of students' week-specific expectancy and task values were moderately-to-highly correlated (*r*s = .63 and .39 for intrinsic/utility values, *r*s = −.58 for psychological/effort costs, *p*s $\leq$ .001; Table 3). Thus, students who felt more confident about mastering the current coursework relative to their peers also experienced working on the current worksheet as more interesting and useful, as well as less stressful and effortful. Furthermore, significant concurrent within-person associations indicated that, within a given time point, feeling more confident than usual about a given worksheet was associated with greater interest and greater perceived usefulness of the content as well as lower feelings of stress and exhaustion (*r*s = .24 to .48 for intrinsic/utility values, *r*s = −.44 to −.14 for psychological/effort costs, *p*s $\leq$ .049; Table 3). Finally, and in contrast to the results for students' course-specific assessments, we did not find significant within-person autoregressive or cross-lagged effects from one week to the next (βs = −.06 to .17, *p*s ≥ .059; Table 4). The only exception was a significant negative autoregressive effect for students' intrinsic value suggesting that, if a student experienced a worksheet as more interesting compared to their individual baseline in one week, the student was less interested a week later (βs = −.16/−.13, *p*s ≤ .027).

Table 4

Autoregressive and Cross-Lagged Parameters for Students' Course-Specific Expectancy-Value Beliefs Across the Entire Semester and Week-Specific Expectancy-Value Beliefs Across Three Weeks at the Beginning of the Semester

	Intrinsic value model	Utility value model	Psychological cost model	Effort cost model
	β [95% CI]	β [95% CI]	β [95% CI]	β [95% CI]
Course-specific assessments				
Autoregressive effects				
Expectancy T1c → T2c	$.56^{***\,a}$ [.38; .75]	$.63^{***\,a}$ [.46; .80]	.25 [−.93; 1.43]	.25 [−.81; 1.31]
Expectancy T2c → T3c	$.77^{***\,a}$ [.48; .91]	$.77^{***\,a}$ [.65; .92]	$.77^{***}$ [.47; 1.06]	$.73^{***}$ [.48; .99]
Task value T1c → T2c	$.47^{***\,b}$ [.33; .61]	$.57^{***\,b}$ [.44; .70]	−.18 [−.86; .49]	.13 [−.27; .53]
Task value T2c → T3c	$.56^{***\,b}$ [.39; .73]	$.72^{***\,b}$ [.58; .85]	.27 [−.03; .56]	$.46^{**}$ [.17; .75]
Cross-lagged effects				
Expectancy T1c → Task value T2c	$.24^{**\,c}$ [.10; .39]	$.15^{*\,c}$ [.05; .25]	.07 [−1.03; 1.16]	.12 [−.50; .73]
Expectancy T2c → Task value T3c	$.30^{**\,c}$ [.12; .48]	$.21^{*\,c}$ [.06; .36]	−.23 [−.54; .07]	−.13 [−.35; .10]
Task value T1c → Expectancy T2c	$.12^{d}$ [−.04; .28]	$.01^{d}$ [−.09; .10]	−.05 [−.41; .31]	−.11 [−.39; .17]
Task value T2c → Expectancy T3c	$.14^{d}$ [−.05; .33]	$.02^{d}$ [−.10; .11]	.13 [−.04; .30]	.12 [−.03; .27]
Week-specific assessments				
Autoregressive effects				
Expectancy T1w → T2w	$.14^{a}$ [−.01; .28]	$.11^{a}$ [−.04; .25]	$.11^{a}$ [−.04; .25]	$.09^{a}$ [−.05; .24]
Expectancy T2w → T3w	$.17^{a}$ [−.01; .31]	$.12^{a}$ [−.05; .30]	$.13^{a}$ [−.05; .30]	$.10^{a}$ [−.07; .28]
Task value T1w → T2w	$−.16^{*\,b}$ [−.30; −.02]	$−.06^{b}$ [−.24; .11]	$.01^{b}$ [−.12; .14]	$.10^{b}$ [−.04; .13]
Task value T2w → T3w	$−.13^{*\,b}$ [−.23; −.02]	$−.06^{b}$ [−.21; .10]	$.01^{b}$ [−.14; .17]	$.11^{b}$ [−.05; .15]
Cross-lagged effects				
Expectancy T1w → Task value T2w	$.07^{c}$ [−.07; .21]	$.07^{c}$ [−.07; .21]	$−.04^{c}$ [−.16; .09]	$.01^{c}$ [−.11; .13]
Expectancy T2w → Task value T3w	$.07^{c}$ [−.07; .20]	$.08^{c}$ [−.08; .22]	$−.05^{c}$ [−.19; .10]	$.01^{c}$ [−.13; .15]
Task value T1w → Expectancy T2w	$−.07^{d}$ [−.18; .05]	$−.04^{d}$ [−.16; .08]	$−.01^{d}$ [−.11; .09]	$.00^{d}$ [−.10; .10]
Task value T2w → Expectancy T3w	$−.06^{d}$ [−.17; .05]	$−.04^{d}$ [−.15; .08]	$−.02^{d}$ [−.13; .10]	$.00^{d}$ [−.12; .12]

Note. T1c–T3c = course-specific, summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet. Equal superscripts indicate that unstandardized coefficients were fixed to be the same. Unstandardized parameter estimates are reported in the online supplemental materials.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Group-Specific Differences

To address our third research question regarding group-specific effects, we added students' gender, high school GPA, SES, and participation in math preparatory courses as predictors of their expectancies and task values in the RI-CLPMs. We examined potential group-level effects for (a) students' expectancy-value beliefs at each time point and (b) the within-person motivational alignment of students' course- and week-specific expectancy-value assessments. The inclusion of these covariates in the RI-CLPMs did not affect the results of the first two research questions presented above. The overall model fit for these RI-CLPMs was good (see online supplemental materials).

Interindividual Differences in Students' Course-Specific Expectancies and Task Values

Students' gender significantly predicted their *course-specific* expectancies at all three time points; female students reported lower expectancies of success than did male students (βs = −.24 to −.16, *p*s ≤ .001; Table 5). The predictive effects of students' gender on their subjective task values were less consistent. Female students reported lower levels of utility value at the midpoint of the semester (T2c: β = −.14, *p* = .002) and higher levels of psychological cost at the beginning and midpoint of the semester (T1c/T2c: βs = .17, *p*s ≤ .001). No significant gender differences emerged for students' intrinsic value and effort cost (βs = −.03 to .05; *p*s ≥ .184). As shown in Table 5, the time-invariance analyses for the effects of gender on students' motivational beliefs revealed that only four of the overall 24 estimated parameters were significantly different. Thus, time-invariance was supported for most gender differences.

Students' high school GPA significantly predicted all course-specific expectancy-value beliefs across all time points. Students with comparatively higher high school GPAs reported higher levels of expectancy, intrinsic value, and utility value and lower levels of perceived psychological and effort costs (expectancy and intrinsic/utility values: βs = .13 to .36, *p*s ≤ .001; costs: βs = −.21 to −.11, *p*s ≤ .002). These predictive effects were mostly time-invariant, with only six exceptions out of 24 predictive effects, four of which concerned the same constructs (see Table 5). Specifically, the predictive effect of students' high school GPA on their expectancy at T1c was significantly lower than the analogous effects at T2c and T3c in all four tested models, accounting for four of the six predictive effects that were not time-invariant. Time-invariance was supported for most constructs and comparisons.

Finally, students' SES and participation in math preparatory courses had no significant predictive effects on their course-specific expectancies and task values (βs = −.06 to .04; *p*s ≥ .127).

Table 5

Standardized Path Coefficients for Predictors of Students' Expectancy-Value Beliefs

Predictors	Intrinsic value model		Utility value model		Psychological cost model		Effort cost model	
	Expectancy	Intrinsic value	Expectancy	Utility value	Expectancy	Psych. cost	Expectancy	Effort cost
	β	β	β	β	β	β	β	β
Course-specific assessments								
Female → T1c	$-.21^{***\,a}$	$-.03^{b}$	$-.20^{***\,a}$	$-.06^{b}$	$-.20^{***\,a}$	$.17^{***\,b}$	$-.22^{***\,a}$	$.05^{b}$
Female → T2c	$-.19^{***\,a}$	$-.02^{b}$	$-.22^{***}$	$-.14^{**}$	$-.24^{***}$	$.17^{***\,b}$	$-.19^{***\,a}$	$.05^{b}$
Female → T3c	$-.17^{***\,a}$	$-.02^{b}$	$-.16^{***\,a}$	$-.06^{b}$	$-.16^{***\,a}$	.07	$-.17^{***\,a}$	$.05^{b}$
SES → T1c	$-.01^{c}$	$.01^{d}$	$-.01^{c}$	$.04^{d}$	$-.01^{c}$	$-.06^{d}$	$-.01^{c}$	$-.01^{d}$
SES → T2c	$-.01^{c}$	$.01^{d}$	$-.01^{c}$	$.04^{d}$	$-.01^{c}$	$-.06^{d}$	$-.01^{c}$	$.00^{d}$
SES → T3c	$-.01^{c}$	$.01^{d}$	$-.01^{c}$	$.04^{d}$	$-.01^{c}$	$-.05^{d}$	$-.01^{c}$	$.00^{d}$
GPA → T1c	$.23^{***}$	$.20^{***}$	$.23^{***}$	$.14^{***\,f}$	$.23^{***}$	$-.12^{**\,f}$	$.23^{***}$	$-.11^{**\,f}$
GPA → T2c	$.36^{***\,e}$	$.29^{***\,f}$	$.34^{***\,e}$	$.13^{***\,f}$	$.36^{***\,e}$	$-.21^{***}$	$.36^{***\,e}$	$-.11^{**\,f}$
GPA → T3c	$.34^{***\,e}$	$.28^{***\,f}$	$.33^{***\,e}$	$.14^{***\,f}$	$.33^{***\,e}$	$-.11^{**\,f}$	$.33^{***\,e}$	$-.12^{**\,f}$
Prep. course → T1c	$-.04^{g}$	$.05^{h}$	$-.04^{g}$	$.04^{h}$	$-.05^{g}$	$-.03^{h}$	$-.05^{g}$	$.02^{h}$
Prep. course → T2c	$-.03^{g}$	$.04^{h}$	$-.03^{g}$	$.04^{h}$	$-.04^{g}$	$-.03^{h}$	$-.04^{g}$	$.02^{h}$
Prep. course → T3c	$-.03^{g}$	$.04^{h}$	$-.03^{g}$	$.04^{h}$	$-.04^{g}$	$-.03^{h}$	$-.04^{g}$	$.02^{h}$
Teacher1 → T1c	$-.08^{*}$	$-.20^{***}$	$-.08^{*}$	$-.26^{***}$	$-.08^{*}$	$.18^{***}$	$-.08^{*}$	$.11^{**}$
Teacher1 → T2c	.05	.00	.05	$-.19^{***}$	.06	−.03	.06	$-.12^{*}$
Teacher1 → T3c	.04	.05	.03	$-.21^{**}$	.03	−.02	.04	$-.16^{**}$
Teacher2 → T1c	−.04	$-.11^{*}$	−.04	$-.35^{***}$	−.05	$.14^{***}$	−.04	$.13^{**}$
Teacher2 → T2c	$.11^{**}$	$.13^{**}$	$.11^{**}$	−.03	$.12^{**}$	−.07	$.11^{**}$	$-.13^{**}$
Teacher2 → T3c	.03	.03	.03	$-.25^{***}$	.02	−.02	.03	$-.12^{**}$
Math → T1c	$-.14^{**}$	$-.17^{***}$	$-.14^{**}$	$-.40^{***}$	$-.14^{**}$	$.29^{***}$	$-.14^{**}$	$.27^{***}$
Math → T2c	$-.14^{**}$	−.07	$-.14^{**}$	$-.29^{***}$	$-.14^{**}$	.08	$-.14^{**}$	−.03
Math → T3c	$-.21^{***}$	$-.18^{**}$	$-.21^{***}$	$-.39^{***}$	$-.21^{***}$	.06	$-.20^{***}$	−.05
Week-specific assessments								
Female → T1w	$-.16^{***\,a}$	$-.10^{**\,b}$	$-.16^{***\,a}$	$-.08^{*\,b}$	$-.15^{***\,a}$	$.06^{*\,b}$	$-.15^{***\,a}$	$.03^{b}$
Female → T2w	$-.15^{***\,a}$	$-.10^{**\,b}$	$-.15^{***\,a}$	$-.09^{*\,b}$	$-.15^{***\,a}$	$.06^{*\,b}$	$-.15^{***\,a}$	$.03^{b}$
Female → T3w	$-.16^{***\,a}$	$-.10^{**\,b}$	$-.16^{***\,a}$	$-.09^{*\,b}$	$-.16^{***\,a}$	$.07^{*\,b}$	$-.16^{***\,a}$	$.03^{b}$
SES → T1w	$.01^{c}$	$.01^{d}$	$.01^{c}$	$.08^{*\,d}$	$.00^{c}$	$.00^{d}$	$.00^{c}$	$.01^{d}$
SES → T2w	$.01^{c}$	$.02^{d}$	$.01^{c}$	$.09^{*\,d}$	$.00^{c}$	$.00^{d}$	$.00^{c}$	$.01^{d}$
SES → T3w	$.01^{c}$	$.02^{d}$	$.01^{c}$	$.08^{*\,d}$	$.00^{c}$	$.00^{d}$	$.00^{c}$	$.01^{d}$
GPA → T1w	$.24^{***\,e}$	$.20^{***\,f}$	$.25^{***\,e}$	$.15^{***\,f}$	$.25^{***\,e}$	.00	$.25^{***\,e}$	$-.01^{f}$
GPA → T2w	$.24^{***\,e}$	$.21^{***\,f}$	$.24^{***\,e}$	$.15^{***\,f}$	$.25^{***\,e}$	$-.09^{*\,f}$	$.25^{***\,e}$	$-.01^{f}$
GPA → T3w	$.26^{***\,e}$	$.21^{***\,f}$	$.26^{***\,e}$	$.15^{***\,f}$	$.27^{***\,e}$	$-.10^{*\,f}$	$.26^{***\,e}$	$-.02^{f}$
Prep. course → T1w	$-.01^{g}$	$.04^{h}$	$-.01^{g}$	$.04^{h}$	$-.02^{g}$	$.01^{h}$	$-.01^{g}$	$.03^{h}$
Prep. course → T2w	$-.01^{g}$	$.05^{h}$	$-.01^{g}$	$.04^{h}$	$-.02^{g}$	$.01^{h}$	$-.01^{g}$	$.03^{h}$
Prep. course → T3w	$-.01^{g}$	$.04^{h}$	$-.01^{g}$	$.04^{h}$	$-.02^{g}$	$.01^{h}$	$-.01^{g}$	$.03^{h}$
Teacher1 → T1w	$.10^{*}$	$.15^{***}$	$.10^{*}$	.03	$.09^{*}$	−.06	$.09^{*}$	$-.11^{*}$
Teacher1 → T2w	.02	−.03	.02	−.07	.02	−.01	.02	−.04
Teacher1 → T3w	.04	.02	.04	−.04	.04	−.04	.04	−.04
Teacher2 → T1w	$.21^{***}$	$.19^{***}$	$.21^{***}$	.07	$.20^{***}$	$-.17^{***}$	$.21^{***}$	$-.25^{***}$
Teacher2 → T2w	$-.12^{*}$	$-.17^{***}$	$-.12^{*}$	$-.17^{***}$	$-.12^{*}$	$.15^{***}$	$-.12^{*}$	$.10^{*}$
Teacher2 → T3w	−.02	.02	−.03	−.08	−.03	−.02	−.03	−.05
Math → T1w	$.13^{**}$	$.21^{***}$	$.13^{**}$	.03	$.13^{**}$	$-.20^{***}$	$.13^{**}$	$-.30^{***}$
Math → T2w	$-.12^{**}$	−.08	$-.12^{**}$	$-.20^{***}$	$-.12^{**}$	$.09^{*}$	$-.12^{**}$	.03
Math → T3w	$-.13^{**}$	−.04	$-.13^{**}$	$-.20^{***}$	$-.13^{**}$	.07	$-.13^{**}$	.02

Note. Psych. cost = psychological cost. T1c–T3c = course-specific, summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet. SES = socioeconomic status; GPA = high school grade point average; Prep. course = participation in math preparatory courses; Teacher1, Teacher2, Math = dummy variables for the math courses (physics was used as the reference category). Equal superscripts indicate that unstandardized coefficients were fixed to be the same. Unstandardized parameter estimates are reported in the online supplemental materials.

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Interindividual Differences in Students' Week-Specific Expectancies and Task Values

Female compared to male students reported lower *week-specific* expectancies, intrinsic and utility values, and higher psychological costs associated with working on their weekly math worksheets (expectancy and positively valenced task values: βs = −.16 to −.08, *p*s ≤ .011; psychological cost: βs = .06/.07, *p*s ≤ .044; Table 5). All of these effects were time-invariant and thus stable, although the effect sizes were relatively small.

In addition, students with lower high school GPAs reported significantly lower levels of expectancy, intrinsic value, and utility value, as well as higher levels of psychological cost compared to students with higher GPAs (expectancy and positively valenced task values: βs = .15 to .27, *p*s ≤ .001; psychological cost: βs = −.09/.10, *p*s ≤ .018). These effects were time-invariant, except for the predictive effect of students' high school GPA on their perceived psychological cost, which was smaller and nonsignificant at T1w compared to the other two time points.

Finally, students' SES significantly predicted their week-specific utility value across all three time points (βs = .08/.09, *p*s = .016; Table 5) but no other significant interindividual differences emerged (βs = .00 to .02, *p*s ≥ .668). Students' participation in preparatory math courses did not have any significant predictive effects on students' week-specific expectancies and task values (βs = −.01 to .05; *p*s ≥ .201).

In summary, female relative to male students and students with comparatively lower achievement in high school perceived the content of the weekly worksheets as less interesting and useful, were more stressed, and less confident that they would do well on the final exam if these contents were to be tested.[4]

Interindividual Differences in Students' Within-Person Motivational Alignment

Finally, we specified multigroup RI-CLPMs to test group-specific differences in the degree of alignment of students' expectancies and task values as a function of students' gender, high school GPA, SES, and participation in math preparatory courses (Mulder & Hamaker, 2021). These analyses are shown in Table S7.3 in the online supplemental materials. Overall, there was little evidence of interindividual differences in the alignment of students' expectancies and task values, which suggests that the developmental process of increasing

[4] In the two models including costs, constraining some predictive effects of students' gender, high school GPA, and participation in preparatory to be time-invariant resulted in increases of RMSEA that were larger than .015, even though the chi-square difference tests were nonsignificant and BIC values favored the constrained models (AIC values were almost identical). We describe these cases in the online supplemental materials.

within-person alignment of students' expectancies and intrinsic and utility values is fairly universal (see chi-square difference tests in the online supplemental materials). The only exception was the association between students' course-specific expectancy and utility value at the midpoint and at the end of the semester, which was significantly higher for students with lower than those with higher high school GPAs (T2c; $r_{\text{lowGPA}} = .64$ vs. $r_{\text{highGPA}} = .28$, $p = .013$; T3c; $r_{\text{lowGPA}} = .69$ vs. $r_{\text{highGPA}} = .22$, $p = .003$).[5]

Discussion

Short-term declines in students' domain-specific expectancies and task values shortly after the transition to higher education predict poor academic performance and course dropout in postsecondary education, especially in demanding academic contexts such as STEM (Benden & Lauermann, 2022; Dresel & Grassinger, 2013; Kosovich et al., 2017). Understanding how and why students' motivations change over short periods and at critical educational stages such as the transition to postsecondary education is therefore important. Accordingly, the present study examined how university students' math-related expectancies and subjective task values develop over the course of a single semester in gateway math courses for students enrolled in physics, math, or math teacher education study programs. In particular, we examined developmental changes in the degree of alignment of different types of motivational beliefs, namely students' expected success and valuing of their math course, whether these motivational beliefs are reciprocally related, and whether the observed motivational (mis)alignment differs as a function of students' gender, prior GPA, SES, and participation in math preparatory courses. Our study is the first to examine these developmental processes and reciprocal links on the *within-person* level, controlling for stable, between-person motivational differences. Different types of motivational assessments captured either students' expectancy and valuing of their course in general (i.e., using course-specific, summative assessments) or the specific content taught in a given week (i.e., using week-specific, situated assessments).

Our analyses revealed an increasing alignment of students' course-specific success expectancy and intrinsic and utility values across the semester, whereas the degree of alignment between students' expectancy and perceived costs remained stable and only low to moderate

[5] In two cases, constraining the covariances to be equal across groups resulted in an increase in RMSEA that was larger than .015 even though the chi-square difference tests were nonsignificant and BIC values favored the constrained models (AIC values were almost identical).We describe these cases in the online supplemental materials.

over time. Similarly, the degree of alignment of students' week-specific expectancies and subjective task values remained relatively stable and relatively low across the three measurement points at the beginning of the semester. Within-person motivational spillover effects—i.e., reciprocal links—emerged only for students' course-specific but not week-specific motivational beliefs. These motivational spillover effects were unidirectional rather than reciprocal. Students' expectancy for success predicted subsequent intraindividual changes in their intrinsic and utility values, but not perceived costs. These results suggest that declines in students' expected success in their math course may be contributing to short-term declines in how interesting and useful students perceive the coursework to be across the semester. Male and comparatively higher-achieving students reported significantly higher levels of expected success and task values across all time points and these effects were mostly time-invariant. Overall, there was little evidence of interindividual differences in the degree of alignment of students' expectancy-value beliefs as a function of their gender, prior achievement, SES, or participation in a preparatory math course, which may suggest that these alignment processes are fairly universal. We discuss these findings in greater detail in the following sections.

Changes in the Within-Person Alignment of Students' Expectancy and Subjective Task Values Over Time

Our finding of an increasing alignment of students' course-specific expectancy and intrinsic and utility values across the semester is consistent with the associations theorized by Eccles and Wigfield (Eccles, 2009; Wigfield & Eccles, 1992). These researchers proposed that the degree of alignment of students' expectancy and value beliefs may affect their level of commitment to academic goals, academic engagement, and well-being in achievement situations. Developmental and educational researchers have further proposed that an increased association of students' competence-related beliefs and valuing of academic domains across their school careers may describe a specialization process (e.g., in the math or verbal domain; Denissen et al., 2007). In other words, an increasing alignment of students' beliefs about how competent they feel in a specific domain and their valuing of that particular domain likely corresponds to an increasing commitment to a given domain. This increasing alignment has been found in a few prior studies that focused on students' competence beliefs and valuing of math across the elementary or secondary school years and used yearly and generalized assessments (Fredricks & Eccles, 2002; Wigfield et al., 1997).

Our results expand upon this evidence by showing that these motivational alignment processes also occur over shorter time periods (i.e., one semester in STEM) and in the context of higher education. After the transition to postsecondary education, students need to adapt to the context of math-intensive STEM programs and calibrate their expectancy-value beliefs to the new demands, workload, and content in their study program (Coertjens et al., 2017; Eccles & Midgley, 1989; Seymour & Hewitt, 1997). Accordingly, the developmental process of motivational (re)alignment observed in the school years (e.g., Denissen et al., 2007) may become restarted as students adjust to this new and challenging educational context.

This developmental process was more pronounced for the alignment of students' (course-specific) expectancy and positively valenced task value components (i.e., intrinsic and utility values) than for their success expectancy and perceived costs (i.e., psychological and effort costs). Context characteristics might have contributed to this pattern. The math courses in the present study were highly demanding and most students likely anticipated a high amount of time and effort needed to invest in the course. Indeed, students reported moderate to high levels of effort costs already at the beginning of the semester, which may have reduced the association of cost and expectancy (see also within-person correlations in Table 2).

Furthermore, we found that the degree of alignment of students' situated, week-specific expectancy-value beliefs remained relatively stable across the three-week period of observation at the beginning of the semester. The only exception was the association of students' expectancy and perceived psychological and effort costs at T2w, which was almost twice as strong compared to the other weeks. Situational characteristics likely contribute to these weekly fluctuations. For instance, the content that was covered each week (e.g., the difficulty and length of each worksheet) and competing demands in other courses or at home may vary from week to week and may affect students' cost perceptions. More research on the effects of situational and context characteristics on students' situated expectancy and subjective task values is thus needed (Eccles & Wigfield, 2020). This could provide insights into which situated expectancy-value beliefs may be most malleable and potentially most suitable for interventions.

These measure-specific differences in the alignment of students' expectancy-value beliefs indicate that situated (week-specific) and summative (course-specific) assessments of students' expectancies and subjective task values may evoke different cognitive processes (M. D. Robinson & Clore, 2002). The summative assessments asked students to reflect on their overall experiences in their math course and thus students needed to aggregate their experiences up until that point. In contrast, the situated assessments were limited to students' experiences with the content assessed on each math worksheet in a given week so that situational and week-specific influences may play a comparatively greater role in this case. The observed increased alignment of students' course-specific expectancies and intrinsic and utility values over the semester likely indicates an adaptation to the new educational context in math-intensive STEM programs (e.g., high workload, new social context with many high-achieving peers). In addition, such aggregated and generalized assessments of students' expectancies and task values may capture students' perceptions of their identity (Eccles, 2009; Eccles et al., 2015; see M. D. Robinson & Clore, 2002, for self-report items on emotions). In particular, students' perceptions of being a "math person" likely shape their overall experiences and cumulative assessments about how much they like their math course. In contrast, the situated (week-specific) assessments of students' expectancy-value beliefs likely describe within-person fluctuations in their motivational beliefs at the beginning of the semester and these fluctuations had little bearing on students' subsequent situated motivations.

However, it remains an open question whether the alignment of students' situated expectancies and task values increases later in the semester as students gain more experience with their math assignments. The situated assessments focused on the first weeks of the semester because motivational changes are particularly likely during this time and declines in students' expectancies and task values shortly after the transition to postsecondary education can be a warning sign for later academic difficulties (Benden & Lauermann, 2022; Zusho et al., 2003). Our results suggest that students' summative (course-specific) expectancies and task values stabilize and converge towards the midterm. Thus, it may be that students' situated expectancy-value beliefs referencing the current worksheet also become better aligned and stabilize after this initial adaptation process.

Associations of Students' Expectancies and Task Values: Between-Person Associations and Within-Person Motivational Spillover Effects

Our study is the first to systematically examine between-person and within-person associations of students' course-specific and week-specific expectancies and task values using the RI-CLPM proposed by Hamaker et al. (2015). As expected, we found positive between-person associations between students' expectancy and intrinsic and utility values as well as negative between-person associations between expectancy and perceived psychological and effort costs (Eccles & Wigfield, 1995, 2020; Perez et al., 2014). Thus, on average, students who had a higher expectancy for success in their math course or on a given worksheet compared to their peers also reported higher valuing of the content of their math course and lower costs.

In addition, and consistent with the assumptions of SEVT (Eccles, 2009; Eccles & Wigfield, 2020), our findings suggest that students who expect to do well in their math course come to value the coursework throughout the semester. As mentioned previously, motivational spillover effects emerged for students' positively valenced task values but not their perceived costs, likely because the perceived costs are quite salient and high in the particular context of our study (e.g., high workload with weekly math worksheets). The identified motivational spillover effects also emerged in prior research over longer time periods, using mostly domain-specific motivational assessments, and relying on traditional CLPM approaches (Arens et al., 2019; Sewasew et al., 2018; Viljaranta et al., 2014). However, our results expand upon this prior work by showing that the autoregressive and cross-lagged effects between students' expectancies and task values depend on whether course-specific (summative) or week-specific (situated) expectancy-value beliefs are studied. After accounting for stable, trait-like differences in students' week-specific motivational beliefs referencing their current worksheet, we found no evidence of within-person carryover or spillover effects from one week to the next (except for one negative autoregressive effect for intrinsic value). Thus, students' experiences with their current math worksheet appear to be relatively self-contained within a given week at the beginning of the semester.

As discussed above, these measure-specific results suggest that summative and situated assessments of students' expectancies and task values likely evoke different cognitive processes that ask students either to aggregate their beliefs across situations or to focus on the content covered in a given week. These assessments likely capture different developmental processes shortly after the transition to postsecondary education. However, it remains an open question how students derive their more generalized expectancies and task values about their math course and whether these generalized beliefs are based on students' situated motivational beliefs. Our results revealed little evidence of week-to-week carryover and spillover effects for students' situated expectancy-value beliefs at the beginning of the semester suggesting that these situated beliefs may not immediately shape students' more generalized beliefs about their math course. Rather, students' more generalized and summative expectancies and task values may only be updated slowly over time.

Several reasons might contribute to whether or not students revise their more generalized expectancy-value beliefs. First, according to SEVT (Eccles & Wigfield, 2020), students' attributions of success and failure likely play a role in this process. For instance, attributing a poor performance on a math worksheet to unstable causes (e.g., lack of effort) may not affect students' expectancy to be successful in their math course, whereas attributing it to relatively stable causes (e.g., lack of talent or aptitude) may do so. Second, individuals strive to maintain coherent self-views (Swann & Schroeder, 1995). Therefore, it seems unlikely that students revise their generalized motivational beliefs based on a few situated experiences that are not coherent with their identity (e.g., "I still like math, even if this worksheet was boring"). Similarly, high levels of more generalized expectancies and task values that result from summative evaluations may serve as a buffer against negative situation-specific experiences (e.g., a boring worksheet, a poor achievement on a worksheet). Accordingly, after the transition to higher education, students' situated, week-to-week experiences may need time to accumulate to form their more generalized beliefs about a course or their study program in general (see also Dietrich et al., 2019).

These differences in the alignment processes and motivational spillover effects between situated (week-specific) and summative (course-specific) motivational beliefs have implications for the design of interventions. Motivationally-supportive interventions that aim to spark positive spillover effects, and buffer negative ones, should target students' situated expectancy-value beliefs across multiple weeks so that students' positive course experiences can accumulate and form their more generalized motivational beliefs (see dynamic, synergistic, and situated interventions; Rosenzweig et al., 2022). In addition, our analyses highlight the role of students' expectancies as a driving force behind declines in students' valuing of their math course at the beginning of their postsecondary education. Thus, a combined intervention approach targeting both students' expectancy for success and task values may be most fruitful to buffer students from short-term motivational declines and increase their retention in STEM (Gaspard, Dicke, Flunger, Brisson, et al., 2015; Rosenzweig et al., 2022).

The Role of Students' Personal Characteristics for Their Expectancies and Task Values and the Alignment of Their Expectancy-Value Beliefs

Our analyses of interindividual differences focused on students' gender, prior achievement, SES, and participation in preparatory math courses. Gender differences in students' *course-specific* motivational beliefs were limited to students' expectancy and psychological cost. By comparison, gender differences in students' *week-specific* motivational beliefs emerged consistently for their expectancies, intrinsic and utility values, and perceived psychological cost across all time points. These differences appear to capture "trait-like," and likely preexisting, gender differences in favor of male students (Mulder & Hamaker, 2021).

This finding is somewhat at odds with our expectations that more generalized (i.e., summative and retrospective) assessments of students' motivations and emotions may reveal greater gender differences than do situation-specific assessments (Eccles et al., 1983; Frieze et al., 1978; M. D. Robinson & Clore, 2002). In particular, we expected that generalized assessments may be comparatively more likely to capture societal stereotypes and general beliefs about gender and math, in addition to students' beliefs about the self. However, situated assessments may also be affected by gender stereotypes. For instance, Frieze et al. (1978) argued that, in novel achievement situations, students have little experience to draw from and may therefore rely on stereotypes about gender and math to form their expectancy beliefs. The math worksheets in the present study represented novel tasks for students, and thus their week-specific ratings may also be affected by generalized beliefs and stereotypes. Context characteristics such as whether or not gender stereotypes are made salient to students might also play a role (e.g., if students are confronted with negative stereotypes about female students in male-dominated STEM fields in class; Murphy et al., 2007).

Our analyses further revealed that students with lower high school GPAs reported lower levels of expectancy and intrinsic and utility values and higher levels of perceived costs than did students with higher levels of prior achievement. This finding is consistent with our expectations and prior evidence (e.g., Guo, Parker, et al., 2015; Perez et al., 2014). Similar to gender, these differences were mostly time-invariant and thus "trait-like" (Mulder & Hamaker, 2021). In contrast, no differences emerged as a function of the students' SES and participation in a preparatory math course. Most students in our sample came from high-SES backgrounds, which may limit the predictive effects of this variable in our study. In general, access to higher education tends to be strongly linked to students' SES (Watermann et al., 2014).

Across all analyses, we found little evidence of interindividual differences in the degree of alignment of students' expectancies and task values within a given time point. Thus, the increased motivational (re)alignment across the semester likely reflects a relatively universal process of adjustment to the new educational context in STEM. Nevertheless, different students may experience different degrees of motivational discordance at the beginning of their studies, and heterogeneous (re)alignment profiles and trajectories may exist that are not linked to students' gender, prior achievement, or SES (cf. Dietrich et al., 2019). Furthermore, features of the learning environment and time-varying influences such as students' weekly interactions with their instructor and peers could influence these alignment processes as well (cf. Coertjens et al., 2017; Eccles & Wigfield, 2020).

Limitations and Directions for Future Research

Several limitations must be considered in the interpretation of our results and suggest possible directions for future research. First, the sample of our study was comparatively high-achieving and homogeneous in terms of students' SES and high school GPA. Group differences in students' expectancy-value beliefs and in the degree of alignment of these beliefs might emerge in more diverse contexts. In addition, even if there are mean-level differences between groups (e.g., between female and male students), individual differences within groups are often quite substantial as well (Wigfield & Eccles, 2002). Thus, it may be interesting to examine if there are groups of students with different degrees of alignment of their motivational beliefs as a function of individual or context characteristics such as past performance experiences or current experiences with worksheets and course content.

Second, in the present study, we focused on the developmental relations of two constructs within the SEVT-framework at a time (i.e., students' expectancy and different task value facets). These analyses allowed us to identify if the alignment processes and reciprocal links among expectancies and task values varied depending on the type of task value. However, given that students' expectancy and subjective task value beliefs are posited to be a dynamic and complex system (Wigfield & Eccles, 2020), alternative modeling approaches, such as psychometric network models (Epskamp, 2020), may reveal a more complete picture of the links between multiple expectancy-value constructs at the same time. In addition, it remains an open question whether students who have well-aligned expectancy-value beliefs within a given domain are comparatively more engaged, have more positive learning experiences, and continue to invest time and resources in that domain, as proposed by Eccles and Wigfield (Eccles, 2009; Wigfield & Eccles, 1992, 2002).

Third, our analyses of reciprocal links and the alignment of students' expectancy-value beliefs were limited to students' intrinsic and utility value and two facets of perceived costs. Further components of subjective task value as proposed by Eccles and colleagues should be included in future research (Eccles & Wigfield, 2020; Wigfield et al., 2017). For instance, Eccles (2009) argued that the importance of attainment value attached to a given task or domain, i.e., the importance of the task or domain for one's identity, should increase over time as students incorporate the task or domain into their identity. Thus, in addition to analyzing reciprocal links among expectancy and different task values, future research could also study reciprocal links among different subjective task value facets to gain a better understanding of the developmental processes of students' motivational beliefs after the transition to postsecondary education.

Conclusion

Informed by Eccles and colleagues' situated expectancy-value theory (Eccles & Wigfield, 2020), we examined the degree of alignment of students' math-related expectancy and subjective task values, within-person reciprocal links among expectancies and task values, and the role of students' personal characteristics for their motivational beliefs and the degree of alignment between these motivational beliefs. Our analyses revealed different results with respect to the alignment of students' motivational beliefs and potential motivational spillover effects over time depending on the type of motivational assessment. We found an increasing alignment between students' course-specific (summative) expectancy and intrinsic and utility values across the semester, whereas the degree of alignment of students' week-specific (situated) expectancies and task values was mostly constant across three weeks at the beginning of the semester. In addition, within-person motivational spillover effects were limited to students' course-specific expectancy-value beliefs: Students' expectancy significantly predicted within-person changes in their intrinsic and utility values but not vice versa. In contrast, students' week-specific motivational beliefs were relatively self-contained in a given week. Finally, the predictive effects of students' gender and prior achievement on their expectancies and task values were mostly time-invariant suggesting that these interindividual differences tend to be mostly "trait-like." Overall, our results underscore the importance of considering both the time lag and the type of assessment in analyses of the alignment and reciprocal links of students' expectancies and task values. Summative in contrast to situation-specific motivational assessments likely capture different developmental processes of students' expectancy and subjective task values over short periods of time.

References

Arens, A. K., Schmidt, I., & Preckel, F. (2019). Longitudinal relations among self-concept, intrinsic value, and attainment value across secondary school years in three academic domains. *Journal of Educational Psychology, 111*(4), 663–684. https://doi.org/10.1037/edu0000313

Benden, D. K., & Lauermann, F. (2022). Students' motivational trajectories and academic success in math-intensive study programs: Why short-term motivational assessments matter. *Journal of Educational Psychology, 114*(5). 1062–1085. https://doi.org/10.1037/edu0000708

Berry, D., & Willoughby, M. T. (2017). On the practical interpretability of cross-lagged panel models: Rethinking a developmental workhorse. *Child Development, 88*(4), 1186–1206. https://doi.org/10.1111/cdev.12660

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal, 14*(3), 464–504. https://doi.org/10.1080/10705510701301834

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling, 9*(2), 233–255. https://doi.org/10.1207/S15328007SEM0902_5

Clem, A.-L., Hirvonen, R., Aunola, K., & Kiuru, N. (2021). Reciprocal relations between adolescents' self-concepts of ability and achievement emotions in mathematics and literacy. *Contemporary Educational Psychology, 65*, Article 101964. https://doi.org/10.1016/j.cedpsych.2021.101964

Coertjens, L., Brahm, T., Trautwein, C., & Lindblom-Ylänne, S. (2017). Students' transition into higher education from an international perspective. *Higher Education, 73*(3), 357–369. https://doi.org/10.1007/s10734-016-0092-y

Denissen, J. J., Zarrett, N. R., & Eccles, J. S. (2007). I like to do it, I'm able, and I know I am: Longitudinal couplings between domain-specific achievement, self-concept, and interest. *Child Development, 78*(2), 430–447. https://doi.org/10.1111/j.1467-8624.2007.01007.x

Dietrich, J., Moeller, J., Guo, J., Viljaranta, J., & Kracke, B. (2019). In-the-moment profiles of expectancies, task values, and costs. *Frontiers in Psychology, 10*. https://doi.org/10.3389/fpsyg.2019.01662

Dietrich, J., Viljaranta, J., Moeller, J., & Kracke, B. (2017). Situational expectancies and task values: Associations with students' effort. *Learning and Instruction, 47*, 53–64. https://doi.org/10.1016/j.learninstruc.2016.10.009

Dormann, C., & Griffin, M. A. (2015). Optimal time lags in panel studies. *Psychological Methods, 20*(4), 489–505. https://doi.org/10.1037/met0000041

Dresel, M., & Grassinger, R. (2013). Changes in achievement motivation among university freshmen. *Journal of Education and Training Studies, 1*(2), 159–173. https://doi.org/10.11114/jets.v1i2.147

Du, C., Qin, K., Wang, Y., & Xin, T. (2021). Mathematics interest, anxiety, self-efficacy and achievement: Examining reciprocal relations. *Learning and Individual Differences, 91*, Article 102060. https://doi.org/10.1016/j.lindif.2021.102060

Eccles, J. S. (2005). Commentary: Studying the development of learning and task motivation. *Learning and Instruction, 15*(2), 161–171. https://doi.org/10.1016/j.learninstruc.2005.04.012

Eccles, J. S. (2009). Who am I and what am I going to do with my life? Personal and collective identities as motivators of action. *Educational Psychologist, 44*(2), 78–89. https://doi.org/10.1080/00461520902832368

Eccles, J. S., Adler, T., Futterman, R., Goff, S., Kaczala, C., Meece, J., & Midgley, C. (1983). Expectancies, values, and academic behaviors. In J. T. Spence (Ed.), *Achievement and achievement motives* (pp. 75–146). Freeman.

Eccles, J. S., Fredricks, J. A., & Epstein, A. (2015). Understanding well-developed interests and activity commitment. In K. A. Renninger, M. Nieswandt, & S. Hidi (Eds.), *Interest in mathematics and science learning* (pp. 315–330). https://doi.org/10.3102/978-0-935302-42-4_18

Eccles, J. S., & Midgley, C. (1989). Stage-environment fit: Developmentally appropriate classrooms for young adolescents. In C. Ames & R. Ames (Eds.), *Research on motivation in education: Goals and cognitions* (Vol. 3, pp. 139–186). Academic Press.

Eccles, J. S., & Wigfield, A. (1995). In the mind of the actor: The structure of adolescents' achievement task values and expectancy-related beliefs. *Personality and Social Psychology Bulletin, 21*(3), 215–225. https://doi.org/10.1177/0146167295213003

Eccles, J. S., & Wigfield, A. (2020). From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation. *Contemporary Educational Psychology, 61*, Article 101859. https://doi.org/10.1016/j.cedpsych.2020.101859

Ehm, J.-H., Hasselhorn, M., & Schmiedek, F. (2019). Analyzing the developmental relation of academic self-concept and achievement in elementary school children: Alternative models point to different results. *Developmental Psychology, 55*(11), 2336–2351. https://doi.org/10.1037/dev0000796

Epskamp, S. (2020). Psychometric network models from time-series and panel data. *Psychometrika, 85*(1), 206–231. https://doi.org/10.1007/s11336-020-09697-3

Flake, J. K., Barron, K. E., Hulleman, C., McCoach, B. D., & Welsh, M. E. (2015). Measuring cost: The forgotten component of expectancy-value theory. *Contemporary Educational Psychology, 41*, 232–244. https://doi.org/10.1016/j.cedpsych.2015.03.002

Fredricks, J. A., & Eccles, J. S. (2002). Children's competence and value beliefs from childhood through adolescence: Growth trajectories in two male-sex-typed domains. *Developmental Psychology, 38*(4), 519–533. https://doi.org/10.1037/0012-1649.38.4.519

Frieze, I. H., Fisher, J., Hanusa, B., McHugh, M. C., & Valle, V. A. (1978). Attributions of the causes of success and failure as internal and external barriers to achievement in women. In J. Sherman & F. Denmark (Eds.), *Psychology of women: Future directions of research.* (pp. 519–552). Psychological Dimensions.

Gale, T., & Parker, S. (2014). Navigating change: A typology of student transition in higher education. *Studies in higher education, 39*(5), 734–753. https://doi.org/10.1080/03075079.2012.721351

Gaspard, H., Dicke, A.-L., Flunger, B., Brisson, B. M., Häfner, I., Nagengast, B., & Trautwein, U. (2015). Fostering adolescents' value beliefs for mathematics with a relevance intervention in the classroom. *Developmental Psychology, 51*(9), 1226–1240. https://doi.org/10.1037/dev0000028

Gaspard, H., Dicke, A.-L., Flunger, B., Schreier, B., Häfner, I., Trautwein, U., & Nagengast, B. (2015). More value through greater differentiation: Gender differences in value beliefs about math. *Journal of Educational Psychology, 107*(3), 663–677. https://doi.org/10.1037/edu0000003

Gaspard, H., Lauermann, F., Rose, N., Wigfield, A., & Eccles, J. S. (2020). Cross-domain trajectories of students' ability self-concepts and intrinsic values in math and language arts. *Child Development, 91*(5), 1800–1818. https://doi.org/10.1111/cdev.13343

Geisler, S. (2021). Early dropout from university mathematics: The role of students' attitudes towards mathematics. In M. Inprasitha, N. Changsri, & N. Boonsena (Eds.), *Interim Proceedings of the 44th Conference of the International Group for the Psychology of Mathematics Education* (pp. 189–198). https://pme44.kku.ac.th/home/uploads/welcome/interim_proceedings.pdf

Goetz, T., Bieg, M., Lüdtke, O., Pekrun, R., & Hall, N. C. (2013). Do girls really experience more anxiety in mathematics? *Psychological Science, 24*(10), 2079–2087. https://doi.org/10.1177/0956797613486989

Graham, J. W. (2003). Adding missing-data-relevant variables to FIML-based structural equation models. *Structural Equation Modeling, 10*(1), 80–100. https://doi.org/10.1207/S15328007SEM1001_4

Guo, J., Marsh, H. W., Parker, P. D., Morin, A. J., & Yeung, A. S. (2015). Expectancy-value in mathematics, gender and socioeconomic background as predictors of achievement and aspirations: A multi-cohort study. *Learning and Individual Differences, 37*, 161–168. https://doi.org/10.1016/j.lindif.2015.01.008

Guo, J., Parker, P. D., Marsh, H. W., & Morin, A. J. (2015). Achievement, motivation, and educational choices: A longitudinal study of expectancy and value using a multiplicative perspective. *Developmental Psychology, 51*(8), 1163–1176. https://doi.org/10.1037/a0039440

Hamaker, E. L., Kuiper, R. M., & Grasman, R. P. (2015). A critique of the cross-lagged panel model. *Psychological Methods, 20*(1), 102–116. https://doi.org/10.1037/a0038889

Harter, S. (1990). Causes, correlates, and the functional role of global self-worth: A life-span perspective. In R. J. Sternberg & J. Kolligian (Eds.), *Competence considered.* (pp. 67–97). Yale University Press.

Jacobs, J. E., Lanza, S., Osgood, D. W., Eccles, J. S., & Wigfield, A. (2002). Changes in children's self-competence and values: Gender and domain differences across grades one through twelve. *Child Development, 73*(2), 509–527. https://doi.org/10.1111/1467-8624.00421

Kosovich, J. J., Flake, J. K., & Hulleman, C. S. (2017). Short-term motivation trajectories: A parallel process model of expectancy-value. *Contemporary Educational Psychology, 49*, 130–139. https://doi.org/10.1016/j.cedpsych.2017.01.004

Lauermann, F., Tsai, Y.-M., & Eccles, J. S. (2017). Math-related career aspirations and choices within Eccles et al.'s expectancy-value theory of achievement-related behaviors. *Developmental Psychology, 53*(8), 1540–1559. https://doi.org/10.1037/dev0000367

Lee, Y.-k., & Seo, E. (2021). Longitudinal relations between South Korean adolescents' academic self-efficacy and values in mathematics and English. *British Journal of Educational Psychology, 91*(1), 217–236. https://doi.org/10.1111/bjep.12357

Lent, R. W., Sheu, H.-B., Singley, D., Schmidt, J. A., Schmidt, L. C., & Gloster, C. S. (2008). Longitudinal relations of self-efficacy to outcome expectations, interests, and major choice goals in engineering students. *Journal of Vocational Behavior, 73*(2), 328–335. https://doi.org/10.1016/j.jvb.2008.07.005

Little, T. D. (2013). *Longitudinal structural equation modeling*. Guilford Press.

Lucas, R. E. (2022). *It's time to abandon the cross-lagged panel model*. PsyArXiv. https://doi.org/10.31234/osf.io/pkec7

Lüdtke, O., & Robitzsch, A. (2021). *A critique of the random intercept cross-lagged panel model*. PsyArXiv. https://doi.org/10.31234/osf.io/6f85c

Marsh, H. W., Hau, K.-T., & Grayson, D. (2005). Goodness of fit in structural equation models. In A. Maydeu-Olivares & J. J. McArdle (Eds.), *Contemporary psychometrics: A festschrift for Roderick P. McDonald* (pp. 275–340). Erlbaum.

Marsh, H. W., Pekrun, R., Parker, P. D., Murayama, K., Guo, J., Dicke, T., & Arens, A. K. (2019). The murky distinction between self-concept and self-efficacy: Beware of lurking jingle-jangle fallacies. *Journal of Educational Psychology, 111*(2), 331–353. https://doi.org/10.1037/edu0000281

Marsh, H. W., Trautwein, U., Lüdtke, O., Köller, O., & Baumert, J. (2005). Academic self-concept, interest, grades, and standardized test scores: Reciprocal effects models of causal ordering. *Child Development, 76*(2), 397–416. https://doi.org/10.1111/j.1467-8624.2005.00853.x

Moeller, J., Viljaranta, J., Tolvanen, A., Kracke, B., & Dietrich, J. (2022, 2022/07/18/). Introducing the DYNAMICS framework of moment-to-moment development in achievement motivation. *Learning and Instruction*, Article 101653. https://doi.org/10.1016/j.learninstruc.2022.101653

Mulder, J. D., & Hamaker, E. L. (2021). Three extensions of the random intercept cross-lagged panel model. *Structural Equation Modeling: A Multidisciplinary Journal, 28*(4), 638–648. https://doi.org/10.1080/10705511.2020.1784738

Murphy, M. C., Steele, C. M., & Gross, J. J. (2007). Signaling threat: How situational cues affect women in math, science, and engineering settings. *Psychological Science, 18*(10), 879–885. https://doi.org/10.1111/j.1467-9280.2007.01995.x

Nagengast, B., Marsh, H. W., Scalas, L. F., Xu, M. K., Hau, K.-T., & Trautwein, U. (2011). Who took the “×” out of expectancy-value theory? A psychological mystery, a substantive-methodological synergy, and a cross-national generalization. *Psychological Science, 22*(8), 1058–1066. https://doi.org/10.1177/0956797611415540

Orth, U., Clark, D. A., Donnellan, M. B., & Robins, R. W. (2021). Testing prospective effects in longitudinal research: Comparing seven competing cross-lagged models. *Journal of Personality and Social Psychology, 120*(4), 1013–1034. https://doi.org/10.1037/pspp0000358

Parrisius, C., Gaspard, H., Zitzmann, S., Trautwein, U., & Nagengast, B. (2022). The “situative nature” of competence and value beliefs and the predictive power of autonomy support: A multilevel investigation of repeated observations. *Journal of Educational Psychology, 114*(4), 791–814. https://doi.org/10.1037/edu0000680

Paulus, W., & Matthes, B. (2013). *Klassifikation der Berufe: Struktur, Codierung und Umsteigeschlüssel [Classification of occupations: Structure, coding, and conversion key]*. http://doku.iab.de/fdz/reporte/2013/MR_08-13.pdf

Perez, T., Cromley, J. G., & Kaplan, A. (2014). The role of identity development, values, and costs in college STEM retention. *Journal of Educational Psychology, 106*(1), 315–329. https://doi.org/10.1037/a0034027

Perez, T., Dai, T., Kaplan, A., Cromley, J. G., Brooks, W. D., White, A. C., Mara, K. R., & Balsai, M. J. (2019). Interrelations among expectancies, task values, and perceived costs in undergraduate biology achievement. *Learning and Individual Differences, 72*, 26–38. https://doi.org/10.1016/j.lindif.2019.04.001

Pinxten, M., Marsh, H. W., De Fraine, B., Van Den Noortgate, W., & Van Damme, J. (2014). Enjoying mathematics or feeling competent in mathematics? Reciprocal effects on mathematics achievement and perceived math effort expenditure. *British Journal of Educational Psychology, 84*(1), 152–174. https://doi.org/10.1111/bjep.12028

Rach, S., & Heinze, A. (2017). The transition from school to university in mathematics: Which influence do school-related variables have? *International Journal of Science and Mathematics Education, 15*(7), 1343–1363. https://doi.org/10.1007/s10763-016-9744-8

Rieger, S., Göllner, R., Spengler, M., Trautwein, U., Nagengast, B., & Roberts, B. W. (2017). Social cognitive constructs are just as stable as the Big Five between grades 5 and 8. *AERA Open, 3*(3), 1–9. https://doi.org/10.1177/2332858417717691

Robinson, K. A., Lee, Y.-k., Bovee, E. A., Perez, T., Walton, S. P., Briedis, D., & Linnenbrink-Garcia, L. (2019). Motivation in transition: Development and roles of expectancy, task values, and costs in early college engineering. *Journal of Educational Psychology, 111*(6), 1081–1102. https://doi.org/10.1037/edu0000331

Robinson, M. D., & Clore, G. L. (2002). Belief and feeling: Evidence for an accessibility model of emotional self-report. *Psychological Bulletin, 128*(6), 934–960. https://doi.org/10.1037/0033-2909.128.6.934

Rosenzweig, E. Q., Wigfield, A., & Eccles, J. S. (2022). Beyond utility value interventions: The why, when, and how for next steps in expectancy-value intervention research. *Educational Psychologist, 57*(1), 11–30. https://doi.org/10.1080/00461520.2021.1984242

Ruzek, E. A., & Schenke, K. (2019). The tenuous link between classroom perceptions and motivation: A within-person longitudinal study. *Journal of Educational Psychology, 111*(5), 903–917. https://doi.org/10.1037/edu0000323

Schafer, J. L., & Graham, J. W. (2002). Missing data: Our view of the state of the art. *Psychological Methods, 7*(2), 147–177. https://doi.org/10.1037//1082-989X.7.2.147

Sewasew, D., Schroeders, U., Schiefer, I. M., Weirich, S., & Artelt, C. (2018). Development of sex differences in math achievement, self-concept, and interest from grade 5 to 7. *Contemporary Educational Psychology, 54*, 55–65. https://doi.org/10.1016/j.cedpsych.2018.05.003

Seymour, E., & Hewitt, N. (1997). *Talking about leaving: Why undergraduates leave the sciences*. Westview Press.

Spinath, B., & Steinmayr, R. (2008). Longitudinal analysis of intrinsic motivation and competence beliefs: Is there a relation over time? *Child Development, 79*(5), 1555–1569. https://doi.org/10.1111/j.1467-8624.2008.01205.x

Swann, W. B., Jr., & Schroeder, D. G. (1995). The search for beauty and truth: A framework for understanding reactions to evaluations. *Personality and Social Psychology Bulletin, 21*(12), 1307–1318. https://doi.org/10.1177/01461672952112008

Tanaka, A., & Murayama, K. (2014). Within-person analyses of situational interest and boredom: Interactions between task-specific perceptions and achievement goals. *Journal of Educational Psychology, 106*(4), 1122–1134. https://doi.org/10.1037/a0036659

Tsai, Y.-M., Kunter, M., Lüdtke, O., & Trautwein, U. (2008). Day-to-day variation in competence beliefs: How autonomy support predicts young adolescents' felt competence. In H. W. Marsh, R. G. Craven, & D. M. McInerney (Eds.), *Self-processes, learning, and enabling human potential: Dynamic new approaches* (pp. 119–143). Information Age Publishing.

Tsai, Y.-M., Kunter, M., Lüdtke, O., Trautwein, U., & Ryan, R. M. (2008). What makes lessons interesting? The role of situational and individual factors in three school subjects. *Journal of Educational Psychology, 100*(2), 460–472. https://doi.org/10.1037/0022-0663.100.2.460

Viljaranta, J., Tolvanen, A., Aunola, K., & Nurmi, J.-E. (2014). The developmental dynamics between interest, self-concept of ability, and academic performance. *Scandinavian Journal of Educational Research, 58*(6), 734–756. https://doi.org/10.1080/00313831.2014.904419

Watermann, R., Daniel, A., & Maaz, K. (2014). Primäre und sekundäre Disparitäten des Hochschulzugangs: erklärungsmodelle, Datengrundlagen und Entwicklungen [Primary and secondary disparaties in university access: Explanatory models, data bases, and developments]. *Zeitschrift für Erziehungswissenschaft, 17*, 233–261. https://doi.org/10.1007/s11618-013-0470-5

Watt, H. M. (2004). Development of adolescents' self-perceptions, values, and task perceptions according to gender and domain in 7th-through 11th-grade Australian students. *Child Development, 75*(5), 1556–1574. https://doi.org/10.1111/j.1467-8624.2004.00757.x

Wigfield, A., & Eccles, J. S. (1992). The development of achievement task values: A theoretical analysis. *Developmental Review, 12*(3), 265–310. https://doi.org/10.1016/0273-2297(92)90011-P

Wigfield, A., & Eccles, J. S. (2002). The development of competence beliefs, expectancies for success, and achievement values from childhood through adolescence. In A. Wigfield & J. S. Eccles (Eds.), *Development of achievement motivation* (pp. 91–120). Academic Press. https://doi.org/10.1016/B978-012750053-9/50006-1

Wigfield, A., & Eccles, J. S. (2020). 35 years of research on students' subjective task values and motivation: A look back and a look forward. In A. Elliot (Ed.), *Advances in motivation science* (Vol. 7, pp. 161–198). Elsevier. https://doi.org/10.1016/bs.adms.2019.05.002

Wigfield, A., Eccles, J. S., Yoon, K. S., Harold, R. D., Arbreton, A. J. A., Freedman-Doan, C., & Blumenfeld, P. C. (1997). Change in children's competence beliefs and subjective task values across the elementary school years: A 3-year study. *Journal of Educational Psychology, 89*(3), 451–469. https://doi.org/10.1037/0022-0663.89.3.451

Wigfield, A., Rosenzweig, E. Q., & Eccles, J. S. (2017). Achievement values: Interactions, interventions, and future directions. In A. Elliot, C. S. Dweck, & D. S. Yeager (Eds.), *Handbook of competence and motivation: Theory and application* (Vol. 2, pp. 116–134). The Guilford Press.

Zusho, A., Pintrich, P. R., & Coppola, B. (2003). Skill and will: The role of motivation and cognition in the learning of college chemistry. *International Journal of Science Education, 25*(9), 1081–1094. https://doi.org/10.1080/0950069032000052207

Supplemental Materials:

Searching for Short-Term Motivational Spillover Effects: A Random Intercept Cross-Lagged Analysis of Students' Expectancies and Task Values in Math-Intensive Study Programs

Supplement S1. Full List of Self-Report Items
Supplement S2. Tests of Measurement Invariance Across Study Programs and Time
Supplement S3. Model Fit of Final Random Intercept Cross-Lagged Panel Models
Supplement S4. Model Fit of Correlational Models with Constrained or Freely Estimated Covariances
Supplement S5. Unstandardized Parameter Estimates for the Analyses Reported in the Manuscript
Supplement S6. Model Comparisons for RI-CLPMs Including Students' Personal Characteristics
Supplement S7. Model Fit of Multigroup Correlational Models with Constrained or Freely Estimated Covariances
Supplement S8. Results of Alternative Models for Students' Course-Specific Expectancy-Value Beliefs

Supplement S1. Full List of Self-Report Items Used in Study 1a and Study 1b

Table S1
List of Self-Report Items

Construct	Instruction and items (translated from German)
Course-specific (summative) expectancy-value beliefs (Weeks 2, 8, and 15)	
Expectancy	Based on my experiences in this class so far, I think I will do well on the exam.[a]
	Based on my experiences in this class so far, I think I am good at my major.[a]
	Based on my experiences in this class so far, I think I will perform at a high level.[a]
Intrinsic value	Doing the coursework and the assignments for this class is something I enjoy.[a]
	Doing the coursework and the assignments for this class is interesting.[a]
Utility value	Doing the coursework and the assignments for this class is useful for my future.[a]
	Doing the coursework and the assignments for this class is important because one just needs the content.[a]
Psychological cost	Doing the coursework and the assignments for this class is stressful for me.[a]
	Doing the coursework and the assignments for this class makes me really nervous.[a]
Effort cost	Doing the coursework and the assignments for this class is exhausting for me.[a]
	Doing the coursework and the assignments for this class drains a lot of my energy.[a]
Week-specific (situated) expectancy-value beliefs (Weeks 3–5)	
	Think about the current worksheet you turned in this week:
Expectancy	If the content of the current worksheet comes up on the exam: How well do you think will you perform on the exam?[b]
Intrinsic value	Doing this week's assignments is something I enjoyed.[a]
Utility value	Doing this week's assignments was generally useful.[a]
Psychological cost	Doing this week's assignments was stressful for me.[a]
Effort cost	Doing this week's assignments drained a lot of my energy.[a]

Note. [a] 6-point scale ranging from 1 = *completely disagree* to 6 = *completely agree*. [b] 6-point scale ranging from 1 = *very poorly* to 6 = *very well*.

Supplement S2. Tests of Measurement Invariance Across Study Programs and Time

In the following tables, tests of measurement invariance across students' study programs and time are reported for students' course-specific expectancy-value beliefs (T1c–T3c). In the configural model, the factor structure was constrained to be equal across groups or time. The model testing weak invariance was specified by additionally constraining the factor loadings to be equal across groups or time. Finally, in the model testing strong measurement invariance, item intercepts were additionally constrained to be the same across groups or time.

Table S2.1

Multigroup Analyses by Study Program

Models and Time Points	χ^2	*df*	CFI	TLI	RMSEA	SRMR	ΔCFI	ΔRMSEA
T1c								
Configural	177.40	102	.977	.963	.055	.042	—	—
Weak	184.87	114	.978	.969	.051	.052	−.001	.004
Strong partial[a]	218.21	124	.971	.962	.056	.058	.007	−.005
T2c								
Configural	147.77	102	.987	.978	.043	.036	—	—
Weak	163.73	114	.985	.979	.042	.048	.002	.001
Strong	211.70	126	.975	.967	.053	.057	.010	−.009
T3c								
Configural	139.68	102	.984	.974	.039	.040	—	—
Weak	159.14	114	.981	.972	.040	.062	.003	−.001
Strong partial[b]	190.38	125	.972	.963	.046	.069	.009	−.006

Note. In all models, one factor loading per construct was fixed at 1.0 for model identification purposes. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual. T1c = beginning of the semester (Week 2), T2c = midpoint of the semester (Week 8), T3c = end of the semester (Week 15).

[a] The intercept of one item assessing psychological cost was freely estimated across groups.

[b] The intercept of one item assessing expectancy was freely estimated in the math teacher education group.

Table S2.2

Tests of Measurement Invariance Across Time

Models	χ^2	*df*	CFI	TLI	RMSEA	SRMR	ΔCFI	ΔRMSEA
Freely estimated parameters (configural)[a]	512.58	359	.986	.980	.024	.035	—	—
Fixed factor loadings (weak)[a]	526.33	371	.986	.980	.024	.035	.000	.000
Fixed factor loadings and item intercepts (strong)[a]	554.66	383	.985	.979	.025	.036	.001	−.001

Note. In all models, one factor loading per construct was fixed at 1.0 for model identification purposes. CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

[a] The residual variances for one item assessing utility value and one item assessing psychological cost at time points T2c and T3c were estimated to be very close to zero and nonsignificant. Therefore, we removed the correlated residual for these items between time points T2c and T3c from the model.

Supplement S3. Model Fit of Final Random Intercept Cross-Lagged Panel Models

Table S3

Model Fit for Random Intercept Cross-Lagged Panel Models Including Students' Course-Specific or Week-Specific Expectancy and Different Task Value Facets

	χ^2 (*df*)	RMSEA	CFI	TLI	SRMR	AIC	BIC	ΔRMSEA	ΔCFI	$\Delta\chi^2$ (*df*)	*p*
Models Including Course-Specific Assessments											
Expectancy and intrinsic value											
M1a: RI-CLPM	207.700 (100)	.037	.981	.971	.030	21836.080	22649.879	—	—	—	—
M1b: RI-CLPM – only RI for expectancy	208.852 (102)	.037	.981	.972	.030	21832.478	22636.976	.000	.000	.476 (2)	.788
M1c: M1b with constrained AR & CL paths	**217.231 (106)**	**.037**	**.981**	**.972**	**.033**	**21833.225**	**22630.422**	**.000**	**.000**	**8.374 (4)**	**.079**
Expectancy and utility value											
M2a: RI-CLPM	186.069 (100)	.033	.983	.974	.035	23651.888	24465.686	—	—	—	—
M2b: RI-CLPM – only RI for expectancy	186.972 (102)	.033	.983	.974	.035	23649.062	24453.561	.000	.000	1.05 (2)	.591
M2c: M2b with constrained AR & CL paths	**192.404 (106)**	**.032**	**.983**	**.975**	**.040**	**23647.958**	**24433.855**	**.001**	**.000**	**5.659 (4)**	**.226**
Expectancy and psychological cost											
M3a: RI-CLPM	**210.987 (100)**	**.038**	**.980**	**.970**	**.034**	**23954.569**	**24768.368**	—	—	—	—
M3b: M3a with constrained AR & CL paths	230.073 (104)	.040	.978	.967	.042	23960.417	24755.615	−.002	.002	40.699 (4)	< .001
Expectancy and effort cost											
M4a: RI-CLPM	**155.535 (100)**	**.027**	**.991**	**.986**	**.028**	**22275.105**	**23088.904**	—	—	—	—
M4b: M4a with constrained AR & CL paths	172.567 (104)	.029	.989	.984	.039	22283.282	23078.480	−.002	.002	18.860 (4)	< .001
Models Including Week-Specific Assessments											
Expectancy and intrinsic value											
M1a: RI-CLPM	1.872 (1)	.034	.999	.979	.007	15153.107	15632.086	—	—	—	—
M1b: M1a with constrained AR & CL paths	**4.015 (5)**	**.000**	**1.000**	**1.000**	**.012**	**15147.693**	**15608.071**	**.034**	**−.001**	**2.375 (4)**	**.667**
Expectancy and utility value											
M2a: RI-CLPM	2.464 (1)	.044	.999	.955	.008	15082.701	15561.679	—	—	—	—
M2c: M2a with constrained AR & CL paths	**8.731 (5)**	**.031**	**.997**	**.977**	**.018**	**15081.656**	**15542.033**	**.013**	**.002**	**6.367 (4)**	**.173**
Expectancy and psychological cost											
M3a: RI-CLPM	0.049 (1)	.000	1.000	1.000	.001	15768.280	16247.259	—	—	—	—
M3b: M3a with constrained AR & CL paths	**6.854 (5)**	**.022**	**.999**	**.990**	**.020**	**15767.941**	**16228.319**	**−.022**	**.001**	**6.655 (4)**	**.155**
Expectancy and effort cost											
M4a: RI-CLPM	0.045 (1)	.000	1.000	1.000	.001	15592.659	16071.638	—	—	—	—
M4b: M4a with constrained AR & CL paths	**3.709 (5)**	**.000**	**1.000**	**1.000**	**.019**	**15588.712**	**16049.090**	**.000**	**.000**	**3.598 (4)**	**.463**

Note. AR = autoregressive, CL = cross-lagged, χ^2 = Satorra-Bentler χ^2; RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; AIC = Akaike information criterion; BIC = Bayesian information criterion. The final model is shown in bold.

Supplement S4. Model Fit of Correlational Models with Constrained or Freely Estimated Covariances

Table S4.1

Model Fit for Random Intercept Cross-Lagged Panel Models Including Students' Course-Specific Expectancy and Different Task Value Facets

Models Including Course-Specific Assessments	χ^2 (*df*)	RMSEA	CFI	TLI	SRMR	AIC	BIC	ΔRMSEA	ΔCFI	$\Delta\chi^2$ (*df*)	*p*
Expectancy and intrinsic value											
M1a: Correlational model	208.048 (100)	.037	.981	.971	.030	21836.078	22649.876	—	—	—	—
M1b: M1a with correlations at T1c and T2c equal	238.868 (101)	.042	.976	.964	.071	21866.482	22675.631	−.005	.005	26.177 (1)	< .001
M1c: M1a with correlations at T2c and T3c equal	209.066 (101)	.037	.981	.972	.032	21835.386	22644.535	.000	−.001	1.128 (1)	.288
M1d: M1a with all correlations equal (T1c–T3c)	248.168 (102)	.043	.975	.962	.091	21874.494	22678.992	−.006	.006	34.939 (2)	< .001
Expectancy and utility value											
M2a: Correlational model	186.269 (100)	.033	.983	.973	.034	23651.808	24465.607	—	—	—	—
M2b: M2a with correlations at T1c and T2c equal	196.617 (101)	.035	.981	.971	.043	23660.748	24469.897	−.002	.002	10.511 (1)	.001
M2c: M2a with correlations at T2c and T3c equal	186.006 (101)	.033	.983	.974	.034	23649.869	24459.018	.000	.000	0.059 (1)	.808
M2d: M2a with all correlations equal (T1c–T3c)	198.941 (102)	.035	.981	.971	.047	23661.545	24466.043	−.002	.002	12.082 (2)	.002
Expectancy and psychological cost											
M3a: Correlational model	211.548 (100)	.038	.980	.970	.035	23955.599	24769.398	—	—	—	—
M3b: M3a with correlations at T1c and T2c equal	214.975 (101)	.038	.980	.970	.040	23957.188	24766.337	.000	.000	3.452 (1)	.063
M3c: M3a with correlations at T2c and T3c equal	211.880 (101)	.038	.981	.970	.036	23953.978	24763.127	.000	.000	0.347 (1)	.555
M3d: M3a with all correlations equal (T1c–T3c)	216.740 (102)	.038	.980	.970	.045	23957.083	24761.581	.000	.000	5.197 (2)	.074
Expectancy and effort cost											
M4a: Correlational model	157.062 (100)	.027	.991	.986	.030	22276.840	23090.639	—	—	—	—
M4b: M4a with correlations at T1c and T2c equal	158.868 (101)	.027	.991	.986	.032	22276.804	23085.952	.000	.000	1.875 (1)	.171
M4c: M4a with correlations at T2c and T3c equal	156.808 (101)	.027	.991	.986	.030	22274.857	23084.005	.000	.000	[a]	
M4d: M4a with all correlations equal (T1c–T3c)	158.979 (102)	.027	.991	.986	.033	22275.268	23079.767	.000	.000	2.079 (2)	.354

Note. T1c–T3c = course-specific summative evaluation of experiences thus far (beginning, midpoint, and end-of-term assessments). χ^2 = Satorra-Bentler χ^2; RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; AIC = Akaike information criterion; BIC = Bayesian information criterion.

[a] The chi-square difference had a negative value due to a negative difference in the scaling factors (see Asparouhov & Muthen, 2013). We did not compute a strictly positive chi-square difference because model indices suggest that the constrained model does not fit significantly worse than the unconstrained model.

Table S4.2

Model Fit for Random Intercept Cross-Lagged Panel Models Including Students' Week-Specific Expectancy and Different Task Value Facets

Models Including Week-Specific Assessments	χ^2 (*df*)	RMSEA	CFI	TLI	SRMR	AIC	BIC	ΔRMSEA	ΔCFI	$\Delta\chi^2$ (*df*)	*p*
Expectancy and intrinsic value											
M1a: Correlational model	1.937 (1)	.035	.999	.977	.007	15153.255	15632.234	—	—	—	—
M1b: M1a with correlations at T1w and T2w equal	3.696 (2)	.033	.999	.980	.017	15152.995	15627.322	.002	.000	1.767 (1)	.184
M1c: M1a with correlations at T2w and T3w equal	1.862 (2)	.000	1.000	1.000	.008	15151.343	15625.671	.035	−.001	0.082 (1)	.774
M1d: M1a with all correlations equal (T1w–T3w)	4.757 (3)	.028	.999	.986	.021	15152.182	15621.860	.007	.000	2.862 (2)	.239
Expectancy and utility value											
M2a: Correlational model	3.095 (1)	.052	.998	.936	.010	15083.490	15562.469	—	—	—	—
M2b: M2a with correlations at T1w and T2w equal	2.852 (2)	.023	.999	.987	.011	15081.518	15555.846	.029	−.001	0.023 (1)	.878
M2c: M2a with correlations at T2w and T3w equal	3.014 (2)	.026	.999	.984	.012	15081.856	15556.184	.026	−.001	0.281 (1)	.560
M2d: M2a with all correlations equal (T1w–T3w)	3.357 (3)	.012	1.000	.996	.014	15080.156	15549.834	.040	−.002	0.563 (2)	.755
Expectancy and psychological cost											
M3a: Correlational model	0.003 (1)	.000	1.000	1.000	.000	15768.233	16247.212	—	—	—	—
M3b: M3a with correlations at T1w and T2w equal	10.730 (2)	.075	.993	.880	.031	15775.860	16250.189	−.075	.007	12.437 (1)	< .001
M3c: M3a with correlations at T2w and T3w equal	10.342 (2)	.073	.994	.885	.034	15775.415	16249.743	−.073	.006	12.155 (1)	< .001
M3d: M3a with all correlations equal (T1w–T3w)	14.251 (3)	.070	.991	.897	.036	15776.861	16246.539	−.070	.009	15.417 (2)	< .001
Expectancy and effort cost											
M4a: Correlational model	0.076 (1)	.000	1.000	1.000	.002	15592.688	16071.667	—	—	—	—
M4b: M4a with correlations at T1w and T2w equal	5.056 (2)	.044	.997	.953	.021	15595.635	16069.963	−.044	.003	4.910 (1)	.027
M4c: M4a with correlations at T2w and T3w equal	5.127 (2)	.045	.997	.952	.024	15595.616	16069.945	−.045	.003	5.066 (1)	.024
M4d: M4a with all correlations equal (T1w–T3w)	6.595 (3)	.039	.997	.963	.025	15595.274	16064.952	−.039	.003	6.422 (2)	.040

Note. χ^2 = Satorra-Bentler χ^2; RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; AIC = Akaike information criterion; BIC = Bayesian information criterion.

Supplement S5. Unstandardized Parameter Estimates for the Analyses Reported in the Manuscript

Table S5.1

Autoregressive and Cross-Lagged Parameters for Students' Expectancy-Value Beliefs Over Time

	Intrinsic value model		Utility value model		Psychological cost model		Effort cost model	
	b (SE)	β [95% CI]	b (SE)	β [95% CI]	b (SE)	β [95% CI]	b (SE)	β [95% CI]
Course-specific assessments								
Autoregressive effects								
Expectancy T1c → T2c	.73*** (.12)^{a}	.56 [.38; .75]	.82*** (.08)^{a}	.63 [.46; .80]	.39 (.80)	.25 [−.93; 1.43]	.38 (.73)	.25 [−.81; 1.31]
Expectancy T2c → T3c	.73*** (.12)^{a}	.77 [.48; .91]	.82*** (.08)^{a}	.77 [.65; .92]	.90*** (.12)	.77 [.47; 1.06]	.85*** (.10)	.73 [.48; .99]
Task value T1c → T2c	.58*** (.09)^{b}	.47 [.33; .61]	.67*** (.07)^{b}	.57 [.44; .70]	−.20 (.37)	−.18 [−.86; .49]	.13 (.22)	.13 [−.27; .53]
Task value T2c → T3c	.58*** (.09)^{b}	.56 [.39; .73]	.67*** (.07)^{b}	.72 [.58; .85]	.32 (.17)	.27 [−.03; .56]	.43** (.13)	.46 [.17; .75]
Cross-lagged effects								
Expectancy T1c → Task value T2c	.34** (.12)^{c}	.24 [.10; .39]	.23* (.09)^{c}	.15 [.05; .25]	.09 (.77)	.07 [−1.03; 1.16]	.19 (.58)	.12 [−.50; .73]
Expectancy T2c → Task value T3c	.34** (.12)^{c}	.30 [.12; .48]	.23* (.09)^{c}	.21 [.06; .36]	−.24 (.09)	−.23 [−.54; .07]	−.12 (.11)	−.13 [−.35; .10]
Task value T1c → Expectancy T2c	.14 (.09)^{d}	.12 [−.04; .28]	.01 (.05)^{d}	.01 [−.09; .10]	−.06 (.23)	−.05 [−.41; .31]	−.12 (.14)	−.11 [−.39; .17]
Task value T2c → Expectancy T3c	.14 (.09)^{d}	.14 [−.05; .33]	.01 (.05)^{d}	.02 [−.10; .11]	.18 (.13)	.13 [−.04; .30]	.13 (.10)	.12 [−.03; .27]
Week-specific assessments								
Autoregressive effects								
Expectancy T1w → T2w	.15 (.08)^{a}	.14 [−.01; .28]	.12 (.08)^{a}	.11 [−.04; .25]	.12 (.08)^{a}	.11 [−.04; .25]	.10 (.08)^{a}	.09 [−.05; .24]
Expectancy T2w → T3w	.15 (.08)^{a}	.17 [−.01; .31]	.12 (.08)^{a}	.12 [−.05; .30]	.12 (.08)^{a}	.13 [−.05; .30]	.10 (.08)^{a}	.10 [−.07; .28]
Task value T1w → T2w	−.14* (.06)^{b}	−.16 [−.30; −.02]	−.06 (.08)^{b}	−.06 [−.24; .11]	.01 (.07)^{b}	.01 [−.12; .14]	.10 (.08)^{b}	.10 [−.04; .13]
Task value T2w → T3w	−.14* (.06)^{b}	−.13 [−.23; −.02]	−.06 (.08)^{b}	−.06 [−.21; .10]	.01 (.07)^{b}	.01 [−.14; .17]	.10 (.08)^{b}	.11 [−.05; .15]
Cross-lagged effects								
Expectancy T1w → Task value T2w	.07 (.07)^{c}	.07 [−.07; .21]	.07 (.07)^{c}	.07 [−.07; .21]	−.05 (.09)^{c}	−.04 [−.16; .09]	.02 (.09)^{c}	.01 [−.11; .13]
Expectancy T2w → Task value T3w	.07 (.07)^{c}	.07 [−.07; .20]	.07 (.07)^{c}	.08 [−.08; .22]	−.05 (.09)^{c}	−.05 [−.19; .10]	.02 (.09)^{c}	.01 [−.13; .15]
Task value T1w → Expectancy T2w	−.06 (.06)^{d}	−.07 [−.18; .05]	−.04 (.06)^{d}	−.04 [−.16; .08]	−.01 (.04)^{d}	−.01 [−.11; .09]	.00 (.05)^{d}	.00 [−.10; .10]
Task value T2w → Expectancy T3w	−.06 (.06)^{d}	−.06 [−.17; .05]	−.04 (.06)^{d}	−.04 [−.15; .08]	−.01 (.04)^{d}	−.02 [−.13; .10]	.00 (.05)^{d}	.00 [−.12; .12]

Note. T1c–T3c = course-specific summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet. Equal superscripts indicate that unstandardized coefficients were fixed to be the same.

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table S5.2

Unstandardized Path Coefficients for Predictors of Students' Expectancy-Value Beliefs

Predictors	Intrinsic value model		Utility value model		Psychological cost model		Effort cost model	
	Expectancy	Intrinsic value	Expectancy	Utility value	Expectancy	Psych. cost	Expectancy	Effort cost
Course-specific assessments								
Female → T1c	−.37$^{***\,a}$	−.04^{b}	−.34$^{***\,a}$	−.12^{b}	−.34$^{***\,a}$	.35$^{***\,b}$	−.37$^{***\,a}$	.10^{b}
Female → T2c	−.37$^{***\,a}$	−.04^{b}	−.45***	−.30**	−.47***	.35$^{***\,b}$	−.37$^{***\,a}$	.10^{b}
Female → T3c	−.37$^{***\,a}$	−.04^{b}	−.34$^{***\,a}$	−.12^{b}	−.34$^{***\,a}$	.16	−.37$^{***\,a}$	.10^{b}
SES → T1c	−.01^{c}	.01^{d}	−.02^{c}	.07^{d}	−.02^{c}	−.12^{d}	−.01^{c}	.00^{d}
SES → T2c	−.01^{c}	.01^{d}	−.02^{c}	.07^{d}	−.02^{c}	−.12^{d}	−.01^{c}	.00^{d}
SES → T3c	−.01^{c}	.01^{d}	−.02^{c}	.07^{d}	−.02^{c}	−.12^{d}	−.01^{c}	.00^{d}
GPA → T1c	.29***	.23***	.29***	.20$^{***\,f}$	.29***	−.18$^{**\,f}$	.30***	−.18$^{**\,f}$
GPA → T2c	.53$^{***\,e}$	.40$^{***\,f}$	.52$^{***\,e}$	.20$^{***\,f}$	.53$^{***\,e}$	−.33***	.52$^{***\,e}$	−.18$^{**\,f}$
GPA → T3c	.53$^{***\,e}$	.40$^{***\,f}$	.52$^{***\,e}$	.20$^{***\,f}$	.53$^{***\,e}$	−.18$^{**\,f}$	.52$^{***\,e}$	−.18$^{**\,f}$
Prep. course → T1c	−.06^{g}	.07^{h}	−.07^{g}	.08^{h}	−.08^{g}	−.06^{h}	−.08^{g}	.05^{h}
Prep. course → T2c	−.06^{g}	.07^{h}	−.07^{g}	.08^{h}	−.08^{g}	−.06^{h}	−.08^{g}	.05^{h}
Prep. course → T3c	−.06^{g}	.07^{h}	−.07^{g}	.08^{h}	−.08^{g}	−.06^{h}	−.08^{g}	.05^{h}
Teacher1 → T1c	−.18*	−.42***	−.19*	−.68***	−.19*	.54***	−.18*	.31**
Teacher1 → T2c	.14	.00	.15	−.54***	.16	−.09	.15	−.35*
Teacher1 → T3c	.10	.12	.10	−.58**	.08	−.07	.11	−.45**
Teacher2 → T1c	−.11	−.27*	−.12	−1.06***	−.12	.48***	−.11	.43**
Teacher2 → T2c	.34**	.37**	.36**	−.11	.36**	−.23	.34**	−.43**
Teacher2 → T3c	.10	.09	.10	−.80***	.05	−.06	.10	−.39**
Math → T1c	−.26**	−.28***	−.26**	−.84***	−.26**	.65***	−.27**	.60***
Math → T2c	−.30**	−.14	−.30**	−.65***	−.31**	.20	−.28**	−.07
Math → T3c	−.47***	−.38**	−.46***	−.85***	−.47***	.14	−.46***	−.11
Week-specific assessments								
Female → T1w	−.35$^{***\,a}$	−.24$^{**\,b}$	−.35$^{***\,a}$	−.18$^{*\,b}$	−.34$^{***\,a}$	.18$^{*\,b}$	−.35$^{***\,a}$	.08^{b}
Female → T2w	−.35$^{***\,a}$	−.24$^{**\,b}$	−.35$^{***\,a}$	−.18$^{*\,b}$	−.34$^{***\,a}$	.18$^{*\,b}$	−.35$^{***\,a}$	.08^{b}
Female → T3w	−.35$^{***\,a}$	−.24$^{**\,b}$	−.35$^{***\,a}$	−.18$^{*\,b}$	−.34$^{***\,a}$	.18$^{*\,b}$	−.35$^{***\,a}$	.08^{b}
SES → T1w	.03^{c}	.03^{d}	.01^{c}	.18$^{*\,d}$	.00^{c}	.00^{d}	.01^{c}	.03^{d}
SES → T2w	.03^{c}	.03^{d}	.01^{c}	.18$^{*\,d}$	.00^{c}	.00^{d}	.01^{c}	.03^{d}
SES → T3w	.03^{c}	.03^{d}	.01^{c}	.18$^{*\,d}$	.00^{c}	.00^{d}	.01^{c}	.03^{d}
GPA → T1w	.41$^{***\,e}$	.37$^{***\,f}$	.41$^{***\,e}$	.24$^{***\,f}$	.43$^{***\,e}$	.00	.42$^{***\,e}$	−.03^{f}
GPA → T2w	.41$^{***\,e}$	.37$^{***\,f}$	.41$^{***\,e}$	.24$^{***\,f}$	.43$^{***\,e}$	−.18$^{*\,f}$	.42$^{***\,e}$	−.03^{f}
GPA → T3w	.41$^{***\,e}$	.37$^{***\,f}$	.41$^{***\,e}$	.24$^{***\,f}$	.43$^{***\,e}$	−.18$^{*\,f}$	.42$^{***\,e}$	−.03^{f}
Prep. course → T1w	−.02^{g}	.10^{h}	−.02^{g}	.09^{h}	−.04^{g}	.02^{h}	−.03^{g}	.08^{h}
Prep. course → T2w	−.02^{g}	.10^{h}	−.02^{g}	.09^{h}	−.04^{g}	.02^{h}	−.03^{g}	.08^{h}
Prep. course → T3w	−.02^{g}	.10^{h}	−.02^{g}	.09^{h}	−.04^{g}	.02^{h}	−.03^{g}	.08^{h}
Teacher1 → T1w	.30*	.51***	.30*	.09	.29*	−.22	.29*	−.37*
Teacher1 → T2w	.06	−.10	.05	−.21	.05	−.04	.05	−.14
Teacher1 → T3w	.12	.06	.12	−.13	.11	−.13	.10	−.12
Teacher2 → T1w	.74***	.74***	.73***	.23	.71***	−.74***	.72***	−1.00***
Teacher2 → T2w	−.43*	−.61***	−.43*	−.58***	−.43*	.67***	−.44*	.40*
Teacher2 → T3w	−.07	.07	−.09	−.26	−.09	−.10	−.09	−.17
Math → T1w	.32**	.57***	.32**	.07	.31**	−.60***	.31**	−.82***
Math → T2w	−.29**	−.19	−.29**	−.46***	−.30**	.29*	−.30**	.07
Math → T3w	−.29**	−.09	−.30**	−.46***	−.30**	.20	−.30**	.05

Note. T1c–T3c = course-specific summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet. SES = socioeconomic status; GPA = high school grade point average; Prep. course = participation in math preparatory courses; Teacher1, Teacher2, Math = dummy variables for the math courses. Equal superscripts indicate that unstandardized coefficients were fixed to be the same. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Supplement S6. RI-CLPMs Including Students' Personal Characteristics

Table S6.1

Model Comparisons for Random Intercept Cross-Lagged Panel Models Including Students' Personal Characteristics as Predictors of Their Course-Specific Expectancy-Value Beliefs

Models Including Course-Specific Assessments	χ^2 (*df*)	RMSEA	CFI	TLI	SRMR	AIC	BIC	ΔRMSEA	ΔCFI	$\Delta\chi^2$ (*df*)	*p*
Expectancy and intrinsic value											
M0: RI-CLPM including all covariates	255.654 (138)	.033	.979	.968	.026	21806.574	22443.662	—	—	—	—
M1a: M0 with time-invariant effects for gender	263.138 (142)	.033	.978	.968	.028	21806.119	22424.606	.000	.001	7.485 (4)	.112
M1b: M0 with time-invariant effects for SES	260.759 (142)	.033	.979	.968	.027	21803.762	22422.249	.000	.000	5.089 (4)	.278
M1c: M0 with time-invariant effects for GPA	277.237 (142)	.035	.976	.964	.036	21820.237	22443.662	−.002	.002	21.583 (4)	< .001
M1d: M0 with time-invariant effects for prep. course	260.411 (142)	.033	.979	.969	.027	21803.405	22421.892	.000	−.001	4.739 (4)	.315
M2: All covariates time-invariant except for GPA on EXP T1c and INT T1c	272.755 (152)	.032	.978	.970	.029	21795.737	22367.721	.001	.001	16.980 (14)	.257
Expectancy and utility value											
M0: RI-CLPM including all covariates	247.625 (138)	.032	.978	.966	.030	23636.121	24273.209	—	—	—	—
M1a: M0 with time-invariant effects for gender	260.027 (142)	.033	.976	.965	.032	23640.762	24259.249	−.001	.002	12.600 (4)	.013
M1b: M0 with time-invariant effects for SES	251.488 (142)	.032	.978	.967	.031	23631.895	24250.382	.000	.000	3.749 (4)	.441
M1c: M0 with time-invariant effects for GPA	265.686 (142)	.034	.975	.963	.037	23646.400	24264.887	−.002	.003	18.834 (4)	< .001
M1d: M0 with time-invariant effects for prep. course	253.370 (142)	.032	.977	.967	.030	23633.512	24251.999	.000	−.001	5.627 (4)	.229
M2: All covariates time-invariant except for gender on EXP T2c, UTL T2c and GPA on EXP T1c	263.059 (151)	.031	.977	.968	.032	23624.899	24201.534	.001	.001	15.017 (13)	.306
Expectancy and psychological cost											
M0: RI-CLPM including all covariates	263.360 (136)	.035	.977	.965	.029	23933.721	24580.110	—	—	—	—
M1a: M0 with time-invariant effects for gender	277.577 (140)	.036	.975	.963	.031	23939.907	24567.694	−.001	.002	14.719 (4)	.005
M1b: M0 with time-invariant effects for SES	266.041 (140)	.034	.978	.966	.029	23928.109	24555.897	.001	−.001	2.420 (4)	.659
M1c: M0 with time-invariant effects for GPA	283.773 (140)	.036	.974	.962	.036	23946.307	24574.095	−.001	.003	21.493 (4)	< .001
M1d: M0 with time-invariant effects for prep. course	264.925 (140)	.034	.978	.967	.034	23927.435	24555.223	.001	−.001	1.625 (4)	.804
M2: All covariates time-invariant except for gender on EX T2c, CSTR T3c and GPA on EXP T1c, CSTR T2c	270.081 (148)	.033	.978	.969	.030	23916.280	24506.865	.002	−.001	6.428 (12)	.893
Expectancy and effort cost											
M0: RI-CLPM including all covariates	207.952 (136)	.026	.988	.981	.024	22256.294	22902.682	—	—	—	—
M1a: M0 with time-invariant effects for gender	216.648 (140)	.027	.987	.981	.026	22256.756	22884.544	−.001	.001	8.824 (4)	.066
M1b: M0 with time-invariant effects for SES	209.794 (140)	.025	.988	.982	.024	22249.954	22877.742	.001	.000	1.708 (4)	.789
M1c: M0 with time-invariant effects for GPA	226.491 (140)	.028	.986	.978	.031	22266.845	22894.632	−.002	.002	18.839 (4)	< .001
M1d: M0 with time-invariant effects for prep. course	211.605 (140)	.026	.988	.982	.024	22252.082	22879.869	.000	.000	3.694 (4)	.449
M2: All covariates time-invariant except for GPA on EXP T1c	222.654 (151)	.025	.988	.983	.026	22240.974	22817.608	.001	.000	14.650 (15)	.477

Note. χ^2 = Satorra-Bentler χ^2; RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; AIC = Akaike information criterion; BIC = Bayesian information criterion. SES = socioeconomic status; GPA = high school grade point average; Prep. course = participation in math preparatory courses.

Table S6.2

Model Comparisons for Random Intercept Cross-Lagged Panel Models Including Students' Personal Characteristics as Predictors of Their Week-Specific Expectancy-Value Beliefs

Models Including Week-Specific Assessments	χ^2 (*df*)	RMSEA	CFI	TLI	SRMR	AIC	BIC	ΔRMSEA	ΔCFI	$\Delta\chi^2$ (*df*)	*p*
Expectancy and intrinsic value											
M0: RI-CLPM including all covariates	2.182 (1)	.039	.999	.950	.005	15153.363	15632.342	—	—	—	—
M1a: M0 with time-invariant effects for gender	2.836 (5)	.000	1.000	1.000	.006	15146.214	15606.591	.039	−.001	0.868 (4)	.929
M1b: M0 with time-invariant effects for SES	8.158 (5)	.029	.998	.973	.009	15151.465	15611.843	.010	.001	6.062 (4)	.195
M1c: M0 with time-invariant effects for GPA	7.196 (5)	.024	.998	.981	.009	15149.948	15610.326	.015	.001	5.061 (4)	.281
M1d: M0 with time-invariant effects for prep. course	2.841 (5)	.000	1.000	1.000	.006	15146.218	15606.595	.039	−.001	0.873 (4)	.928
M2: All covariates time-invariant	16.283 (17)	.000	1.000	1.000	.012	15135.273	15539.847	.039	−.001	14.260 (16)	.579
Expectancy and utility value											
M0: RI-CLPM including all covariates	2.815 (1)	.048	.998	.901	.006	15082.955	15561.934	—	—	—	—
M1a: M0 with time-invariant effects for gender	4.142 (5)	.000	1.000	1.000	.007	15076.395	15536.772	.048	−.002	1.466 (4)	.833
M1b: M0 with time-invariant effects for SES	2.952 (5)	.000	1.000	1.000	.006	15075.276	15535.654	.048	−.002	0.323 (4)	.988
M1c: M0 with time-invariant effects for GPA	7.516 (5)	.026	.998	.973	.010	15079.323	15539.700	.022	.000	4.719 (4)	.317
M1d: M0 with time-invariant effects for prep. course	3.155 (5)	.000	1.000	1.000	.007	15075.52	15535.898	.048	−.002	0.558 (4)	.968
M2: All covariates time-invariant	10.085 (17)	.000	1.000	1.000	.011	15058.258	15462.832	.048	−.002	7.428 (16)	.964
Expectancy and psychological cost											
M0: RI-CLPM including all covariates	0.168 (1)	.000	1.000	1.000	.002	15768.393	16247.371	—	—	—	—
M1a: M0 with time-invariant effects for gender	8.957 (5)	.032	.997	.962	.008	15769.147	16229.525	−.032	.003	8.723 (4)	.068
M1b: M0 with time-invariant effects for SES	2.766 (5)	.000	1.000	1.000	.005	15762.916	16223.294	.000	.000	2.596 (4)	.628
M1c: M0 with time-invariant effects for GPA	11.132 (5)	.040	.995	.941	.011	15770.949	16231.327	−.040	.005	10.973 (4)	.027
M1d: M0 with time-invariant effects for prep. course	7.825 (5)	.027	.998	.973	.010	15768.240	16228.618	−.027	.002	7.561 (4)	.109
M2: All covariates time-invariant except for GPA on CSTR T1w	23.220 (16)	.024	.994	.978	.015	15761.405	16170.630	−.024	.006	23.009 (15)	.084
Expectancy and effort cost											
M0: RI-CLPM including all covariates	0.279 (1)	.000	1.000	1.000	.002	15592.884	16071.863	—	—	—	—
M1a: M0 with time-invariant effects for gender	7.296 (5)	.024	.998	.976	.008	15592.005	16052.382	−.024	.002	6.956 (4)	.138
M1b: M0 with time-invariant effects for SES	2.106 (5)	.000	1.000	1.000	.004	15586.669	16047.046	.000	.000	1.826 (4)	.768
M1c: M0 with time-invariant effects for GPA	8.190 (5)	.029	.997	.967	.010	15592.692	16053.070	−.029	.003	7.884 (4)	.096
M1d: M0 with time-invariant effects for prep. course	7.496 (5)	.025	.998	.974	.009	15591.922	16052.300	−.025	.002	7.211 (4)	.125
M2: All covariates time-invariant	26.253 (17)	.027	.992	.972	.017	15586.771	15991.345	−.027	.008	25.940 (16)	.055

Note. χ^2 = Satorra-Bentler χ^2; RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; AIC = Akaike information criterion; BIC = Bayesian information criterion. SES = socioeconomic status; GPA = high school grade point average; Prep. course = participation in math preparatory courses.

Model comparisons in Table S6.2 show that in the models including students' expectancy and psychological as well as effort cost, constraining the predictive effects of some of the covariates (gender, high school GPA, participation in math preparatory courses) to be time-invariant, led to increases in RMSEA that was larger than .015 even though the chi-square difference tests were not significant (BIC values favored the constrained models and AIC values were similar for the constrained and unconstrained models). We therefore report these predictive effects of students' covariates on their expectancy and perceived costs both for the constrained model as well as for an unconstrained model in Table S6.3. In the constrained models, the predictive effects are constrained to be time-invariant, whereas these predictive effects were estimated freely in the unconstrained models. Table S6.3 shows that the standardized parameter estimates were mostly similar in the unconstrained and constrained models. One small difference occurred for the predictive effect of students' gender on their perceived psychological and effort cost, which was estimated to be significant at T2w in the unconstrained model, but nonsignificant at the other two time points. However, in terms of the effect size, these differences were comparatively small.

Table S6.3

Parameter Estimates for Within-Person Correlations of Students' Expectancy and Task Values in the Multigroup Correlational Models for Constrained and Unconstrained Models

	Psychological cost model			
	Unconstrained Model		Constrained Model	
	Expectancy	Psych. cost	Expectancy	Psych. cost
	β	β	β	β
Week-specific assessments				
Female → T1w	−.18***	.02	−.15*** a	.06* b
Female → T2w	−.15***	.13**	−.15*** a	.06* b
Female → T3w	−.15***	.06	−.16*** a	.07* b
Prep. course → T1w	−.01	−.02	−.02 g	.01 h
Prep. course → T2w	.01	−.05	−.02 g	.01 h
Prep. course → T3w	−.02	.08	−.02 g	.01 h
	Effort cost model			
	Unconstrained Model		Constrained Model	
	Expectancy	Effort cost	Expectancy	Effort cost
	β	β	β	β
Week-specific assessments				
Female → T1w	−.18***	.02	−.15*** a	.03 b
Female → T2w	−.14***	.10*	−.15*** a	.03 b
Female → T3w	−.15***	.00	−.16*** a	.03 b
GPA → T1w	.21***	.04	.25*** e	−.01 f
GPA → T2w	.28***	−.07	.25*** e	−.01 f
GPA → T3w	.28***	−.03	.26*** e	−.02 f
Prep. course → T1w	−.01	.04	−.01 g	.03 h
Prep. course → T2w	.01	−.05	−.01 g	.03 h
Prep. course → T3w	−.02	.08	−.01 g	.03 h

Note. Psych. cost = psychological cost. T1w–T3w = week-specific experiences on a given math worksheet. GPA = high school grade point average; Prep. course = participation in math preparatory courses. Equal superscripts indicate that unstandardized coefficients were fixed to be the same.

*$p < .05$, **$p < .01$, ***$p < .001$.

Supplement S7. Multigroup Correlational Models with Constrained or Freely Estimated Covariances

Table S7.1

Model Fit for Random Intercept Cross-Lagged Panel Models Including Students' Course-Specific Expectancy and Different Task Value Facets

Models Including Course-Specific Assessments	χ^2 (*df*)	RMSEA	CFI	TLI	SRMR	AIC	BIC	ΔRMSEA	ΔCFI	$\Delta\chi^2$ (*df*)	*p*
Expectancy and intrinsic value											
M1a: Multigroup correlational model for gender	542.482 (216)	.065	.942	.918	.077	20581.583	21898.401	—	—	—	—
M1b: M1a with constrained covariances across groups	544.217 (219)	.064	.942	.919	.083	20579.224	21882.324	.001	.000	2.862 (3)	.413
M1c: Multigroup correlational model for SES	472.670 (216)	.062	.950	.929	.071	18352.784	19629.471	—	—	—	—
M1d: M1c with constrained covariances across groups	476.042 (219)	.061	.950	.930	.077	18351.268	19614.655	.001	.000	3.822 (3)	.281
M1e: Multigroup correlational model for GPA	501.198 (216)	.062	.946	.924	.083	19622.535	20928.266	—	—	—	—
M1f: M1e with constrained covariances across groups	509.178 (219)	.062	.945	.923	.085	19626.321	20918.451	.000	.001	7.787 (3)	.051
M1g: Multigroup correlational model for prep. course	512.234 (216)	.066	.946	.923	.074	18919.029	20199.396	—	—	—	—
M1h: M1g with constrained covariances across groups	512.527 (219)	.065	.946	.925	.076	18914.235	20181.265	.001	.000	1.066 (3)	.785
Expectancy and utility value											
M2a: Multigroup correlational model for gender	500.495 (216)	.061	.943	.919	.077	22295.056	23611.873	—	—	—	—
M2b: M2a with constrained covariances across groups	504.446 (219)	.060	.943	.920	.078	22293733	23596.834	.001	.000	4.202 (3)	.241
M2c: Multigroup correlational model for SES	406.627 (216)	.053	.958	.941	.072	19773.330	21050.016	—	—	—	—
M2d: M2c with constrained covariances across groups	413.224 (219)	.053	.958	.941	.071	19774.674	21038.063	.000	.000	6.494 (3)	.090
M2e: Multigroup correlational model for GPA	424.319 (216)	.053	.955	.937	.081	21297.733	22603.464	—	—	—	—
M2f: M2e with constrained covariances across groups	441.751 (219)	.054	.952	.933	.079	21310.482	22602.612	−.001	.003	16.346 (3)	< .001
M2g: Multigroup correlational model for prep. course	472.998 (216)	.061	.947	.925	.068	20527.011	21807.378	—	—	—	—
M2h: M2g with constrained covariances across groups	476.992 (219)	.061	.947	.925	.073	20525.985	21793.015	.000	.000	4.282 (3)	.233
Expectancy and psychological cost											
M3a: Multigroup correlational model for gender	532.221 (216)	.064	.943	.920	.087	22638.374	23955.192	—	—	—	—
M3b: M3a with constrained covariances across groups	535.238 (219)	.064	.943	.921	.087	22635.979	23939.079	.000	.000	3.275 (3)	.351
M3c: Multigroup correlational model for SES	439.076 (216)	.058	.956	.938	.081	20171.542	21448.228	—	—	—	—
M3d: M3c with constrained covariances across groups	440.048 (219)	.057	.957	.939	.080	20166.359	21429.747	.001	−.001	0.786 (3)	.853
M3e: Multigroup correlational model for GPA	486.584 (216)	.060	.949	.928	.091	21674.781	22980.513	—	—	—	—
M3f: M3e with constrained covariances across groups	488.919 (219)	.060	.949	.929	.089	21671.447	22963.577	.000	.000	2.484 (3)	.478
M3g: Multigroup correlational model for prep. course	513.215 (216)	.066	.945	.922	.079	20891.244	22171.611	—	—	—	—
M3h: M3g with constrained covariances across groups	515.698 (219)	.066	.945	.923	.083	20888.432	22155.462	.000	.000	2.839 (3)	.417
Expectancy and effort cost											
M4a: Multigroup correlational model for gender	508.329 (216)	.062	.952	.933	.082	21000.373	22317.190	—	—	—	—
M4b: M4a with constrained covariances across groups	509.711 (219)	.061	.953	.934	.081	20995.891	22298.992	.001	−.001	1.504 (3)	.681
M4c: Multigroup correlational model for SES	421.185 (216)	.055	.963	.947	.075	18718.337	19995.024	—	—	—	—
M4d: M4c with constrained covariances across groups	424.987 (219)	.055	.963	.948	.076	18716.298	19979.686	.000	−.001	3.888 (3)	.274
M4e: Multigroup correlational model for GPA	479.759 (216)	.060	.954	.935	.086	20037.577	21343.309	—	—	—	—
M4f: M4e with constrained covariances across groups	483.015 (219)	.059	.954	.936	.084	20035.472	21327.601	.001	−.001	3.591 (3)	.309
M4g: Multigroup correlational model for prep. course	490.024 (216)	.063	.953	.933	.077	19362.760	20643.127	—	—	—	—
M4h: M4g with constrained covariances across groups	493.701 (219)	.063	.953	.934	.082	19360.951	20627.981	.000	.000	3.908 (3)	.272

Note. χ^2 = Satorra-Bentler χ^2; RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; AIC = Akaike information criterion; BIC = Bayesian information criterion. SES = socioeconomic status; GPA = high school grade point average; Prep. course = participation in math preparatory courses.

Table S7.2

Model Fit for Random Intercept Cross-Lagged Panel Models Including Students' Week-Specific Expectancy and Different Task Value Facets

Models Including Week-Specific Assessments	χ^2 (*df*)	RMSEA	CFI	TLI	SRMR	AIC	BIC	ΔRMSEA	ΔCFI	$\Delta\chi^2$ (*df*)	*p*
Expectancy and intrinsic value											
M1a: Multigroup correlational model for gender	1.381 (2)	.000	1.000	1.000	.006	13484.505	14298.372	—	—	—	—
M1b: M1a with constrained covariances across groups	7.544 (5)	.038	.998	.975	.027	13484.956	14285.106	−.038	.002	5.955 (3)	.114
M1c: Multigroup correlational model for SES	4.415 (2)	.062	.998	.936	.012	11967.721	12756.785	—	—	—	—
M1d: M1c with constrained covariances across groups	8.072 (5)	.044	.998	.967	.029	11965.606	12741.371	.018	.000	3.789 (3)	.285
M1e: Multigroup correlational model for GPA	2.075 (2)	.010	1.000	.998	.007	12774.483	13581.497	—	—	—	—
M1f: M1e with constrained covariances across groups	10.144 (5)	.055	.996	.946	.025	12776.720	13570.133	−.045	.004	7.645 (3)	.054
M1g: Multigroup correlational model for prep. course	0.997 (2)	.000	1.000	1.000	.006	12178.274	12969.612	—	—	—	—
M1h: M1g with constrained covariances across groups	2.715 (5)	.000	1.000	1.000	.016	12174.139	12952.140	.000	.000	1.702 (3)	.637
Expectancy and utility value											
M2a: Multigroup correlational model for gender	5.358 (2)	.069	.997	.894	.012	13441.299	14255.165	—	—	—	—
M2b: M2a with constrained covariances across groups	7.943 (5)	.041	.997	.963	.021	13438.727	14238.876	.028	.000	2.981 (3)	.395
M2c: Multigroup correlational model for SES	7.111 (2)	.091	.995	.826	.017	11891.937	12681.000	—	—	—	—
M2d: M2c with constrained covariances across groups	10.707 (5)	.061	.995	.922	.025	11890.484	12666.248	.030	.000	4.074 (3)	.254
M2e: Multigroup correlational model for GPA	6.199 (2)	.078	.996	.860	.014	12726.457	13533.472	—	—	—	—
M2f: M2e with constrained covariances across groups	7.072 (5)	.035	.998	.972	.017	12722.168	13515.581	.043	−.002	1.460 (3)	.692
M2g: Multigroup correlational model for prep. course	3.595 (2)	.050	.998	.942	.012	12138.778	12930.116	—	—	—	—
M2h: M2g with constrained covariances across groups	4.451 (5)	.000	1.000	1.000	.015	12134.301	12912.302	.050	−.002	1.236 (3)	.745
Expectancy and psychological cost											
M3a: Multigroup correlational model for gender	0.097 (2)	.000	1.000	1.000	.002	14091.608	14905.475	—	—	—	—
M3b: M3a with constrained covariances across groups	3.077 (5)	.000	1.000	1.000	.013	14088.641	14888.790	.000	.000	3.066 (3)	.382
M3c: Multigroup correlational model for SES	2.220 (2)	.019	1.000	.993	.010	12522.801	13311.864	—	—	—	—
M3d: M3c with constrained covariances across groups	2.907 (5)	.000	1.000	1.000	.013	12517.415	13293.179	.019	.000	0.647 (3)	.886
M3e: Multigroup correlational model for GPA	0.177 (2)	.000	1.000	1.000	.003	13322.858	14129.872	—	—	—	—
M3f: M3e with constrained covariances across groups	2.274 (5)	.000	1.000	1.000	.016	13318.855	14112.268	.000	.000	2.174 (3)	.537
M3g: Multigroup correlational model for prep. course	0.053 (2)	.000	1.000	1.000	.001	12714.348	13505.687	—	—	—	—
M3h: M3g with constrained covariances across groups	1.891 (5)	.000	1.000	1.000	.014	12710.071	13488.072	.000	.000	1.918 (3)	.590
Expectancy and effort cost											
M4a: Multigroup correlational model for gender	0.160 (2)	.067	1.000	1.000	.003	13900.941	14714.807	—	—	—	—
M4b: M4a with constrained covariances across groups	2.928 (5)	.000	1.000	1.000	.016	13897.840	14697.990	.067	.000	2.748 (3)	.432
M4c: Multigroup correlational model for SES	2.010 (2)	.004	1.000	1.000	.010	12413.456	13202.520	—	—	—	—
M4d: M4c with constrained covariances across groups	3.315 (5)	.000	1.000	1.000	.013	12408.841	13184.605	.004	.000	1.357 (3)	.716
M4e: Multigroup correlational model for GPA	0.423 (2)	.000	1.000	1.000	.004	13189.238	13996.252	—	—	—	—
M4f: M4e with constrained covariances across groups	2.017 (5)	.000	1.000	1.000	.007	13184.852	13978.265	.000	.000	1.573 (3)	.666
M4g: Multigroup correlational model for prep. course	2.155 (2)	.016	1.000	.995	.010	12594.714	13386.052	—	—	—	—
M4h: M4g with constrained covariances across groups	4.597 (5)	.000	1.000	1.000	.020	12591.096	13369.097	.016	.000	2.452 (3)	.484

Note. χ^2 = Satorra-Bentler χ^2; RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; AIC = Akaike information criterion; BIC = Bayesian information criterion. SES = socioeconomic status; GPA = high school grade point average; Prep. course = participation in math preparatory courses.

Table S7.3

Within-Person Correlations of Students' Expectancy and Task Values in the Multigroup Correlational Models

	Intrinsic value model	Utility value model	Psych. cost model	Effort cost model	Intrinsic value model	Utility value model	Psych. cost model	Effort cost model
	r	*r*	*r*	*r*	*r*	*r*	*r*	*r*
	Female				Male			
Course-specific assessments								
Within-person correlation T1c	.35*	.27*	−.39**	−.26*	.46**	.43*	−.51**	−.33*
Within-person correlation T2c	.74***	.41***	−.49***	−.40***	.77***	.51***	−.59***	−.37***
Within-person correlation T3c	.68***	.48***	−.54***	−.46***	.75***	.57***	−.47***	−.33***
Week-specific assessments								
Within-person correlation T1w	.31***	.30***	−.25***	−.17*	.32***	.28***	−.28***	−.20**
Within-person correlation T2w	.54***	.26**	−.45***	−.33***	.46***	.23*	−.48***	−.35***
Within-person correlation T3w	.49***	.34*	−.25**	−.19**	.50***	.32***	−.27**	−.24**
	Low SES				High SES			
Course-specific assessments								
Within-person correlation T1c	.66	.46	−.47*	−.31	.40**	.22	−.38*	−.21
Within-person correlation T2c	.83***	.49***	−.55***	−.36***	.78***	.45***	−.56***	−.43***
Within-person correlation T3c	.76***	.43**	−.40***	−.28**	.72***	.47***	−.49***	−.36***
Week-specific assessments								
Within-person correlation T1w	.32***	.28***	−.27***	−.20**	.32***	.27***	−.27***	−.19*
Within-person correlation T2w	.46***	.26*	−.49***	−.36***	.49***	.21*	−.45***	−.34***
Within-person correlation T3w	.43***	.28***	−.18*	−.12	.54***	.40***	−.23**	−.15
	Low GPA				High GPA			
Course-specific assessments								
Within-person correlation T1c	.42*	.45	−.46**	−.35*	.38*	.27	−.42**	−.32*
Within-person correlation T2c	.74***	.64$^{***\,a}$	−.45***	−.33***	.76***	.28^{b}	−.65***	−.43***
Within-person correlation T3c	.69***	.69$^{***\,a}$	−.42***	−.30**	.73***	.22^{b}	−.51***	−.40***
Week-specific assessments								
Within-person correlation T1w	.29***	.30***	−.22**	−.14*	.29***	.27***	−.27***	−.17*
Within-person correlation T2w	.48***	.20	−.43***	−.29***	.43***	.20	−.45***	−.34***
Within-person correlation T3w	.44***	.31***	−.21**	−.16*	.55***	.37***	−.31***	−.21**
	No participation in prep. course				Participation in prep. course			
Course-specific assessments								
Within-person correlation T1c	.40	.39	−.48**	−.27*	.33	.30	−.44**	−.30*
Within-person correlation T2c	.73***	.42***	−.55***	−.40***	.79***	.51***	−.55***	−.42***
Within-person correlation T3c	.76***	.66**	−.41*	−.31**	.70***	.46***	−.49***	−.40***
Week-specific assessments								
Within-person correlation T1w	.31***	.25***	−.27***	−.15	.29***	.26***	−.23**	−.13
Within-person correlation T2w	.50***	.23	−.45***	−.37***	.40***	.21	−.40***	−.28***
Within-person correlation T3w	.43***	.33***	−.24**	−.24**	.46***	.35***	−.30***	−.28***

Note. T1c–T3c = course-specific summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet. SES = socioeconomic status; GPA = high school grade point average; Prep. course = participation in math preparatory courses. Psych. cost = psychological cost.

[ab] Unequal superscripts within a row indicate significant differences between groups. If no superscripts are shown, there were no statistically significant differences between groups.

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Model comparisons in Table S7.2 show that in the model including students' expectancy and intrinsic value, constraining the covariances to be equal for female and male students as well as for students with low and high GPA, the increases in RMSEA in the constrained model was larger than .015 even though the chi-square difference tests were not significant (BIC values favored the constrained models and AIC values were similar for the constrained and unconstrained models). We therefore report the within-person correlations for the constrained model as well as for an unconstrained model in Table S7.4. In the constrained models, the covariances are constrained to be equal across groups, whereas covariances were estimated separately for female and male students in the unconstrained models. Table S7.4 shows that the within-person correlations were mostly of similar size in the unconstrained and constrained models. There was a tendency that the within-person correlations between students' week-specific expectancy and intrinsic value were somewhat larger for students with low compared to high GPAs.

Table S7.4

Parameter Estimates for Within-Person Correlations of Students' Expectancy and Task Values in the Multigroup Correlational Models for Constrained and Unconstrained Models

	Intrinsic value model			
	Unconstrained model		Constrained model	
	r	*r*	*r*	*r*
	Female	*Male*	*Female*	*Male*
Week-specific assessments				
Within-person correlation T1w	$.33^{***}$	$.31^{***}$	$.31^{***}$	$.32^{***}$
Within-person correlation T2w	$.36^{\dagger}$	$.53^{***}$	$.54^{***}$	$.46^{***}$
Within-person correlation T3w	$.32^{**}$	$.57^{***}$	$.49^{***}$	$.50^{***}$
	Low GPA	*High GPA*	*Low GPA*	*High GPA*
Week-specific assessments				
Within-person correlation T1w	$.44^{***}$	.14	$.29^{***}$	$.29^{***}$
Within-person correlation T2w	$.60^{***}$	$.31^{*}$	$.48^{***}$	$.43^{***}$
Within-person correlation T3w	$.45^{**}$	$.54^{***}$	$.44^{***}$	$.55^{***}$

Note. T1w–T3w = week-specific experiences on a given math worksheet. GPA = high school grade point average.
$^{\dagger}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Supplement S8. Results of Alternative Models for Students' Course-Specific Expectancy-Value Beliefs

As recommended by Mulder & Hamaker (2021), we fixed the variance of the random intercept for intrinsic/utility values and the covariance with the random intercept of expectancy to zero due to lower AIC and BIC values (see Table S3). However, we repeated our main analyses with a model including random intercepts for both expectancy and intrinsic/utility values. The estimated within-person autoregressive and cross-lagged effects are reported in Table S8. The results are consistent with the results reported in the manuscript; however, the standard errors for the task value effects are somewhat larger compared to the models reported in the paper. Thus, the within-person cross-lagged effect from expectancy on utility value is only marginally significant (p = .058), but the effect size is similar compared to the model reported in the manuscript (βs = .15/.21 vs. βs = .17/.26).

Furthermore, chi-square difference tests suggested that the within-person autoregressive and cross-lagged parameters in the models including psychological and effort cost were not invariant over time; yet, model fit indices (i.e., BIC, RMSEA, CFI) suggested that there were little differences between the unconstrained and constrained models. We thus report the estimated autoregressive and cross-lagged effects for a model with time-invariant effects in Table S8. The results are consistent with the unconstrained versions of the models reported in the manuscript.

Table S8

Autoregressive and Cross-Lagged Parameters for Students' Course-Specific Expectancy-Value Beliefs Across the Entire Semester

	Intrinsic value model		Utility value model		Psychological cost model		Effort cost model	
	b (SE)	β [95% CI]	b (SE)	β [95% CI]	b (SE)	β [95% CI]	b (SE)	β [95% CI]
Course-specific assessments								
Autoregressive effects								
Expectancy T1c → T2c	.72*** (.12)^{a}	.53 [.30; .76]	.82*** (.08)^{a}	.59 [.37; .81]	.81*** (.10)^{a}	.59 [.30; .88]	.81*** (.10)^{a}	.61 [.33; .89]
Expectancy T2c → T3c	.72*** (.12)^{a}	.68 [.47; .90]	.82*** (.08)^{a}	.78 [.64; .92]	.81*** (.10)^{a}	.77 [.58; .96]	.81*** (.10)^{a}	.77 [.60; .94]
Task value T1c → T2c	.55** (.19)^{b}	.42 [.09; .75]	.56** (.19)^{b}	.42 [.03; .82]	.25 (.53)^{b}	.22 [−.62; 1.06]	.45** (.16)^{b}	.40 [.14; .66]
Task value T2c → T3c	.55** (.19)^{b}	.52 [.16; .88]	.56** (.19)^{b}	.62 [.25; .98]	.25 (.53)^{b}	.26 [−.90; 1.42]	.45** (.16)^{b}	.55 [.19; .90]
Cross-lagged effects								
Expectancy T1c → Task value T2c	.34* (.17)^{c}	.24 [−.04; .52]	.25 (.13)^{c}	.17 [−.03; .37]	−.25 (.32)^{c}	−.21 [−.82; .41]	−.07 (.11)^{c}	−.05 [−.21; .11]
Expectancy T2c → Task value T3c	.34* (.17)^{c}	.31 [−.01; .64]	.25 (.13)^{c}	.26 [−.04; .55]	−.25 (.32)^{c}	−.30 [−1.16; .55]	−.07 (.11)^{c}	−.09 [−.35; .18]
Task value T1c → Expectancy T2c	.13 (.11)^{d}	.11 [−.07; .28]	−.02 (.07)^{d}	−.01 [−.12; .09]	.00 (.09)^{d}	.00 [−.15; .14]	−.01 (.06)^{d}	−.01 [−.12; .10]
Task value T2c → Expectancy T3c	.13 (.11)^{d}	.13 [−.08; .34]	−.02 (.07)^{d}	−.02 [−.15; .11]	.00 (.09)^{d}	.00 [−.15; .15]	−.01 (.06)^{d}	−.01 [−.12; .11]

Note. T1c–T3c = course-specific summative evaluation of experiences thus far, T1w–T3w = week-specific experiences on a given math worksheet. Equal superscripts indicate that unstandardized coefficients were fixed to be the same.

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Supplemental References

Asparouhov, T., & Muthén, B. (2013). Computing the strictly positive Satorra-Bentler chi-square test in Mplus. *Mplus Web Notes*, *12*, 1–12. https://www.statmodel.com/examples/webnotes/SB5.pdf

3.2 Summary of the Main Results of the Three Empirical Studies

Study 1a and Study 1b (*Students' Motivational Trajectories and Academic Success in Math-Intensive Study Programs: Why Short-Term Motivational Assessments Matter*) examined the short-term trajectories of students' expectancies and task values shortly after the transition to math-intensive study programs, interindividual differences in these motivational trajectories as a function of students' personal characteristics (i.e., gender, prior achievement, SES, and participation in preparatory math courses), and whether potential motivational declines predict students' academic achievement, study program satisfaction, and course dropout at the end of their first semester in math-intensive STEM programs. Study 1a focused on motivational changes across students' first semester in demanding math courses (beginning, midpoint, and end-of-semester data collections) and Study 1b focused on potential motivational changes in the first weeks of the semester (data collections in Weeks 2 through 5). Latent change score analyses in Study 1a revealed a significant decline in students' expectancies and task values from the beginning towards the midpoint of the semester and relatively little additional change towards the end of the semester. Analogous analyses in Study 1b showed that students experienced a motivational shock at the very beginning of the semester that was characterized by sharp declines in students' intrinsic and utility values and significant increases in their perceived psychological and effort costs. Supplemental analyses in Study 1b using a subsample from Study 1b (one cohort in the math and physics study programs, respectively) suggested that students' first performance feedback on mandatory math worksheets contributed to the motivational shock. In both studies, female students and students with comparatively lower prior achievement in high school had greater motivational declines. The motivational decline in Study 1a and the motivational shock in Study 1b negatively predicted students' end-of-term exam performance and study program satisfaction and positively predicted course dropout during the semester. These results underscore the importance of short-term motivational declines as early warning signs of academic difficulties and dropout tendencies in math-intensive STEM fields.

Study 2 (*Geschlechtsunterschiede in der Variabilität situationsspezifischer Erwartungs- und Wertüberzeugungen und selbsteingeschätzter Leistung in mathematik-intensiven Studienfächern: Eine Mehrebenenanalyse von motivationalen Schwankungen*) further examined potential gender differences in the variability of students' expectancies and task values as well as their self-assessed performance on mandatory math worksheets. Multilevel analyses identified significant gender differences in the variability of students' expectancy of success and self-assessed performance, but not task values across the semester (beginning, midpoint, and end-of-term time points). Furthermore, significant gender differences emerged in the degree of variability between students' expectancy, task values, and performance self-assessment at two of the three time points (i.e., how consistent these beliefs were with each other). The identified gender differences remained significant after controlling for students' personal and family background characteristics. These results suggest that female students' expectancies, task values, and performance self-assessments may be comparatively less consistent within a situation and that female students' expectancies of success and self-rated performances may be comparatively more sensitive to situational fluctuations in gateway math courses.

Further analyses in Study 3 (*Searching for Short-Term Motivational Spillover Effects: A Random Intercept Cross-Lagged Panel Analysis of Students' Expectancies and Task Values in Math-Intensive Study Programs*) investigated the developmental processes of students' expectancy-value beliefs on a within-person level, controlling for stable between-person motivational differences over time. Similar to Study 1, analogous analyses were conducted for course-specific (summative) assessments of students' expectancies and task values across the entire semester and week-specific (situated) assessments across three weeks at the beginning of the semester. Random intercept cross-lagged panel models revealed an increase in the within-person alignment of students' course-specific expectancies and intrinsic and utility values across the semester, whereas the association of students' expectancy and psychological and effort costs remained stable over time. Similarly, significant motivational spillover effects (i.e., cross-lagged effects) were limited to students' expectancies and positively-valenced task values and were unidirectional: within-person deviations in students' expectancy to do well in their math course from their personal baseline significantly positively predicted subsequent within-person deviations in their intrinsic and utility values across the semester. In contrast, no significant changes in the within-person alignment and no significant motivational spillover effects emerged for students' week-specific (situated) assessments at the beginning of the semester, suggesting that these motivational beliefs were relatively self-contained within each week. Mean-level differences in students' expectancies and task values as a function of their gender and prior achievement were relatively stable over time and in favor of male and comparatively higher-performing students. These findings highlight the importance of differentiating within-person and between-person motivational differences and suggest that summative vs. situated assessments of students' expectancies and task values may reveal different developmental processes.

3.3 Discussion of the Main Results

In the following sections, I will discuss the main results of the empirical studies with respect to the three central research questions of the present dissertation, namely (a) the developmental processes of students' expectancies and task values across the first semester in gateway math courses, (b) interindividual differences in these developmental processes as a function of students' personal characteristics, and (c) motivational changes across the semester as predictors of students' end-of-term exam performance, study program satisfaction, and course dropout.

3.3.1 Short-Term Developmental Processes of Students' Math-Related Expectancies and Task Values

As proposed by Eccles and Wigfield (2020), the present dissertation took a situated perspective on students' expectancy-value beliefs shortly after the transition to math-intensive study programs and examined the role of students' situation- and course-specific expectancies and task values in predicting students' end-of-term academic achievement, study program satisfaction, and course dropout from gateway math courses. The analyses conducted in the present dissertation underscore the importance of examining short-term motivational changes shortly after the transition to math-intensive study programs in postsecondary education and contribute to a better understanding of the developmental processes of students' expectancy-value beliefs in their first semester in math-intensive STEM fields. A main contribution of the present dissertation is the inclusion of both situation-specific (i.e., week-specific) and course-specific (i.e., summative) expectancy-value beliefs across multiple time points in gateway math courses. This design allowed for fine-grained analyses of the developmental processes of students' expectancy-value beliefs by using shorter time lags compared to prior research and situation-specific measures that were suitable to reveal motivational declines across these short time periods. In the following sections, I will discuss key findings from the empirical studies regarding how students' expectancy-value beliefs changed across the semester, how the alignment of these motivational beliefs changed over time, and whether these beliefs influenced each other over time. I will focus particularly on differences that emerged in these developmental processes depending on the specific construct of the expectancy-value framework and the level of specificity of the measures (and time lag between assessments).

Short-Term Changes in Students' Situated Expectancies and Task Values

Consistent with prior research in math-intensive STEM fields (Perez et al., 2014; K. A. Robinson et al., 2019; Zusho et al., 2003), the analyses in Study 1a revealed a decline in students' expectancy-value beliefs across the first half of the semester in gateway math courses and comparatively little change in students' motivational beliefs in the second half of the semester. Analyses in Study 1b extended prior research by showing that most students experienced a motivational shock in the very first weeks of the semester, which coincided with the first performance feedback students received on mandatory math worksheets. Thus, both types of motivational assessments (i.e., situation- and course-specific) captured motivational declines shortly after the transition to math-intensive study programs. However, the situation-specific assessments at the beginning of the semester, referencing students' current math worksheet, revealed a much greater decline and differences in the magnitude of the motivational shock depending on the specific expectancy-value facet (i.e., sharp decline in intrinsic and utility values, sharp increase in psychological cost). Taken together, these results suggest that motivational declines in gateway math courses, which are often a barrier to further engagement and success in STEM fields (Chen, 2013; Gasiewski et al., 2012; Seymour & Hewitt, 1997), are most likely to happen and most pronounced in the very first weeks of the semester. Motivational declines thus seem to be a part of students' adaptation to the high demands and workload in math-intensive STEM fields. As discussed in Study 1, these results suggest that students may have started their physics, math, or math teacher education program with unrealistic expectations about the type of math that is covered at university (Gueudet, 2008). In addition, Study 1b revealed differential change patterns depending on the specific expectancy-value facet: the motivational shock was more pronounced for students' valuing of the coursework compared to their expectancy to be successful in their math course. These results suggest that there were particularly stark discrepancies between students' prior expectations of the value of the coursework and their experiences within the first weeks of the semester. Identifying motivational facets that are most likely to decline can be informative for the design of motivational interventions. However, the analyses in Study 1b also revealed that the motivational shock was comparatively stronger for students who had already received their first performance feedback in their math course, suggesting that this performance feedback was detrimental to students' motivation. This indicates avenues for further research and educational practice to implement feedback practices that support students' motivation, which I will discuss in the section on implications for future research and educational practice.

Motivational Alignment Processes and Reciprocal Links Among Students' Situated Expectancies and Task Values

A contribution of the present dissertation is that motivational alignment and spillover processes of students' expectancy beliefs and task values were examined on the within-person level, controlling for stable between-person motivational differences. These developmental processes have been proposed in SEVT (Eccles, 2009; Wigfield & Eccles, 1992; Wigfield et al., 1997) but have not been examined at the within-person level within the same sample. It is important to better understand how students' expectancy-value beliefs develop and influence each other over time in order to buffer students' from motivational declines. Three important results emerged in the analyses of students' motivational alignment and reciprocal links among students' expectancies and task values in Study 3 that I want to discuss in more detail.

First, motivational spillover effects and motivational alignment processes among students' expectancies and task values go hand in hand, consistent with Eccles and colleagues' assumptions (Eccles, 2009; Wigfield & Eccles, 1992). The results of Study 3 suggest that an increasing alignment of students' expectancies and task values occurred through unidirectional spillover effects among expectancies and values: deviations in students' course-specific expectancy from their personal baseline significantly predicted further within-person deviations in intrinsic and utility values half a semester later. Similar to the calibration process of students' ability self-concepts at the beginning of elementary school, this alignment process likely describes students' adaptation to the new educational context and demands in math-intensive STEM programs (Eccles & Wigfield, 1995; Wigfield, 1994; Wigfield & Cambria, 2010). Students' expectancies and task values at the beginning of their math-intensive study program are likely primarily shaped by their experiences in school, an educational context in which most of them were likely high performing compared to their peers. In addition, students may start their studies with unrealistic expectations about the type of math and coursework in math-intensive STEM programs (Hasenberg & Schmidt-Atzert, 2013; Rach & Heinze, 2017). As students gain experiences in their math course and receive their first performance feedback on math worksheets, they likely first calibrate their expectancies of success to the new demands and subsequently align their valuing of the course material with their expectancies of success. This alignment of students' task values to their expectancies can happen through different processes, depending on students' performance experiences. Students who make positive learning experiences likely come to value the coursework, whereas students with repeated experiences of failure may align their expectancies and task values by devaluing the coursework in order to protect their well-being and self-worth (Eccles, 2009; Eccles & Wigfield, 1995; Harter, 1990). Study 1 showed that most students experienced declines in their expectancy of success and valuing of their math course, which indicates that most students may have devalued the course material to align their task values and expectancies of success.

Second, the motivational alignment and spillover effects were limited to course-specific assessments of students' expectancies and task values. Analogous developmental processes were not found for students' situation-specific expectancy-value beliefs referencing their current worksheet at the beginning of the semester. These results suggest that the emergence of motivational alignment and motivational spillover processes depends on whether course-specific (i.e., summative) or situation-specific (i.e., self-contained) assessments of expectancy-value beliefs are used. This underscores Eccles' (2005) reasoning that there should be a match between the developmental process of students' expectancy-value beliefs that researchers want to capture and the level of specificity of the measures used to assess students' expectancy-value beliefs. As described above, students' adaptation to the new educational context necessitates a calibration of one's expectancy-value beliefs to the new content and demands. Assessing such adaptation and alignment processes thus relies on more generalized assessments because the reference point of these items remains constant and allows students to aggregate multiple situational experiences to form their generalized beliefs (i.e., course- or domain-specific beliefs; M. D. Robinson & Clore, 2002). In contrast, situation-specific items reference specific learning content (e.g., the math worksheets) that changes from one situation to the next, so that these assessments are likely unable to disentangle calibration processes from variability caused by the changing learning content.

Third, as mentioned above, these significant alignment and spillover processes were found only between students' course-specific expectancy of success and intrinsic and utility values but not between students' course-specific expectancies and psychological and effort costs. As discussed in Study 3, the specific context of highly-demanding math courses may have contributed to these differences between students' positively-valenced task values and perceived costs. However, it may also be that motivational alignment and spillover effects among students' motivational beliefs function differently for students' perceived costs compared to positively-valenced task values. In research on SEVT, there remain ongoing debates about whether students' perceived costs are part of the task value construct along with students' positively-valenced values or whether values and costs should be separated into different constructs in the expectancy-value framework (Barron & Hulleman, 2015; Eccles & Wigfield, 2020; Wigfield & Eccles, 2020). Students' perceptions of costs are—by definition—

aspects of a given task that are perceived as drawbacks from engaging with the task and thus include comparisons to other valued tasks and activities in a given situation (Eccles & Wigfield, 2020; Wigfield et al., 2020). In the postsecondary context, these comparisons may include other courses that students are enrolled in or competing obligations such as employment. These competing tasks and obligations might affect students' cost perceptions for a given course more strongly than their values (Wigfield et al., 2020), so that the developmental trajectories of students' perceived costs are somewhat uncoupled from their expectancies. For instance, students might find the coursework in different courses interesting and expect to do well in these courses, but perceive engaging with the coursework in one course as too stressful and requiring too much effort, if the demands are also high in another course due to the limited resources of investing time and effort. No studies to date have examined such comparison processes between different courses in the postsecondary context.

According to Eccles and colleagues (Eccles, 2009; Wigfield et al., 2020), dimensional comparisons are assumed to influence the relative weighting of different tasks and activities, that is, individuals develop an intraindividual hierarchy of tasks and domains. Research from the school context supports this assumption and shows that dimensional comparisons, for instance, between the math and verbal domain, play a role in the development of students' intraindividual hierarchies of different domains (e.g., Gaspard et al., 2018; Schurtz et al., 2014). Importantly, these intraindividual hierarchies are key determinants of students' educational and occupational choices: students choose educational and occupational paths that fit best with their personal hierarchies of expectancies and task values (e.g., Eccles, 2009; Gaspard et al., 2020; Lauermann et al., 2015). It is unclear how these intraindividual hierarchies look like once students have decided to major in a specific study program (Wigfield et al., 2020). Similar to the school context, students might compare their expectancies and task values across different courses they are enrolled in (e.g., analysis vs. algebra in a math study program, math vs. physics in a physics study program). Furthermore, after experiencing a potential motivational shock and repeated failure experiences in their study program, students may also start thinking about possible alternatives to their math-intensive study program (e.g., a less math-intensive study program, vocational training; see Heublein et al., 2017). Examining these processes is an important avenue for future research in order to better understand students' short-term decision-making (e.g., whether to invest effort in one course or another) and long-term educational choices and behaviors (e.g., whether or not to drop out of one's study program). A better understanding of these processes could also inform the design of motivational interventions to support students' motivational beliefs (Wigfield et al., 2020).

3.3.2 Interindividual Differences in Students' Situated Expectancies and Task Values as a Function of Students' Personal Characteristics

In the following sections, I will discuss similarities and differences with respect to interindividual differences in the short-term developmental processes of students' expectancy-value beliefs as a function of students' personal characteristics that emerged in the three empirical studies. Overall, the findings from the three studies suggest that the developmental processes of students' expectancies and task values across their first semester in gateway math courses were similar, regardless of students' prior achievement, gender, or SES. Results from Studies 1a and 1b indicate that most students experienced motivational declines throughout the semester regardless of their personal characteristics. Nevertheless, some interindividual differences in students' motivational trajectories emerged that may contribute to a better understanding of why certain groups of students are still at a higher risk of dropping out of math-intensive STEM programs (e.g., female students; Meyer & Strauß, 2019; Shaw & Barbuti, 2010).

Across all studies, no or only little interindividual differences in students' expectancy-value beliefs, their trajectories over time, and their alignment emerged as a function of students' SES. As discussed in the individual papers, this may be due to the relatively homogeneous sample of students who participated in the BONNS study. Nevertheless, these results are consistent with prior research grounded in SEVT that found relatively small mean-level differences in students' expectancy-value beliefs (Guo, Marsh, et al., 2015; Guo, Parker, et al., 2015; Harackiewicz et al., 2016; K. A. Robinson et al., 2019) or motivational trajectories across the first two years in college as a function of students' SES or first-generation status (K. A. Robinson et al., 2019). In the following sections, I will therefore focus on interindividual differences in the developmental processes of students' expectancy-value beliefs across the semester, depending on students' prior achievement and gender that emerged in the three empirical studies.

First, with respect to students' prior achievement, the results of Study 1 and Study 3 reveal consistent differences in students' expectancy-value beliefs as a function of students' high school GPA. In line with the theoretical assumptions and numerous studies grounded in SEVT (Perez et al., 2014; K. A. Robinson et al., 2019; Steinmayr & Spinath, 2010), students with comparatively higher levels of achievement in school consistently reported higher expectancies of success and values and lower levels of psychological and effort costs. Furthermore, the analyses in Study 1 showed that comparatively higher levels of high school

GPA served as a protective factor against the motivational decline across the semester and the motivational shock shortly after the transition to math-intensive study programs, extending the literature linking students' prior achievement to the strength of subsequent motivational declines (K. A. Robinson et al., 2019; Sonnert et al., 2015).

Unexpectedly, one exception to the protective role of students' high school GPA emerged in Study 1b: Students with comparatively higher achievement in high school experienced a greater motivational shock in their perceived psychological and effort costs compared with students who had lower achievement in high school. As discussed in Study 1, students may have used different strategies in the adaptation to the high demands and workload of the weekly mandatory worksheets depending on their ability level. High-achieving students may have responded to this motivational shock and the first performance feedback by increasing their effort, whereas low-achieving students may have lowered their performance aspirations. These results are consistent with work by Rach and Heinze (2011, 2017) who found that students use different strategies while working on the mandatory math worksheets in a gateway math course for mathematics majors depending on their math achievement in school. Rach and Heinze (2011, 2017) identified three groups of students based on their self-reported strategies of solving the math worksheets: a "self-solving type" who often solves the math problems on their own, a "self-explanation type" who tries comprehending the solutions of other students by explaining the solutions to themselves, and a "reproducing type" who mostly copies the solutions from other students but rarely tries explaining them to themselves. Students who solve the math problems by themselves had significantly higher math grades in school compared to students who mostly copied the solutions (Rach & Heinze, 2017). Notably, Rach and Heinze (2011) also report results that indicate that students' motivational trajectories differed as a function of their study type. Specifically, the authors found that students who typically solve the math worksheets by themselves experienced an increase in their interest and stable levels of math self-concept of ability across the first half of the semester, whereas the other two groups of students experienced declines in their interest and math self-concept. There was also a tendency that the motivational decline was somewhat smaller for students who tried explaining the solutions to themselves if they copied them from others (i.e., "self-explanation type") compared to students who only copied the solutions (i.e., "reproducing type"). Overall, these results suggest that a greater engagement with the worksheets can also trigger students' interest in the math problems and that motivational declines may be linked to different study strategies students use. More work on the links between students' motivational beliefs and study behaviors is needed to better understand the interplay of students' motivation and study behaviors and to help students develop efficient study strategies that may buffer them from motivational declines.

Second, all three empirical studies examined potential gender differences in students' expectancy-value beliefs. Compared to male students, female students are still more likely to drop out of their math-intensive study programs in STEM fields (Isphording & Qendrai, 2019; Meyer & Strauß, 2019; Shaw & Barbuti, 2010). One aim of the present dissertation was therefore to examine gender differences in the developmental processes of students' expectancies and task values in gateway math courses that may contribute to the gender differences in dropout from STEM majors. Specifically, the three studies in this dissertation examined gender differences in students' mean levels of their expectancy-value beliefs, in their motivational trajectories over time, and in the associations of students' expectancies of success and task values (i.e., their level of alignment in a given situation). Consistent with prior evidence from math-intensive STEM fields (e.g., Gaspard, Dicke, Flunger, Schreier, et al., 2015; K. A. Robinson, Lee, et al., 2022; Watt, 2004), Study 1 and Study 3 found that female students reported lower levels of expectancy compared with their male peers. Compared to research from the school context (e.g., Arens, 2021; Gaspard, Dicke, Flunger, Schreier, et al., 2015; Nagy et al., 2006), gender differences in students' valuing of math were relatively small, with the exception of students' psychological costs, which were comparatively higher for female students. These results suggest that gender differences in students' math-related task values may be somewhat smaller in math-intensive STEM programs compared to the school context, because students self-selected into these study programs so that their valuing of math may be relatively high regardless of their gender (Perez et al., 2019; K. A. Robinson, Lee, et al., 2022; K. A. Robinson et al., 2019).

Similarly, gender differences in students' motivational trajectories across the semester emerged in favor of male students, which suggests that female students are more at risk of maladaptive motivational trajectories in math-intensive STEM fields (K. A. Robinson, Lee et al., 2022; Sonnert et al., 2015; but see K. A. Robinson et al., 2019). Even though female and male students experienced the motivational shock at the beginning of the semester, female students experienced greater motivational declines than male students in Study 1. Analyses in Study 2 complement these results by showing that female students' expectancy of success and self-rated performance on their mandatory worksheets fluctuated more across the semester compared to male students' assessments. This greater variability in female students' expectancy and self-rated performance may be a sign of vulnerability and may be linked to generally lower confidence in their own abilities in math compared to their male peers (i.e., trait differences). For instance, Malmberg et al. (2016) found that high school students with higher trait levels of perceived competence experienced less variability in their competence perceptions across one week. Lower (trait) levels of confidence in their math ability for female compared with male students may be associated with adverse attribution processes (e.g., attributing low levels of achievement to a lack of ability). These gendered attribution processes might therefore make female students more prone to situation-specific fluctuations in their expectancy to be successful in their math class depending on the specific math content in a given situation (Beyer, 1998).

Finally, analyses of gender differences in the alignment of students' expectancy-value beliefs in Study 2 and Study 3 revealed mixed results. No significant gender differences in the within-person alignment of students' expectancy and task values were found in Study 3, whereas results in Study 2 suggested that female students' expectancies, task values, and their self-rated performance were less closely aligned with each other within a given situation. These differences may be due to the different analytical approaches (i.e., testing bivariate within-person associations vs. examining the variability of multiple constructs within a given situation) and suggest that students' task value facets were less closely aligned for female compared to male students, which may be a sign that female students experience more internal conflicts in engaging in their math course (Wigfield & Eccles, 1992).

Overall, the present dissertation suggests that gender differences in students' math-related expectancy-value beliefs in math-intensive STEM programs were most pronounced in students' expectancy of success, with female students reporting consistently lower levels of expected success (both in course-specific and situation-specific assessments) and experiencing more maladaptive trajectories and fluctuations in their expectancy of success across the semester. The analyses further showed that even after controlling for students' prior achievement in high school, female students reported lower levels of expectancy in their math course compared to their male peers. Persistent gender stereotypes about female students in math-intensive STEM fields may contribute to these gender differences in students' expected success in favor of male students (i.e., the belief that women have lower math ability than men; Ertl et al., 2017). Thus, female students' lower levels of expected success in math are likely a key driver of comparatively higher dropout rates for female students in math-intensive STEM fields and should be addressed in interventions to support female students' retention in STEM fields (Ellis et al., 2016; Sanabria & Penner, 2017; see also K. A. Robinson, Lee, et al., 2022).

3.3.3 Students' Situated Expectancy-Value Beliefs as Predictors of Their Academic Success in STEM Majors

Consistent with prior studies that examined motivational changes across secondary or postsecondary education (Gaspard et al., 2020; K. A. Robinson et al., 2019; Totonchi et al., 2021) or across one semester in postsecondary education (Dresel & Grassinger, 2013; Kosovich et al., 2017; Zusho et al., 2003), analyses in Study 1a showed that declines in students' expectancy-value beliefs across the semester are a precursor to low academic achievement and dropout tendencies in math-intensive STEM programs. Importantly, Study 1b expanded upon these results by showing that the motivational shock students experienced immediately after the transition also emerged as a significant predictor of students' end-of-term academic achievement, study program satisfaction, and course dropout in gateway math courses. Together, the results of both studies suggest that motivational declines are particularly likely in the first weeks after the transition to postsecondary education, and that motivational interventions are needed in the very early stages of students' postsecondary educational careers to support students' motivation in math-intensive STEM fields. I return to this point in the section about the implications for future research and educational practice.

Study 1 tested separate models for the different expectancy and task value beliefs and examined the predictive effects of students' initial levels of motivational beliefs and their changes over time as predictors of student outcomes. The results suggested that initial levels and changes in all expectancy-value facets significantly predicted students' end-of-term exam performance and study program satisfaction. These results are consistent with prior studies examining the predictive effects of different motivational beliefs on student outcomes (e.g., Durik et al., 2006; Kryshko et al., 2022; K. A. Robinson et al., 2019) and underscore the importance of students' expectancies and task values as predictors of students' academic achievement and well-being in higher education. However, the same pattern was not found for students' course dropout towards the end of the semester. Initial levels of expectancy, intrinsic value, and perceived psychological and effort costs at the beginning of the semester significantly predicted course dropout, whereas only declines in students' expectancy and intrinsic value were significant predictors of a course dropout across the semester (in Studies 1a and 1b). One possible explanation for this finding is that students who experienced stronger declines in their expectancy and intrinsic value may have started their studies with particularly unrealistic expectations about math-intensive study programs or overconfident expectancies of success, which may contribute to early dropout tendencies (Gueudet, 2008; Rach & Heinze, 2017). For instance, students' view of math at the beginning of their semester is likely largely driven by school math in contrast to math as a scientific discipline at the university, leading to unrealistic assumptions about the coursework and structure of math courses at the university. Indeed, Rach and Heinze (2017) found that students who failed their math course or dropped out of the course during the semester had not only significantly lower math grades in school but also significantly lower levels of prior math knowledge regarding math as a scientific discipline at the beginning of their studies compared to students who successfully completed the math course. However, unsuccessful students (i.e., students who failed the exam or dropped out of the course) reported similar levels of math self-concept and interest in school math as students who completed the course successfully, indicating that their initial motivational beliefs may have been poorly calibrated to their math competence compared to students who completed the course successfully.

Furthermore, the results of Study 1 also suggest differences in the strength of the predictive effects of students' motivational beliefs depending on the specific outcome. In line with prior research from school and postsecondary education contexts (e.g., Guo, Parker, et al., 2015; Perez et al., 2014; K. A. Robinson et al., 2019), students' expectancy of success emerged as the strongest motivational predictor of their exam performance at the end of the semester across Study 1a and Study 1b (based on the amount of variance explained by the separate models for each expectancy-value facet). Similarly, the model including students' expectancy of success explained the largest amount of variance in students' end-of-term study program satisfaction across the four weeks at the beginning of the semester in Study 1b (41% vs. 20%–33%), whereas students' intrinsic value emerged as the strongest motivational predictor of their end-of-term study program satisfaction across the entire semester in Study 1a (explained variance: 58% vs. 24%–51%). These results suggest that there were changes in the relative importance of students' expectancy-value beliefs for students' study program satisfaction across the semester, in that students' expectancies of success were particularly powerful and important predictors of students' end-of-term study program satisfaction and exam performance at the beginning of the semester. This is an interesting finding because the analyses of students' motivational changes at the beginning of the semester revealed that students' expectancy showed the least amount of change across the four-week period at the beginning of the semester. Thus, targeting motivational facets in interventions that show the greatest amount of change after the transition to postsecondary education may not be the most fruitful approach for increasing students' achievement and retention in STEM fields (see also K. A. Robinson et al., 2019). However, more research is needed to systematically examine the relative importance of different motivational beliefs for early dissatisfaction with one's study program and dropout intentions (including their unique predictive effects). A better understanding of the relative importance of different motivational beliefs and whether the relative importance of these beliefs changes over time could inform the design of targeted intervention approaches at specific points in students' postsecondary education in STEM fields (see also Eccles & Wigfield, 2020; Rosenzweig et al., 2022).

3.4 Strengths and Limitations of the Present Dissertation

Several strengths and limitations of the present dissertation must be considered in the interpretation of the main results. A major strength of the present dissertation is the large sample of students, who were followed in an authentic educational context, namely, required math courses, which are often a gatekeeper to further engagement and success in STEM majors (Chen, 2013; Seymour & Hewitt, 1997). Across two cohorts of students enrolled in physics, math, or math teacher education programs at a German university, students responded to paper-and-pencil questionnaires at six time points within their first-semester required math courses. The data collections took place during the math lectures in which students had to submit their weekly mandatory math worksheets. Therefore, nearly all students who were enrolled in the math courses attended the lecture (response rates between 98% and 100% at each data collection), so that course attendance and attrition could be inferred.

Furthermore, the present dissertation has several methodological strengths. In contrast to prior research in postsecondary STEM contexts, the present work included six time points with intensive data collections at the beginning of the semester that made it possible to identify the most critical time period for motivational declines shortly after the transition to postsecondary education (for an exception in a psychology program, see Johnson et al., 2014). In addition, the inclusion of course-specific and situation-specific measures of students' expectancy-value beliefs allowed for fine-grained analyses of motivational changes and reciprocal links among expectancies and task values across two different time lags within the semester. Prior research that relied mainly on domain-specific measures may have overlooked such short-term declines in or reciprocal links among students' expectancies and task values (e.g., Hardin & Longhurst, 2016; Spinath & Steinmayr, 2008). Furthermore, the fact that multiple cohorts of students enrolled in three different math-intensive study programs in the STEM domain were included in the sample and that a motivational shock was found across all courses represents another strength of the present dissertation.

Lastly, the data were analyzed using state-of-the-art analytical approaches that were tailored to the specific research questions. For instance, latent change score models in Study 1a and Study 1b allowed for the identification of non-linear trajectories of students' expectancies and task values over time (McArdle, 2009). Furthermore, Study 3 used random intercept cross-lagged panel analyses to separate between- and within-person variability in students' expectancies and task values, so that motivational spillover and alignment processes could be studied at the appropriate level (i.e., the within-person level; Hamaker et al., 2015).

However, several limitations of the present dissertation also need to be considered and suggest possible directions for future research. First, the analyses in Study 1b also suggested that there were course-specific differences in the timing and strength of the motivational shock at the beginning of the semester (course-specific differences also emerged for the motivational decline observed across the semester in Study 1a). Even though supplemental analyses using a subsample of the data in Study 1b revealed that the first performance feedback contributed to the initial motivational shock at the beginning of the semester, no other context-specific factors were examined that may be linked to the observed motivational declines across Studies 1a and 1b. Thus, it also remains unclear whether context-specific factors may have helped students recover from the initial motivational shock. Students' experiences in their weekly study sections may have affected their motivational trajectories across the semester, depending on whether the climate of these sections was perceived as performance- or mastery-oriented and thus more or less motivationally supportive. For instance, K. A. Robinson, Lira, et al. (2022) found that students who perceived the study sections of their engineering course as more autonomy- and competence-supportive experienced comparatively smaller declines in their valuing of engineering across the academic year (i.e., across two consecutive engineering courses).

Second, the data of the present dissertation stem from students who were enrolled in physics, math, or math teacher education programs at one university in Germany. The sample of students was comparatively homogeneous, in that most students came from relatively high-SES backgrounds, had comparatively high grades in high school, and had taken math as an advanced course in high school. For instance, no interindividual differences in students' expectancies and task values were found as a function of students' SES, and the identified gender differences in students' expectancy-value beliefs, their trajectories over time, and in their alignment were mostly small (with the exception of students' expectancy of success). Thus, the results regarding interindividual differences in the developmental processes of students' expectancy-value beliefs may not be generalizable to more diverse contexts in STEM fields. More research across different postsecondary institutions is therefore needed.

Third, several limitations of prior work and untested theoretical assumptions in SEVT that I outlined in the introduction and theoretical framework were not fully or systematically addressed in this dissertation. For instance, it remains an open question whether a high alignment of students' expectancies of success and subjective task values is indeed linked to positive learning experiences, high achievement, and long-term engagement. Furthermore, although Studies 1a and 1b provide some evidence of situation-specific changes in the relative importance of students' expectancies and task values for their academic success in STEM fields, I did not systematically examine such shifts in the relative importance of different expectancy- and task-value facets. Such analyses could improve our understanding of the motivational processes leading to low academic achievement and dropout tendencies in math-intensive STEM fields and inform the design of motivational interventions, for instance, regarding which expectancy-value facets should be targeted in these interventions.

Finally, in the present dissertation, the type of assessment (course-specific vs. situation/week-specific) and time lag between the measurement points (half a semester vs. one week) were varied together so that it is unclear if the observed alignment processes and reciprocal links for students' course-specific beliefs across the semester were due to the type of assessment or time lag between measurement points. More research across different contexts and theorizing about the "correct" time lag for capturing motivational alignment processes and spillover effects is necessary to gain a better understanding of the developmental processes of students' expectancy of success and subjective task values in math-intensive STEM fields (Eccles, 2005).

3.5 Implications for Future Research and Educational Practice

Beyond the limitations and open questions that have been discussed in the previous sections, the findings of the present dissertation suggest some more general directions for future research and implications for educational practice. In the next sections, I will focus on what I consider important next steps for research on short-term developmental processes of students' expectancy beliefs and subjective task values based on Eccles and colleagues' SEVT, and outline the relevance of the key findings of this dissertation for educational practice.

3.5.1 Implications for Future Research

The papers of the present dissertation used a situated perspective guided by SEVT to examine short-term developmental processes of students' expectancy-value beliefs and links to student outcomes at the end of students' first semester in math-intensive STEM programs. However, more work is needed to better understand the short-term processes that shape students' expectancy-value beliefs and their implications for both short- and long-term educational choices. I will focus specifically on (a) the need for further analyses of the weighting processes of students' expectancy-value beliefs for a specific achievement-related choice, (b) the need for further analyses of the link between students' situation-specific expectancy-value beliefs and more global, domain-specific motivational beliefs, and (c) the need for a more explicit definition of a "situation".

The Weighting of Students' Expectancy-Value Beliefs for Their Educational and Occupational Choices

As mentioned before, the underlying mechanisms of how students weight their expectancies of success and different task value facets are relatively unclear. Eccles and Wigfield (2020) assume that developmental processes, situational/contextual processes, personal characteristics, and person by situation processes affect these weighting processes. For example, first, the relative weight of students' attainment value should increase across adolescence, as students start thinking about such important choices as potential major or career options that are linked to their identity (Eccles, 2009). Second, the perceived utility value of different courses that are a prerequisite for majoring in a specific study program may be quite salient in a situation, in which students need to decide on which courses to take (Wigfield, 1994). Third, the perceived cost of math-intensive study programs may be more salient for female compared to male students because of fears of confirming stereotypes about female students in male-dominated STEM fields or beliefs that they need to invest more effort to be successful in STEM compared to their male peers (Ramsey & Sekaquaptewa, 2010). Finally, however, female students may not weight their perceived costs higher than male students unless these stereotypes are made salient in the situation, for instance, by an instructor in their math class (Murphy et al., 2007).

More research on the situation-specific factors and person by context interactions that influence the salience of different expectancy-value facets is needed to better understand why, how, and for whom motivational interventions based on SEVT work in supporting students' motivations, achievement, and retention in STEM fields. For instance, Study 1 suggested that students' expectancy of success may have been weighted quite strongly at the beginning of the semester, as students received their first performance feedback and gained experience with the math worksheets. Thus, receiving performance feedback for the first time might have temporarily increased the relative weighting of students' expectancy of success for their end-of-term study success because it increased the salience of the expectancy component (e.g., by triggering such questions as "Am I good enough to be successful in this course?"). These results suggest that situational characteristics such as the provision of feedback can change the salience of different expectancy-value facets in determining students' academic achievement, engagement, and well-being. Accordingly, intervention efforts could focus on motivational beliefs that are particularly salient to students or target specific expectancy-value facets by increasing their salience that can help students feel competent and see value in their coursework (e.g., by reflecting on personal progress, on personal resources to deal with challenging coursework, or on how learning the course material in one course can be beneficial for another course).

The Link Between Students' Situation-Specific Expectancy-Value Beliefs and More Global, Domain-Specific Motivational Beliefs

Another important question for future research grounded in SEVT is how students' situated expectancies and task values relate to and shape their more general motivational beliefs about a task or domain. Eccles (2022) proposed that these more general, individual beliefs emerge from repeated similar situational experiences in a given context, analogous to the assumptions in Hidi and Renninger's (2006) four-phase model of interest development. Such "bottom-up" processes would imply that repeated experiences of high levels of expected success and valuing of similar math tasks would lead to high domain-specific expectancies and task values towards math in general (see also Moeller et al., 2022). On the other hand, once more stable and generalized motivational beliefs are established, it is likely that these motivational beliefs also affect students' situation-specific expectancies and task values. For instance, students who are good at math and find math generally interesting may be more likely to be interested in a specific math task in class compared with their peers with lower levels of self-concept and interest in math. Similarly, these high levels of domain-specific motivational beliefs may also buffer these students from experiencing fluctuations and declines in their situation-specific motivational beliefs (see, for instance, Study 1). Such "top-down" processes are also in line with the assumptions of SEVT because more global self-concepts of ability and identity-related beliefs are posited to be key factors influencing students' expectancy of success and task values for a given task or domain (Eccles et al., 1983; see also Moeller et al., 2022).

However, to date, little is known about the interplay of students' situation-specific and domain-specific expectancy-value beliefs. This is an important gap in the literature because interindividual differences in students' more global, domain-specific motivational beliefs are key factors contributing to interindividual differences in students' long-term educational and occupational choices (Eccles et al., 1983; Lüdtke & Robitzsch, 2021). Yet, important situation-specific experiences that cause within-person fluctuations in students' situation-specific motivations, such as the motivational shock students experienced in Study 1b or other formative experiences in a given educational context, are likely to shape students' more global, domain-specific motivational beliefs (Dietrich et al., 2019). Thus, more research is needed on the interplay of situational and domain-specific expectancies and task values and whether these beliefs become increasingly well-aligned over time. In order to address these questions, appropriate methodology is needed, including analytical approaches that separate state- vs. trait variability in students' expectancy-value beliefs (e.g., latent state-trait models; Eid et al., 2017; Geiser et al., 2017) and repeated simultaneous assessments of situation- and domain-specific motivational beliefs to examine the role of top-down vs. bottom-up processes (see, for example, Rentzsch & Schröder-Abé, 2022).

What is a "Situation"?

In order to examine the questions raised in the previous two sections, a clear understanding of the term "situation" is needed. Thus, an important next step for research on students' situation-specific expectancy-value beliefs and their developmental trajectories over time is to more purposefully define what a "situation" is (Eccles, 2022; see also Pekrun & Marsh, 2022). Prior research, particularly research using experience-sampling methodology, has primarily defined a situation as a "moment" in time and has thus focused mostly on moment-to-moment fluctuations in students' expectancies and task values (Eccles, 2022; for an example, see Dietrich et al., 2017). However, Eccles (2022) argued that such a definition of a situation does not fully capture important contextual factors, which are a key aspect of any situation according to Eccles and Wigfield (2020). Thus, Eccles (2022) proposed a differentiation of "moment" and "situation" and further argued that the type of variability captured by "moments" refers to unstable processes in a given context over time (i.e., random within-person fluctuations), whereas variability across "situations" takes into account key context characteristics and describes students' repeated experiences in similar contexts over time (e.g., bottom-up processes that capture the development of more stable, individual motivational beliefs).

In order to better align our research questions and study designs with the assumptions of SEVT, that is, in order to capture the "dynamics of the situation" (Eccles, 2022, p. 3), it is thus important for future research to define what a situation is in the educational context of interest. This includes more purposeful thinking about the timing of motivational assessments (e.g., immediately after an educational transition to capture motivational declines), the time lag between measurement points depending, for instance, on context-specific features (e.g., weekly worksheets), or the level of specificity of the motivational assessments depending on the type of process that researchers want to capture (e.g., alignment processes that require summative evaluations rather than situation-specific assessments that reference varying content). Defining these aspects of a situation in a specific context is necessary not only to better understand students' situation-specific expectancies and task values and their short-term developmental processes over time, but also to support students' motivation, achievement, well-being, and retention in these specific contexts (e.g., in the STEM domain).

3.5.2 Implications for Educational Practice

Several implications for educational practice can be derived from the results of the present dissertation, even though more research is needed to replicate and extend the key findings of the three empirical studies. First, the results of this dissertation have important implications for the design of motivational interventions grounded in SEVT. Specifically, motivational interventions targeting students' expectancy of success and subjective task values are needed in the early stages of math-intensive study programs because Study 1 revealed that students' expectancy-value beliefs declined rapidly in the very first weeks of their studies. In line with the recommendations by Rosenzweig et al. (2022), the results of Study 1 and Study 3 suggest that motivational interventions are needed that target multiple facets of the expectancy-value framework, namely, both students' expectancy of success and their valuing of the course material in order to buffer students from motivational declines and increase their academic achievement and retention in STEM fields. Supporting students' expectancy of success seems particularly important given that within-person changes in students' expectancy of success predicted subsequent changes in their intrinsic and utility values in Study 3. In addition, since gender differences were most pronounced in students' expectancy of success across all studies, boosting female students' expected success may be most important for closing gender gaps in math-intensive STEM programs (see also Ellis et al., 2016; Sanabria & Penner, 2017). Specifically, in the early stages of students' STEM programs, it might be particularly important to emphasize that most students initially struggle with the high workload in their math-intensive study program and to help students reflect on their own progress rather than comparing their performance with the performance of their peers (Rosenzweig et al., 2022). The analyses in Studies 1a and 1b further suggested that students' expectancy of success and task values emerged as significant predictors of their exam performance, study program satisfaction, and (to some extent) course dropout. Thus, targeting both expectancies and task values might enhance the strength of the intervention due to unique and synergistic predictive effects of students' expectancies and task values on students' academic achievement, well-being, and retention in STEM fields (Rosenzweig et al., 2022). Interventions targeting students' subjective task values grounded in SEVT have mostly aimed at boosting students' perceived utility of the learning content (e.g., Canning et al., 2018; Gaspard, Dicke, Flunger, Brisson, et al., 2015) but more recently cost reduction interventions have also been developed (Rosenzweig et al., 2020). These interventions have been shown to improve college students' academic achievement and retention in STEM fields (Canning et al., 2018; Kosovich et al., 2019; Rosenzweig et al., 2020), although more work is needed to better understand under which context-specific conditions and for whom these motivational interventions based on SEVT work (Rosenzweig et al., 2022).

Second, other types of interventions beyond motivational interventions could be implemented to mitigate motivational declines shortly after the transition to math-intensive STEM programs. For instance, intervention measures could target students' expectations about their math-intensive study programs prior to the beginning of postsecondary education. Consistent with prior research (Gueudet, 2008; Hasenberg & Schmidt-Atzert, 2013; Rach & Heinze, 2017), the motivational shock in Study 1b suggested that students might have started their math-intensive study program with unrealistic expectations about the type of math and day-to-day coursework and poorly calibrated expectancies of success. Thus, providing students with information about the content and structure of study programs that they are planning to enroll in may be one way of calibrating students' expectations about their study program prior to the beginning of their studies. For instance, Stoll and Spinath (2015) found that students who participated in online self-assessments prior to university entry reported significantly more realistic expectations regarding their study program at the beginning of their studies compared with students who did not participate in such online self-assessments. In addition, more realistic expectations at the beginning of one's studies were significantly positively associated with students' study choice satisfaction and achievement, and negatively associated with students' dropout intentions at the end of their first semester at the university. Taken together, these results suggest that more realistic study expectations might be a way to reduce motivational declines and support students' achievement and study satisfaction in the introductory phase in postsecondary education settings.

Lastly, instead of implementing intervention measures aimed at supporting students' motivation or realistic expectations about their study program at the beginning of their studies, intervention measures could alternatively target the learning contexts and culture in math-intensive STEM programs (Eccles & Midgley, 1989; Rosenzweig et al., 2022). The analyses in Study 1b suggested that the first performance feedback students received on their weekly mandatory math worksheets contributed to the initial motivational shock. Students in gateway math courses typically need to pass these worksheets to qualify for the exam at the end of the semester (i.e., typically solve at least 50% of all problems correctly). Students with comparatively lower math achievement in high school might perceive these requirements as particularly stressful, leading them to copy the answers from their peers instead of trying to solve them on their own (Rach & Heinze, 2017). In addition, such assessment practices in gateway courses in STEM fields are often perceived as being misaligned with the course material and with instructors being indifferent about students' mastery of the course material, promoting a competitive culture in STEM fields (Weston et al., 2019). Thus, removing the performance threshold needed to qualify for the exam could free up resources for students to engage with the material without the need to worry about their level of achievement. The study sections, in which the solutions to the math problems are typically presented, could instead focus on teaching appropriate learning strategies and discussing specific steps of the solutions of the math problems that were difficult for students (e.g., stressing the importance of solving the problems on their own and discussing problematic steps; Rach & Heinze, 2017). Moving away from "traditional" lecture-based gateway math courses to more inclusive and interactive teaching methods would be another alternative to boost students' motivation in introductory math courses (e.g., peer instruction; Watkins & Mazur, 2013). Together, such interventions targeting the learning context in math-intensive STEM fields could be a first step in moving from a culture of competition to a culture of collaboration, and might be particularly beneficial to underrepresented students (e.g., female students, first generation students) in math-intensive STEM fields.

3.6 Conclusion

Low levels of motivation are a key factor contributing to high dropout rates in math-intensive study programs in STEM fields. Most dropout from math-intensive STEM fields occurs in the first year of postsecondary education and particularly after experiences of low interest and performance struggles in gateway math courses. Understanding the development of students' motivations in gateway math courses is thus not only an important objective to better understand the reasons for students' decisions to persist in or drop out of STEM fields, but also because students' motivational beliefs are malleable and can thus be targeted in motivational interventions to improve students' achievement and retention in STEM fields. Informed by Eccles and colleagues' situated expectancy-value theory, the goal of the present dissertation was to examine (a) short-term developmental processes of students' expectancies of success and subjective task values in gateway math courses shortly after the transition to higher education, (b) interindividual differences in these developmental processes, and (c) whether potential motivational changes across the first semester in math-intensive STEM programs significantly predicted students' study success at the end of their first semester in STEM fields. The central finding of the present work is that students experienced a motivational shock shortly after the transition to higher education in math-intensive STEM fields, which coincided with the students' first performance feedback on mandatory math worksheets. Analyses of within-person reciprocal links further suggest that negative deviations in students' expectancy from their personal baseline significantly predicted within-person declines in intrinsic and utility values half a semester later. The motivational shock emerged as a risk factor for low academic achievement, dissatisfaction with one's study program, and course dropout towards the end of the first semester. Female students and students with comparatively lower high school GPAs were at risk of more negative motivational trajectories, even though the motivational shock was experienced by the majority of all students. Additional gender differences were most pronounced in students' expectancy of success, suggesting trait-like differences between female and male students. Taken together, these results underscore the importance of short-term motivational declines as early warning signs of low academic achievement and dropout tendencies in math-intensive STEM programs, particularly for students at-risk for maladaptive motivational trajectories (e.g., female students). Motivational interventions are thus needed in the very early stages of students' postsecondary education in math-intensive STEM fields in order to increase students' study success and retention in STEM fields.

References II

Arens, A. K. (2021). Wertfacetten im Grundschulalter in drei Fächern: Differenzierung, Entwicklung, Geschlechtseffekte und Zusammenhänge zu Noten. *Zeitschrift für Pädagogische Psychologie, 35*(1), 32–52. https://doi.org/10.1024/1010-0652/a000257

Barron, K. E., & Hulleman, C. S. (2015). Expectancy-value-cost model of motivation. In J. S. Eccles & K. Salmela-Aro (Eds.), *International encyclopedia of social and behavioral sciences: Motivational psychology* (2nd ed., pp. 503–509). Elsevier. https://doi.org/10.1016/B978-0-08-097086-8.26099-6

Beyer, S. (1998). Gender differences in causal attributions by college students of performance on course examinations. *Current Psychology, 17*(4), 346–358.

Canning, E. A., Harackiewicz, J. M., Priniski, S. J., Hecht, C. A., Tibbetts, Y., & Hyde, J. S. (2018). Improving performance and retention in introductory biology with a utility-value intervention. *Journal of Educational Psychology, 110*(6), 834–849. https://doi.org/10.1037/edu0000244

Chen, X. (2013). *STEM attrition: College students' paths into and out of STEM fields. Statistical Analysis Report (NCES 2014-001)*. https://nces.ed.gov/pubs2014/2014001rev.pdf

Dietrich, J., Moeller, J., Guo, J., Viljaranta, J., & Kracke, B. (2019). In-the-moment profiles of expectancies, task values, and costs. *Frontiers in Psychology, 10*. https://doi.org/10.3389/fpsyg.2019.01662

Dietrich, J., Viljaranta, J., Moeller, J., & Kracke, B. (2017). Situational expectancies and task values: Associations with students' effort. *Learning and Instruction, 47*, 53–64. https://doi.org/10.1016/j.learninstruc.2016.10.009

Dresel, M., & Grassinger, R. (2013). Changes in achievement motivation among university freshmen. *Journal of Education and Training Studies, 1*(2), 159–173. https://doi.org/10.11114/jets.v1i2.147

Durik, A. M., Vida, M., & Eccles, J. S. (2006). Task values and ability beliefs as predictors of high school literacy choices: A developmental analysis. *Journal of Educational Psychology, 98*(2), 382–393. https://doi.org/10.1037/0022-0663.98.2.382

Eccles, J. S. (2005). Commentary: Studying the development of learning and task motivation. *Learning and Instruction, 15*(2), 161–171. https://doi.org/10.1016/j.learninstruc.2005.04.012

Eccles, J. S. (2009). Who am I and what am I going to do with my life? Personal and collective identities as motivators of action. *Educational Psychologist, 44*(2), 78–89. https://doi.org/10.1080/00461520902832368

Eccles, J. S. (2022). Commentary on within-person designs and motivational science. *Learning and Instruction*, Article 101662. https://doi.org/10.1016/j.learninstruc.2022.101662

Eccles, J. S., Adler, T., Futterman, R., Goff, S., Kaczala, C., Meece, J., & Midgley, C. (1983). Expectancies, values, and academic behaviors. In J. T. Spence (Ed.), *Achievement and achievement motives* (pp. 75–146). Freeman.

Eccles, J. S., & Midgley, C. (1989). Stage-environment fit: Developmentally appropriate classrooms for young adolescents. In C. Ames & R. Ames (Eds.), *Research on motivation in education: Goals and cognitions* (Vol. 3, pp. 139–186). Academic Press.

Eccles, J. S., & Wigfield, A. (1995). In the mind of the actor: The structure of adolescents' achievement task values and expectancy-related beliefs. *Personality and Social Psychology Bulletin, 21*(3), 215–225. https://doi.org/10.1177/0146167295213003

Eccles, J. S., & Wigfield, A. (2020). From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation. *Contemporary Educational Psychology, 61*, Article 101859. https://doi.org/10.1016/j.cedpsych.2020.101859

Eid, M., Holtmann, J., Santangelo, P., & Ebner-Priemer, U. (2017). On the definition of latent-state-trait models with autoregressive effects: Insights from LST-R theory. *European Journal of Psychological Assessment, 33*(4), 285–295. https://doi.org/10.1027/1015-5759/a000435

Ellis, J., Fosdick, B. K., & Rasmussen, C. (2016). Women 1.5 times more likely to leave STEM pipeline after calculus compared to men: Lack of mathematical confidence a potential culprit. *PloS one, 11*(7), e0157447.

Ertl, B., Luttenberger, S., & Paechter, M. (2017). The impact of gender stereotypes on the self-concept of female students in STEM subjects with an under-representation of females. *Frontiers in Psychology, 8*. https://doi.org/10.3389/fpsyg.2017.00703

Fleischer, J., Leutner, D., Brand, M., Fischer, H., Lang, M., Schmiemann, P., & Sumfleth, E. (2019). Vorhersage des Studienabbruchs in naturwissenschaftlich-technischen Studiengängen. *Zeitschrift für Erziehungswissenschaft, 22*(5), 1077–1097. https://doi.org/10.1007/s11618-019-00909-w

Gasiewski, J. A., Eagan, M. K., Garcia, G. A., Hurtado, S., & Chang, M. J. (2012). From gatekeeping to engagement: A multicontextual, mixed method study of student academic engagement in introductory STEM courses. *Research in higher education, 53*(2), 229–261. https://doi.org/10.1007/s11162-011-9247-y

Gaspard, H., Dicke, A.-L., Flunger, B., Brisson, B. M., Häfner, I., Nagengast, B., & Trautwein, U. (2015). Fostering adolescents' value beliefs for mathematics with a relevance intervention in the classroom. *Developmental Psychology, 51*(9), 1226–1240. https://doi.org/10.1037/dev0000028

Gaspard, H., Dicke, A.-L., Flunger, B., Schreier, B., Häfner, I., Trautwein, U., & Nagengast, B. (2015). More value through greater differentiation: Gender differences in value beliefs about math. *Journal of Educational Psychology, 107*(3), 663–677. https://doi.org/10.1037/edu0000003

Gaspard, H., Lauermann, F., Rose, N., Wigfield, A., & Eccles, J. S. (2020). Cross-domain trajectories of students' ability self-concepts and intrinsic values in math and language arts. *Child Development, 91*(5), 1800–1818. https://doi.org/10.1111/cdev.13343

Gaspard, H., Wigfield, A., Jiang, Y., Nagengast, B., Trautwein, U., & Marsh, H. W. (2018). Dimensional comparisons: How academic track students' achievements are related to their expectancy and value beliefs across multiple domains. *Contemporary Educational Psychology, 52*, 1–14. https://doi.org/10.1016/j.cedpsych.2017.10.003

Geiser, C., Götz, T., Preckel, F., & Freund, P. A. (2017). States and traits: Theories, models, and assessment. *European Journal of Psychological Assessment, 33*(4), 219–223. https://doi.org/10.1027/1015-5759/a000413

Gueudet, G. (2008). Investigating the secondary–tertiary transition. *Educational Studies in Mathematics, 67*(3), 237–254. https://doi.org/10.1007/s10649-007-9100-6

Guo, J., Marsh, H. W., Parker, P. D., Morin, A. J., & Yeung, A. S. (2015). Expectancy-value in mathematics, gender and socioeconomic background as predictors of achievement and aspirations: A multi-cohort study. *Learning and Individual Differences, 37*, 161–168. https://doi.org/10.1016/j.lindif.2015.01.008

Guo, J., Parker, P. D., Marsh, H. W., & Morin, A. J. (2015). Achievement, motivation, and educational choices: A longitudinal study of expectancy and value using a multiplicative perspective. *Developmental Psychology, 51*(8), 1163–1176. https://doi.org/10.1037/a0039440

Hamaker, E. L., Kuiper, R. M., & Grasman, R. P. (2015). A critique of the cross-lagged panel model. *Psychological Methods, 20*(1), 102–116. https://doi.org/10.1037/a0038889

Harackiewicz, J. M., Canning, E. A., Tibbetts, Y., Priniski, S. J., & Hyde, J. S. (2016). Closing achievement gaps with a utility-value intervention: Disentangling race and social class. *Journal of Personality and Social Psychology, 111*(5), 745–765. https://doi.org/10.1037/pspp0000075

Hardin, E. E., & Longhurst, M. O. (2016). Understanding the gender gap: Social cognitive changes during an introductory stem course. *Journal of Counseling Psychology, 63*(2), 233–239. https://doi.org/10.1037/cou0000119

Harter, S. (1990). Causes, correlates, and the functional role of global self-worth: A life-span perspective. In R. J. Sternberg & J. Kolligian (Eds.), *Competence considered.* (pp. 67–97). Yale University Press.

Hasenberg, S., & Schmidt-Atzert, L. (2013). Die Rolle von Erwartungen zu Studienbeginn: Wie bedeutsam sind realistische Erwartungen über Studieninhalte und Studienaufbau für die Studienzufriedenheit? *Zeitschrift für Pädagogische Psychologie, 27*(1-2), 87–93. https://doi.org/10.1024/1010-0652/a000091

Heublein, U., Ebert, J., Hutzsch, C., Isleib, S., König, R., Richter, J., & Woisch, A. (2017). *Zwischen Studienerwartungen und Studienwirklichkeit: Ursachen des Studienabbruchs, beruflicher Verbleib der Studienabbrecherinnen und Studienabbrecher und Entwicklung der Studienabbruchquote an deutschen Hochschulen*. https://www.dzhw.eu/pdf/pub_fh/fh-201701.pdf

Hidi, S., & Renninger, K. A. (2006). The Four-Phase Model of Interest Development. *Educational Psychologist, 41*(2), 111–127. https://doi.org/10.1207/s15326985ep4102_4

Isphording, I., & Qendrai, P. (2019). *Gender differences in student dropout in STEM (IZA research report no. 87)*. http://ftp.iza.org/report_pdfs/iza_report_87.pdf

Johnson, M. L., Edwards, O. V., & Dai, T. (2014). Growth trajectories of task value and self-efficacy across an academic semester. *Universal Journal of Educational Research, 2*(1), 10–18. https://doi.org/10.13189/ujer.2014.020102

Kosovich, J. J., Flake, J. K., & Hulleman, C. S. (2017). Short-term motivation trajectories: A parallel process model of expectancy-value. *Contemporary Educational Psychology, 49*, 130–139. https://doi.org/10.1016/j.cedpsych.2017.01.004

Kosovich, J. J., Hulleman, C. S., Phelps, J., & Lee, M. (2019). Improving algebra success with a utility-value intervention. *Journal of Developmental Education, 42*(2), 2–10.

Kryshko, O., Fleischer, J., Grunschel, C., & Leutner, D. (2022). Self-efficacy for motivational regulation and satisfaction with academic studies in STEM undergraduates: The mediating role of study motivation. *Learning and Individual Differences, 93*, Article 102096. https://doi.org/10.1016/j.lindif.2021.102096

Lauermann, F., Chow, A., & Eccles, J. S. (2015). Differential effects of adolescents' expectancy and value beliefs about math and english on math/science-related and human services-related career plans. *International Journal of Gender, Science and Technology, 7*(2), 205–228.

Lüdtke, O., & Robitzsch, A. (2021). *A critique of the random intercept cross-lagged panel model*. PsyArXiv. https://doi.org/10.31234/osf.io/6f85c

Malmberg, L.-E., Lim, W. H., Tolvanen, A., & Nurmi, J.-E. (2016). Within-students variability in learning experiences, and teachers' perceptions of students' task-focus. *Frontline Learning Research, 4*(5), 62–82. https://doi.org/10.14786/flr.v4i5.227

McArdle, J. J. (2009). Latent variable modeling of differences and changes with longitudinal data. *Annual Review of Psychology, 60*, 577–605. https://doi.org/10.1146/annurev.psych.60.110707.163612

Meyer, J., & Strauß, S. (2019). The influence of gender composition in a field of study on students' drop-out of higher education. *European Journal of Education, 54*(3), 443–456. https://doi.org/10.1111/ejed.12357

Moeller, J., Viljaranta, J., Tolvanen, A., Kracke, B., & Dietrich, J. (2022). Introducing the DYNAMICS framework of moment-to-moment development in achievement motivation. *Learning and Instruction*, Article 101653. https://doi.org/10.1016/j.learninstruc.2022.101653

Murphy, M. C., Steele, C. M., & Gross, J. J. (2007). Signaling threat: How situational cues affect women in math, science, and engineering settings. *Psychological Science, 18*(10), 879–885. https://doi.org/10.1111/j.1467-9280.2007.01995.x

Nagy, G., Trautwein, U., Baumert, J., Köller, O., & Garrett, J. (2006). Gender and Course Selection in Upper Secondary Education: Effects of academic self-concept and intrinsic value. *Educational Research and Evaluation, 12*(4), 323–345. https://doi.org/10.1080/13803610600765687

Pekrun, R., & Marsh, H. W. (2022). Research on situated motivation and emotion: Progress and open problems. *Learning and Instruction*, Article 101664. https://doi.org/10.1016/j.learninstruc.2022.101664

Perez, T., Cromley, J. G., & Kaplan, A. (2014). The role of identity development, values, and costs in college STEM retention. *Journal of Educational Psychology, 106*(1), 315–329. https://doi.org/10.1037/a0034027

Perez, T., Wormington, S. V., Barger, M. M., Schwartz-Bloom, R. D., Lee, Y. k., & Linnenbrink-Garcia, L. (2019). Science expectancy, value, and cost profiles and their proximal and distal relations to undergraduate science, technology, engineering, and math persistence. *Science Education, 103*(2), 264–286. https://doi.org/10.1002/sce.21490

Rach, S., & Heinze, A. (2011). Studying mathematics at the university: the influence of learning strategies. In B. Ubuz (Ed.), *Proceedings of the 35th Conference of the International Group for the Psychology of Mathematics Education: Vol. 4* (pp. 9–16).

Rach, S., & Heinze, A. (2017). The transition from school to university in mathematics: Which influence do school-related variables have? *International Journal of Science and Mathematics Education, 15*(7), 1343–1363. https://doi.org/10.1007/s10763-016-9744-8

Ramsey, L. R., & Sekaquaptewa, D. (2011). Changing stereotypes, changing grades: A longitudinal study of stereotyping during a college math course. *Social Psychology of Education, 14*(3), 377–387. https://doi.org/10.1007/s11218-010-9150-y

Rentzsch, K., & Schröder-Abé, M. (2022). Top down or bottom up? Evidence from the longitudinal development of global and domain-specific self-esteem in adulthood. *Journal of Personality and Social Psychology, 122*(4), 714–730. https://doi.org/10.1037/pspp0000393

Robinson, K. A., Lee, S. Y., Friedman, S., Christiaans, E., McKeague, M., Pavelka, L., & Sirjoosingh, P. (2022). "You know what, I can do this": Heterogeneous joint trajectories of expectancy for success and attainment value in chemistry. *Contemporary Educational Psychology, 69*, Article 102055. https://doi.org/10.1016/j.cedpsych.2022.102055

Robinson, K. A., Lee, Y.-k., Bovee, E. A., Perez, T., Walton, S. P., Briedis, D., & Linnenbrink-Garcia, L. (2019). Motivation in transition: Development and roles of expectancy, task values, and costs in early college engineering. *Journal of Educational Psychology, 111*(6), 1081–1102. https://doi.org/10.1037/edu0000331

Robinson, K. A., Lira, A. K., Walton, S. P., Briedis, D., & Linnenbrink-Garcia, L. (2022). Instructional Supports for Motivation Trajectories in Introductory College Engineering. *AERA Open, 8*(1), 1–18. https://doi.org/10.1177/23328584221083662

Robinson, M. D., & Clore, G. L. (2002). Belief and feeling: Evidence for an accessibility model of emotional self-report. *Psychological Bulletin, 128*(6), 934–960. https://doi.org/10.1037/0033-2909.128.6.934

Rosenzweig, E. Q., Wigfield, A., & Eccles, J. S. (2022). Beyond utility value interventions: The why, when, and how for next steps in expectancy-value intervention research. *Educational Psychologist, 57*(1), 11–30. https://doi.org/10.1080/00461520.2021.1984242

Rosenzweig, E. Q., Wigfield, A., & Hulleman, C. S. (2020). More useful or not so bad? Examining the effects of utility value and cost reduction interventions in college physics. *Journal of Educational Psychology, 112*(1), 166–182. https://doi.org/10.1037/edu0000370

Sanabria, T., & Penner, A. (2017). Weeded Out? Gendered Responses to Failing Calculus. *Social Sciences, 6*(2), Article 47. https://doi.org/10.3390/socsci6020047

Schurtz, I. M., Pfost, M., Nagengast, B., & Artelt, C. (2014). Impact of social and dimensional comparisons on student's mathematical and English subject-interest at the beginning of secondary school. *Learning and Instruction, 34*, 32–41. https://doi.org/10.1016/j.learninstruc.2014.08.001

Seymour, E., & Hewitt, N. (1997). *Talking about leaving: Why undergraduates leave the sciences*. Westview Press.

Shaw, E. J., & Barbuti, S. (2010). Patterns of persistence in intended college major with a focus on STEM majors. *NACADA Journal, 30*(2), 19–34. https://doi.org/10.12930/0271-9517-30.2.19

Sonnert, G., Sadler, P. M., Sadler, S. M., & Bressoud, D. M. (2015). The impact of instructor pedagogy on college calculus students' attitude toward mathematics. *International Journal of Mathematical Education in Science and Technology, 46*(3), 370–387. https://doi.org/10.1080/0020739X.2014.979898

Spinath, B., & Steinmayr, R. (2008). Longitudinal analysis of intrinsic motivation and competence beliefs: Is there a relation over time? *Child Development, 79*(5), 1555–1569. https://doi.org/10.1111/j.1467-8624.2008.01205.x

Steinmayr, R., & Spinath, B. (2010). Konstruktion und erste Validierung einer Skala zur Erfassung subjektiver schulischer Werte (SESSW). *Diagnostica, 56*(4), 195–211. https://doi.org/10.1026/0012-1924/a000023

Stoll, G., & Spinath, F. (2015). Unterstützen Self-Assessments die Studienfachwahl? Erfahrungen und Befunde aus dem Projekt Study-Finder. In A. Hanft, O. Zawacki-Richter, & W. B. Gierke (Eds.), *Herausforderung Heterogenität beim Übergang in die Hochschule* (pp. 113–131). Waxmann.

Totonchi, D. A., Perez, T., Lee, Y.-k., Robinson, K. A., & Linnenbrink-Garcia, L. (2021). The role of stereotype threat in ethnically minoritized students' science motivation: A four-year longitudinal study of achievement and persistence in STEM. *Contemporary Educational Psychology, 67*, Article 102015. https://doi.org/10.1016/j.cedpsych.2021.102015

Watkins, J., & Mazur, E. (2013). Retaining Students in Science, Technology, Engineering, and Mathematics (STEM) Majors. *Journal of College Science Teaching, 42*(5), 36–41. http://www.jstor.org/stable/43631580

Watt, H. M. (2004). Development of adolescents' self-perceptions, values, and task perceptions according to gender and domain in 7th-through 11th-grade Australian students. *Child Development, 75*(5), 1556–1574. https://doi.org/10.1111/j.1467-8624.2004.00757.x

Weston, T. J., Seymour, E., Koch, A. K., & Drake, B. M. (2019). Weed-Out Classes and Their Consequences. In E. Seymour & A.-B. Hunter (Eds.), *Talking about Leaving Revisited: Persistence, Relocation, and Loss in Undergraduate STEM Education* (pp. 197–243). Springer International Publishing. https://doi.org/10.1007/978-3-030-25304-2_7

Wigfield, A. (1994). Expectancy-value theory of achievement motivation: A developmental perspective. *Educational Psychology Review, 6*(1), 49–78. https://doi.org/10.1007/BF02209024

Wigfield, A., & Cambria, J. (2010). Expectancy-value theory: Retrospective and prospective. In T. C. Urdan & S. A. Karabenick (Eds.), *The decade ahead: Theoretical perspectives on motivation and achievement* (pp. 35–70). Emerald Group Publishing Limited. https://doi.org/10.1108/S0749-7423(2010)000016A005

Wigfield, A., & Eccles, J. S. (1992). The development of achievement task values: A theoretical analysis. *Developmental Review, 12*(3), 265–310. https://doi.org/10.1016/0273-2297(92)90011-P

Wigfield, A., & Eccles, J. S. (2020). 35 years of research on students' subjective task values and motivation: A look back and a look forward. In A. Elliot (Ed.), *Advances in motivation science* (Vol. 7, pp. 161–198). Elsevier. https://doi.org/10.1016/bs.adms.2019.05.002

Wigfield, A., Eccles, J. S., & Möller, J. (2020). How dimensional comparisons help to understand linkages between expectancies, values, performance, and choice. *Educational Psychology Review, 32*(3), 657–680. https://doi.org/10.1007/s10648-020-09524-2

Wigfield, A., Eccles, J. S., Yoon, K. S., Harold, R. D., Arbreton, A. J. A., Freedman-Doan, C., & Blumenfeld, P. C. (1997). Change in children's competence beliefs and subjective task values across the elementary school years: A 3-year study. *Journal of Educational Psychology, 89*(3), 451–469. https://doi.org/10.1037/0022-0663.89.3.451

Zusho, A., Pintrich, P. R., & Coppola, B. (2003). Skill and will: The role of motivation and cognition in the learning of college chemistry. *International Journal of Science Education, 25*(9), 1081–1094. https://doi.org/10.1080/0950069032000052207

4 Appendix

4.1 Übersicht der Einzelarbeiten

Benden, D. K., & Lauermann, F. (2022). Students' motivational trajectories and academic success in math-intensive study programs: Why short-term motivational assessments matter. *Journal of Educational Psychology, 114*(5), 1062–1085. https://doi.org/10.1037/edu0000708

Benden, D. K. & Lauermann, F. (2022). Geschlechtsunterschiede in der Variabilität situationsspezifischer Erwartungs- und Wertüberzeugungen und selbsteingeschätzter Leistung in mathematikintensiven Studienfächern. In F. Lauermann, C. Jöhren, N. McElvany, M. Becker, & H. Gaspard (Hrsg.), *Jahrbuch der Schulentwicklung (Band 22): Multiperspektivität von Unterrichtsprozessen* (S. 184–213). Beltz Juventa.

Benden, D. K., & Lauermann, F. (2022). *Searching for Short-Term Motivational Spillover Effects: A Random Intercept Cross-Lagged Panel Analysis of Students' Expectancies and Task Values in Math-Intensive Study Programs*. PsyArXiv. https://doi.org/10.31234/osf.io/buv9a

4.2 Eigenanteile der Doktorandin bei den Einzelarbeiten

Im Folgenden werden für die drei Einzelarbeiten die Eigenanteile der Doktorandin beschrieben. Dabei wird auf die folgenden Aspekte eingegangen: Formulierung der Fragestellung, Konzeption der Studie, Durchführung und Auswertung der Studie und Verfassen des Beitrags.

4.2.1 Veröffentlichte Beiträge der kumulativen Dissertation

Beitrag 1:

Benden, D. K., & Lauermann, F. (2022). Students' motivational trajectories and academic success in math-intensive study programs: Why short-term motivational assessments matter. *Journal of Educational Psychology, 114*(5), 1062–1085. https://doi.org/10.1037/edu0000708

- *Formulierung der Fragestellung:* Die Fragestellung wurde von Daria Katharina Benden und Fani Lauermann gemeinsam formuliert.
- *Konzeption der Studie:* Die Studie wurde von Daria Katharina Benden und Fani Lauermann gemeinsam konzeptuell entworfen.
- *Durchführung und Auswertung der Studie:* Die Studie sowie die statistischen Analysen wurden vollständig von Daria Katharina Benden durchgeführt.
- *Verfassen des Beitrags:* Der Beitrag wurde von Daria Katharina Benden verfasst. Fani Lauermann war beratend tätig und hat Feedback zu früheren Textentwürfen gegeben.

Beitrag 2:

Benden, D. K. & Lauermann, F. (2022). Geschlechtsunterschiede in der Variabilität situationsspezifischer Erwartungs- und Wertüberzeugungen und selbsteingeschätzter Leistung in mathematikintensiven Studienfächern. In F. Lauermann, C. Jöhren, N. McElvany, M. Becker, & H. Gaspard (Hrsg.), *Jahrbuch der Schulentwicklung (Band 22): Multiperspektivität von Unterrichtsprozessen* (S. 184–213). Beltz Juventa.

- *Formulierung der Fragestellung:* Die Fragestellung wurde von Daria Katharina Benden und Fani Lauermann gemeinsam formuliert.
- *Konzeption der Studie:* Die Studie wurde von Daria Katharina Benden und Fani Lauermann gemeinsam konzeptuell entworfen.
- *Durchführung und Auswertung der Studie:* Die Studie sowie die statistischen Analysen wurden vollständig von Daria Katharina Benden durchgeführt.
- *Verfassen des Beitrags:* Der Beitrag wurde von Daria Katharina Benden verfasst. Fani Lauermann war beratend tätig und hat Feedback zu früheren Textentwürfen gegeben.

4.2.2 Beiträge zu weiteren Analysen

Beitrag 3:

Benden, D. K., & Lauermann, F. (2022). *Searching for Short-Term Motivational Spillover Effects: A Random Intercept Cross-Lagged Panel Analysis of Students' Expectancies and Task Values in Math-Intensive Study Programs*. PsyArXiv. https://doi.org/10.31234/osf.io/buv9a

- *Formulierung der Fragestellung:* Die Fragestellung wurde von Daria Katharina Benden und Fani Lauermann gemeinsam formuliert.
- *Konzeption der Studie:* Die Studie wurde von Daria Katharina Benden und Fani Lauermann gemeinsam konzeptuell entworfen.
- *Durchführung und Auswertung der Studie:* Die Studie sowie die statistischen Analysen wurden vollständig von Daria Katharina Benden durchgeführt.
- *Verfassen des Beitrags:* Der Beitrag wurde von Daria Katharina Benden verfasst. Fani Lauermann war beratend tätig und hat Feedback zu früheren Textentwürfen gegeben.

4.3 Eidesstattliche Erklärung

Hiermit versichere ich **schriftlich** und **eidesstattlich** gemäß § 11 Abs. 2 PromO v. 08.02.2011/08.05.2013:

1. Die von mir vorgelegte Dissertation ist selbstständig verfasst und alle in Anspruch genommenen Quellen und Hilfen sind in der Dissertation vermerkt worden.
2. Die von mir eingereichte Dissertation ist weder in der gegenwärtigen noch in einer anderen Fassung an der Technischen Universität Dortmund oder an einer anderen Hochschule im Zusammenhang mit einer staatlichen oder akademischen Prüfung vorgelegt worden.

Ort, Datum　　　　　　　　　　Unterschrift

3. Weiterhin erkläre ich **schriftlich** und **eidesstattlich**, dass mir der „Ratgeber zur Verhinderung von Plagiaten“ und die „Regeln guter wissenschaftlicher Praxis der Technischen Universität Dortmund“ bekannt und von mir in der vorgelegten Dissertation befolgt worden sind.

Ort, Datum　　　　　　　　　　Unterschrift