technische universität
dortmund

Do I want to work with this AI?

A closer look at an individual's personality, AI advice framing, and historical AI performance in an unrelated task

DISSERTATION

submitted in partial fulfillment of the requirement for the

degree of doctor rerum politicarum (Dr. rer. pol.) at the

Department of Business and Economics

of the TU Dortmund University

by

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After a successful oral examination, this dissertation was approved by the examination committee consisting of Prof. Dr. Lorenz Graf-Vlachy, Prof. Dr. Andreas Fügener, and Prof. Dr. Manuel Wiesche, on the 28th of October 2024, in Dortmund, Germany.

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Summary

As many economies transition to Industry 4.0, Artificial Intelligences (AIs) permeate the workflows of countless organizations. While organizations often implement AIs as decision support systems, their employees frequently seem to fail at fully leveraging the potential of their new decision aids. In an attempt to help organizations reap more of the benefits of AIs as decision support systems, research has started to investigate antecedents of the willingness to collaborate with AIs. However, important questions regarding these antecedents remain and this dissertation aspires to reduce the number of open questions.

Data from 3,169 participants across five experiments offer insights into four areas. Firstly, findings align with theoretical expectations that personality, as defined by the Big Five personality traits, influences use of AI advice. Secondly, while persuasive message framing positively impacts use of algorithmic advice, customizing the AI's message to match an individual's personality (regulatory focus) does not alter the effect. Thirdly, individuals show a consistent preference for AI over human collaboration, regardless of the counterparts' historical relative performance compared to the individual in an unrelated task. Additionally, superior AI performance relative to the individual in an unrelated task decreases willingness to collaborate. Fourthly, the type of support for an opponent – be it a human, a non-human-like AI, or a human-like AI – does not influence a focal person's competitive irrationality.

My work bears considerable implications for both theory and practice. Regarding the former, my findings expand literature by experimentally testing and empirically supporting new antecedents of the willingness to collaborate with AIs and for the actual collaboration with AIs. Regarding the latter, my findings can help organizations and economies reap more of the large potential of AIs as decision support systems for humans. Lastly, I stimulate various future research avenues that may shine more light on this work's important focus.

Acknowledgements

This dissertation is the product of a ~2.5 year-long journey and I am deeply thankful for the many people who accompanied me and made this dissertation possible.

Firstly, I would like to thank my “Doktorvater” Prof. Dr. Lorenz Graf-Vlachy for investing your time and energy in supervising me. The number of edits and comments on my written pieces was intimidating at times, showed your commitment as an advisor as well as a dedicated researcher, and certainly pushed our papers to new heights. Having seen different supervising models, I highly appreciate how available and involved you were from start to finish of this dissertation.

Secondly, I would like to thank Prof. Dr. Andreas Fügener for co-supervising all my papers. You were always available when needed and your high-level ideas were sometimes difficult to grasp, but they drastically improved the quality of our papers.

Thirdly, I am grateful for my doctoral cohort, who supported me through brainstorming sessions, proofreading papers, and discussing dissertation-related challenges. My thanks extend to, but are not limited to, the cohort at the TU Dortmund University, the University of Cologne, and the Cologne office of the Boston Consulting Group.

Fourthly, I would like to thank the Boston Consulting Group and the “Stiftung der Deutschen Wirtschaft” for providing office facilities, financial support, and training throughout my doctoral studies.

Fifthly, I am deeply grateful for my friends and family supporting me along the way. You might have shared an office with me, forced me into power hours, challenged my research ideas with common sense thoughts, discussed optimization methods, laughed, cried, shined a light in difficult times, or danced the night away with me. While some of you are very different from me, you always respected and supported my path. I am deeply thankful for the gift of calling you my friends and family.

Overview of Research Papers

Research Paper 1 – The Type to Listen to the Machine? The Effect of Personality on the Use of AI Advice

- Asbach, S., Graf-Vlachy, L., Fügener. A. (2023). Accepted and presented at the 18th International Conference for Business Informatics (WI23). Published in the proceedings of the same conference. Paper Number: 324.
- https://aisel.aisnet.org/wi2023/70

Research Paper 2 – Seizing the Potential of Algorithms: The Power of Personalized Persuasive Messages on the Use of Algorithmic Advice

- Asbach, S., Graf-Vlachy, L., Fügener. A. (2023). Accepted and presented at the 18th International Conference for Business Informatics (WI23). Published in the proceedings of the same conference. Paper Number: 320.
- https://aisel.aisnet.org/wi2023/68

Research Paper 3 – Can Superior AI Performance Reduce People's Willingness to Collaborate With the AI? A Closer Look at Relative Performance in Unrelated Tasks

- Asbach, S., Graf-Vlachy, L., Fügener. A. (2024). Accepted and presented at the 33rd European Conference for Information Systems (ECIS 2025). Published in the proceedings of the same conference. Paper Number: ECIS2025-1967.
- https://aisel.aisnet.org/ecis2025/human_ai/human_ai/1

Research Paper 4 – Does AI Reduce Competitive Irrationality? The Effect of the Opponent's AI Support

- Asbach, S., Graf-Vlachy, L., Fügener. A. (2023). Submitted to the 34th European Conference for Information Systems (ECIS 2026).

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List of Abbreviations and Acronyms

ANOVA	Analysis of Variance
AI	Artificial Intelligence
BFI	Big Five Inventory
CASA	Computers are Social Actors Paradigm
DV	Dependent Variable
GLM	General Linear Model
IE	Indirect Effect
IV	Independent Variable
JAS	Judge Advisor System
MTurk	Mechanical Turk
OLS	Ordinary Least Squares
SD	Standard Deviation
SE	Standard Error
WOA	Weight on Advice

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1 Introduction

Artificial Intelligence (AI) systems are at the heart of the fourth industrial revolution (Industry 4.0), widely integrating into the operations of many organizations. Organizations value AIs because their capabilities to perceive, reason, learn, solve problems, and make decisions lead to outcomes that often surpass human performance in terms of speed and cost efficiency (Acemoglu & Restrepo, 2019; Dawes et al., 1989; Rai et al., 2019; Topol, 2019). Since 2017, the adoption of AIs in organizations has surged, reaching 50% by 2022 (Chui et al., 2022), with projections indicating continued growth (Ellingrud et al., 2023). A notable instance is OpenAI's ChatGPT, which achieved a remarkable adoption rate of 80% by Fortune 500 companies within nine months of its launch (OpenAI, 2023). Responding to this demand, OpenAI introduced ChatGPT Enterprise in 2023, a tool extensively used by large corporations, including global management consultancies, for rapid analysis of extensive textual data to assist employees (George & George, 2023; OpenAI, 2023).

While AIs have permeated the workflows of countless organizations, their members often seem to fail at fully leveraging an AI's potential because they reject helpful advice of this powerful decision support system. For instance, in a major retail e-commerce company, employees frequently disregarded AI-based packing suggestions, missing opportunities for enhanced packing efficiency and reduced operational costs (Sun et al., 2021). Similarly, the 2015 crash of Google's autonomous car exemplifies suboptimal AI utilization: The driver manually applied the brakes instead of relying on the car's AI, which resulted in the car being hit from behind by a trailing car (Richtel & Dougherty, 2015). Lastly, even with superior algorithms, which should theoretically be followed at a rate of 100%, rates mostly hover around only 30%-50% (Logg et al., 2019).

Research has made advances in investigating antecedents of the willingness to collaborate with AIs to help companies reap more of the benefits of implementing AIs as decision support systems on a large scale. Antecedents that scholars have investigated include, but are not limited to, the human-likeness of AIs (Qiu & Benbasat, 2009; Schanke et al., 2021), the explainability of AIs (Bauer et al., 2023; Lehmann et al., 2022), the domain of the task at hand (Logg et al., 2019), the complementarity of AIs and their users (Fügener et al., 2021a, 2021b), and the absolute AI performance (Burton et al., 2020; Shin, 2020).

However, important questions regarding the antecedents of the willingness to collaborate with AIs remain (Kelly et al., 2023), and this dissertation aspires to reduce the number of open questions. My four research papers will each focus on one important area that is motivated by current research and practice. More specifically, I will test how an individual's personality affects the use of AI advice (research paper 1), how a user-personalized persuasive message that frames algorithmic advice affects the use of algorithmic advice (research paper 2), and how historical AI performance relative to the prospective user in an unrelated task affects the willingness to collaborate with this AI in a task at hand (research paper 3). Lastly, I will turn to a field that is closely related to collaboration with AIs, namely competition with AIs. More specifically, I will test how AI support for an opponent affects an individual's competitive irrationality (research paper 4).

Data from 3,169 participants across five experiments reveal insights along the four areas that I targeted. Firstly, results support theoretical predictions that an individual's personality, as measured by the Big Five personality traits, is associated with the use of AI advice. Secondly, while results support a positive effect of a persuasive message framing the algorithmic advice on the use of algorithmic advice, tailoring the message to an individual's personality (i.e., to their regulatory focus) does not affect the use of algorithmic advice. Thirdly, independent of the counterparts' historical relative performance compared to the individual in an unrelated task, people prefer to collaborate with an AI compared to a human in a task at hand. Additionally, superior compared to similar AI performance relative to the individual in an unrelated task affects an individual's willingness to collaborate with an AI negatively. Fourthly, results reveal that the type of an opponent's support – human, non-human-like AI, or human-like AI – does not affect an individual's competitive irrationality (i.e., irrational competitive behavior toward the opponent).

My research both contributes to literature and yields important practical implications. Regarding the former, my findings expand literature by experimentally testing new antecedents of the willingness to collaborate and for the actual collaboration with AIs. For example, while existing research argues that high absolute performance usually affects willingness to collaborate with AIs positively, I find that a parallel effect may not apply if an AI shows superior, as opposed to similar, performance compared to the individual in an unrelated task. This novel finding challenges the applicability of existing theories in a new and practically relevant context. Regarding practical implications, my findings help practitioners reap more of the large potential of AIs as decision support systems for numerous organizations and economies. For example, I provide empirical evidence that adding a persuasive message to an ex-ante perfect AI advice increases the use of this AI from previously 51% to 69%. This delta can have a large positive impact on an organization's performance.

2 Summary of Research Papers

The current chapter offers a concise summary of each of this dissertation's four research papers, setting the stage for the following chapters that will provide the full version of each research paper. In the final chapter, I will synthesize the main findings of this dissertation and discuss their implications as well as limitations. Additionally, I will offer concluding remarks.

2.1 Research Paper 1 – The Type to Listen to the Machine?

The first research paper is motivated by the potential role of an individual's personality in their use of AI advice. Psychological research indicates that personality substantially shapes humans' advice-taking behavior (Kausel et al., 2015; Schultze et al., 2018). Personality also appears to be central in the adoption and use of diverse AI systems, including robots and recommender systems (Esterwood et al., 2021; Tkalcic & Chen). While preliminary studies have started to unravel factors that lead to the imperfect use of AI advice, many questions remain. Notably, despite identified antecedents like increased trust and confidence in AI advice, the tendency to underutilize AI and algorithmic advice remains prevalent (Alvarado-Valencia & Barrero, 2014; Dietvorst et al., 2015; Logg et al., 2019). Furthermore, it is unclear if this underutilization is consistent among different individuals. Although some personality traits have been recognized as determinants in various behavioral domains, including decision-making (Ajzen, 2005; Lauriola & Levin, 2001), there is a lack of experimental research that comprehensively examines the effect of personality traits on the use of AI advice.

To understand the role of an individual's personality in their use of AI advice, I test the Big Five personality traits as antecedents of use of AI advice in an experimental study. I use the Big Five model as it is widely used and considered to comprehensively describe a person's personality structure (Costa & McCrae, 1992a, 1992b; Matthews et al., 2003; McCrae & Costa Jr., 2008). I gathered data from 595 participants, who performed a previously validated task that involved forecasting the demand for ten distinct products, both prior to and after receiving AI advice (Lehmann et al., 2022). I assessed the Big Five traits using the Big Five Inventory (BFI) (John et al., 1991; John et al., 2008).

My results support the idea that personality plays an important role in an individual's use of AI advice, bearing implications for both theory and practice. In line with my expectations, both agreeableness and neuroticism are positively associated with use of AI advice. Unexpectedly, however, openness is negatively associated with use of AI advice, while extraversion and conscientiousness appear to have no significant association. Despite some unexpected findings, the current paper adds to literature by exploring the underrepresented area of personality research in the field of use of AI advice. Thus, these findings show the promise of and open the path for, further personality research in this field. Moreover, this paper provides crucial insights that may be of use to practitioners and organizations in personalizing AI advice in an attempt to improve the use of these systems.

2.2 Research Paper 2 – Seizing the Potential of Algorithms

The second research paper builds upon the personality focus of the first paper and is motivated by the potential of tailoring AI advice to the user's personality in order to increase the use of superior algorithmic advice. Despite the advantages of algorithmic advice, humans often fail to fully reap the benefits of algorithms. Studies show that even when presented with a superior algorithm, which ideally should be followed completely, humans usually only follow its advice at a rate of 30%–50% (Logg et al., 2019). While research has made advances in increasing human use of algorithmic advice, these advances have had limited success. For example, increasing the transparency of a complex algorithm only marginally increases the use of its advice from 49% to 56% (even when 100% would have been optimal). Surprisingly, this transparency in simpler algorithms may even decrease the use of advice (Lehmann et al., 2022). Notably, research has not yet considered the role of user personality in finding concrete interventions to increase humans' use of advice from superior algorithms. This seems surprising because personality influences people's behavior to a large extent (Ajzen, 2005).

To increase the use of superior algorithmic advice, I collected data from 605 participants to experimentally test two ideas: (1) delivering algorithmic advice via a persuasive message and (2) tailoring the persuasive message to the user's regulatory focus orientation, i.e., tailoring the message to an important personality trait to create regulatory fit (Cesario et al., 2004; Higgins et al., 2003). Participants undertook the same task as described in research paper 1, namely a validated task that asks participants to forecast the demand for ten different products, before and after receiving advice from an algorithm (Lehmann et al., 2020). The algorithmic advice differed across three experimental conditions: (1) control condition without a persuasive message, (2) experimental condition with a persuasive message representing regulatory fit, and (3) experimental condition with a persuasive message representing non-fit. In addition to measuring the use of algorithmic advice, I measured participants' chronic regulatory focus, persuasiveness of the message, and trust in the algorithm.

My study yields both expected results and intriguing new insights, allowing us to contribute to theory and practice. As expected, I find that administering a persuasive message leads to increased use of algorithmic advice. This main effect is mediated by trust in the algorithm. However, contrary to expectations, I find that a message representing regulatory fit (versus a message representing non-fit) does not increase the use of advice. These results add to literature by providing a new theory and successfully testing its effectiveness to increase the use of superior algorithmic advice to a substantially higher level (51% to 69% on average) than any other study I know of. Regarding practical implications, humans regularly make the final call on whether to follow advice or not (Khosrowabadi et al., 2022; Perera et al., 2019), often leading to algorithms being ultimately undervalued (Dietvorst et al., 2015; Logg et al., 2019). My paper suggests persuasive messages as a powerful mitigation to this problem.

2.3 Research Paper 3 – A Closer Look at Relative AI Performance in Unrelated Tasks

The third paper of this dissertation broadens the personality perspective established in the first two papers, examining the influence of an AI's performance relative to the prospective user in an unrelated task on an individual's willingness to collaborate in a task at hand. Scholars highlight the importance of AI performance (Burton et al., 2020; Davis, 1989; Dietvorst et al., 2018; Shin, 2020) when attempting to increase the willingness to collaborate with AIs. For example, people use AIs less when they see them err (Dietvorst et al., 2015, 2018) and perceived competence in AI voice assistants correlates with greater intention to use them (Choung et al., 2023). However, the impact of an AI's relative performance in an unrelated task on the willingness to collaborate in a subsequent task remains unexplored. This is notable because superior AI performance, as opposed to similar, compared to the individual may reduce willingness to collaborate as individuals may resent counterparts that beat them (Garcia et al., 2013; Smith, 2000; Smith & Kim, 2007). This effect bears practical relevance because practitioners may use the increasing multi-functionality of AIs (Ko et al., 2023; Vanian, 2022) to promote AIs in new tasks through relative performance in unrelated tasks.

I collected data from 797 participants to experimentally test how superior historical AI performance in an unrelated task affects people's willingness to collaborate with an AI in the task at hand. More specifically, I tested (1) how historical relative AI performance in an unrelated task affects people's preference to collaborate with an AI compared to a human, and (2) whether superior AI performance, as opposed to similar performance, in an unrelated task increases willingness to collaborate with an AI. Additionally, I explored whether the two main effects can be explained by trust toward the relevant counterparts. To generate answers, I ran a

2 (human or AI as counterpart) x 2 (counterpart with superior performance or similar performance as the participant in an unrelated task) between-subjects design. I omitted an inferior performance condition because it seemed practically irrelevant: AIs that perform worse than individuals would most likely not be promoted in unrelated tasks. Further, I adapted a vignette from psychology (Garcia et al., 2006), manipulating performance by describing how the participant compared to the counterpart (either human or AI) performed in a fictional poker tournament. Following the vignette, participants indicated the likelihood to collaborate with the counterpart in an unrelated task.

My study provides two key insights with theoretical and practical implications. Firstly, people consistently prefer to collaborate with an AI compared to a human, independent of the counterparts' performance in a previous and unrelated task. Secondly, superior, as opposed to similar, AI performance in an unrelated task decreases people's willingness to collaborate with an AI. This effect is attributable to decreased trust in benevolence and integrity. Surprisingly, this effect is additionally partly due to decreased trust in competence toward an AI that shows superior, as opposed to similar, performance compared to the focal individual.

2.4 Research Paper 4 – Does AI Reduce Competitive Irrationality?

The fourth research paper broadens the scope of this dissertation's first three papers by investigating a different context: human competition against an opponent, who is supported by an AI. Historically, humans have mostly competed with other humans (Garcia et al., 2020; Garcia et al., 2013), but today, AI has become a new form of competitor (Bécue et al., 2021; Krakowski et al., 2023). Recent research has begun to understand how an AI system as an opponent affects the behavior of a focal human. For example, research has found that humans make lower bids when bidding and bargaining against computer counterparts (Adam et al., 2018; Häubl & Popkowski Leszczyc, 2019). Yet, the scenario of a human competing against another human supported by an AI remains unexplored. This is mainly surprising because humans are more likely to face human opponents using AI as a support tool rather than directly competing against an AI system. This context is largely due to ethical (Awad et al., 2018; Zhang et al., 2020) and legal (Kingston, 2016) reasons, where AI typically serves as a decision support system with humans making the final call.

Collecting data from 613 participants, I experimentally tested how AI support for a human opponent changes the behavior of the individual, with a particular focus on competitive irrationality. This concept refers to the behavioral tendency to prioritize relative gains over absolute ones, often resulting in suboptimal outcomes, such as overbidding in auctions despite no strategic benefit (Graf et al., 2012; Güth et al., 1982; Häubl & Popkowski Leszczyc, 2019; Ku et al., 2005; Malhotra, 2010). My experimental set-up involved four groups, incorporating human-like AIs in response to the growing trend among practitioners to design AI systems with human-like characteristics (Pelau et al., 2021). The two control groups pitted participants against a human opponent (1) without support and (2) with another human supporting the opponent. The two experimental groups pitted participants against a human opponent (3) with a non-human-like AI supporting the opponent and (4) a human-like AI supporting the opponent. I measured competitive irrationality by measuring the extent to which participants bid past a pre-set limit to win an auction against the opponent.

My study reveals both expected and unexpected findings. As expected, results indicate higher levels of competitive irrationality when competing with an unsupported opponent compared to an opponent with support (by a human or an AI system). Counter to expectations, the type of support – human, non-human-like AI, or human-like AI – does not seem to affect competitive irrationality. Lastly, as expected, desire to win partly explains competitive irrationality levels. These results challenge existing theories on how AI systems affect competitive irrationality. Prior research suggests that AI systems as opponents reduce competitive arousal compared to humans as opponents (Adam et al., 2018; Häubl & Popkowski Leszczyc, 2019). My study suggests that this effect does not transfer to a setting with high practical relevance, namely a setting in which AI systems support a human opponent. Thus, organizations should be warned that competitive irrationality may not vanish with the implementation of AIs as support systems for their employees.

3 Research Paper 1 – The Type to Listen to the Machine?

The Type to Listen to the Machine? The Effect of Personality on the Use of AI Advice

- Asbach, Simon; Graf-Vlachy, Lorenz; and Fügener, Andreas, "The Type to Listen to the Machine? The Effect of Personality on the Use of AI Advice" (2023). *Wirtschaftsinformatik 2023 Proceedings*. 70.
- https://aisel.aisnet.org/wi2023/70

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4 Research Paper 2 – Seizing the Potential of Algorithms

Seizing the Potential of Algorithms: The Power of Personalized Persuasive Messages on the Use of Algorithmic Advice

- Asbach, Simon; Graf-Vlachy, Lorenz; and Fügener, Andreas, "Seizing the Potential of Algorithms: The Power of Personalized Persuasive Messages on the Use of Algorithmic Advice" (2023). *Wirtschaftsinformatik 2023 Proceedings*. 68.
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5 Research Paper 3 – A Closer Look at Relative AI Performance in Unrelated Tasks

Can Superior AI Performance Reduce People's Willingness to Collaborate With the AI? A Closer Look at Relative Performance in Unrelated Tasks

- Asbach, Simon; Graf-Vlachy, Lorenz; Fuegener, Andreas; and Schinnen, Matthias H., "Can Superior AI Performance in Unrelated Tasks Reduce People's Willingness to Collaborate with the AI?" (2025). *ECIS 2025 Proceedings*. 1.
- https://aisel.aisnet.org/ecis2025/human_ai/human_ai/1

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6 Research Paper 4 – Does AI Reduce Competitive Irrationality?

Does AI Reduce Competitive Irrationality? The Effect of the Opponent's AI Support

- Asbach, S., Graf-Vlachy, L., Fügener. A. (2023). Submitted to the 34th European Conference for Information Systems (ECIS 2026).
- Under review and thus, unpublished

Abstract

Artificial Intelligence (AI) has recently entered the arena of human competition. However, research has not yet studied the competition between a focal human and a human opponent who is supported by an AI. This is surprising as AI systems often support humans in practice. Building on human-AI competition and competitive irrationality (i.e., irrational competitive behavior) literature, we hypothesize that AI compared to human support for the opponent reduces competitive irrationality. The AI's human-likeness should attenuate this effect and desire to win should mediate both effects. Data from 613 participants reveals that the type of the opponent's support – human, non-human-like AI, or human-like AI – does not affect competitive irrationality. However, desire to win mediates differences between the absence and presence of the opponent's support. Next, we plan to explore whether the observed effects change when a focal human competes directly with an AI. We discuss theoretical and practical implications.

Keywords: Human-AI Interaction, Competitive Behavior, Competitive Irrationality.

6.1 Introduction

In recent years, the context of competitive behavior, i.e., the pursuit of resources that are perceived as limited and contested (Deutsch, 1949), has changed substantially. Whereas humans used to compete only with other humans (Garcia et al., 2013; Garcia et al., 2020), today Artificial Intelligence (AI) systems have entered the set of competitors (Bécue et al., 2021; Krakowski et al., 2023).

Recent research has made initial advances in understanding whether and how an AI system as an opponent affects the behavior of a focal human. For example, research found that humans show less anterior insula (an area of the brain related to emotions) activation when responding to unfair offers from machines compared to unfair offers from humans (Rilling et al., 2008; Sanfey et al., 2003), show less physiological arousal, and make lower bids when bidding and bargaining against computer counterparts (Adam et al., 2018; Häubl and Popkowski Leszczyc, 2019). Outside of competitive contexts, scholars have researched the effect of a machine's level of human-likeness on peoples' reactions. Human-likeness denotes the outcome of attributing human-like qualities, such as appearance and behavior, to non-human entities, such as machines (Duffy, 2003). It seems to lead to an increased social presence, to increased social interactions, and to increased emotional responses in people (Mende et al., 2019; Qiu and Benbasat, 2009). In essence, initial advances have focused on humans interacting directly with (more or less human-like) machines and have found effects on human's competitive and emotional responses that differ from a human-human interaction.

However, research has not yet studied competition between a focal human and a human opponent who is supported by an AI system. This is surprising for three reasons. Firstly, in many practical contexts, a focal human is more likely to compete with a human opponent who is supported by an AI system than to directly compete with an AI system. This is because AI systems are typically deployed as support systems due to ethical (Awad et al., 2018; Zhang et al., 2020) or legal (Kingston, 2016) considerations, with a human making final decisions. Secondly, only very little research on competitive behavior has considered AI systems. While competition has been studied extensively in psychology, sociology, economics, business, and political science for many decades (Garcia et al., 2013), it is fairly new to the human-machine interaction literature (Adam et al., 2018; Häubl and Popkowski Leszczyc, 2019). The importance of better understanding AI systems is self-evident due to the increasing deployment of such systems in private and professional contexts. Thirdly, there is no research on the effect of a human-like AI system entering the setting of human competition. While researchers debate whether human-likeness leads to desired outcomes, such as increased acceptance of AI systems (Mende et al., 2019; Schanke et al., 2021), practitioners increasingly design AI systems to be human-like (Pelau et al., 2021). As such, their role in competitive settings should not be neglected.

To address this shortcoming, we investigate if and how the presence of an AI system supporting a human opponent changes the behavior of a focal human, with a particular focus on competitive irrationality. The paradox of competitive irrationality between humans – the behavioral preference for relative gains, even when winning comes at a personal loss with no strategic upside – has sparked research over decades (Güth et al., 1982; Graf et al., 2012; Häubl and Popkowski Leszczyc, 2019; Ku et al., 2005). The dysfunctionality of such competitive irrationality can be seen, for instance, in overbidding. The desire to beat rival bidders may lead to auction participants paying much more than an item is worth to them (Häubl and Popkowski Leszczyc, 2019; Ku et al., 2005; Malhotra, 2010). To test if and how AI support for an opponent affects competitive irrationality, we ran an experiment with four groups and 613 participants. The two control groups pitted the experiment subjects against a human opponent (1) without any support and (2) with another human supporting the opponent. The two experimental groups pitted the subjects against a human opponent (3) with a non-human-like AI supporting the opponent and (4) a human-like AI supporting the opponent. Competitive irrationality was operationalized as the likelihood of bidding past the pre-set limit to win an auction against the opponent.

We mainly expected that the presence of an AI system would reduce the focal human's competitive irrationality. Firstly, research has found that humans show lower competitive arousal and irrationality when bidding and bargaining against computers compared to humans (Adam et al., 2018; Häubl and Popkowski Leszczyc, 2019). This effect should at least partially transfer and result in lower levels of competitive irrationality when competing with a human opponent who is supported by an AI system compared to a human opponent who is not supported by an AI system. Secondly, extant literature indicates that human-likeness of machines increases their perceived social presence and emotional responses toward machines (Mende et al., 2019; Qiu and Benbasat, 2009). Thus, higher human-likeness should attenuate the main effect, resulting in higher levels of competitive irrationality. Thirdly, prior work indicates that desire to win can lead to competitive irrationality in auction games (Häubl and Popkowski Leszczyc, 2019; Malhotra, 2010). We expected the same effect in our study.

Our results both partially support expected effects and reveal unexpected null effects. As expected, results indicate higher levels of competitive irrationality when competing with an opponent who is not supported compared to an opponent who is supported (by a human or an AI system). Counter to expectations, the type of the opponent's support – human, non-human-like AI, or human-like AI – does not seem to affect the focal human's level of competitive irrationality. Lastly, and in support of our expectations, desire to win seems to explain parts of the observed competitive irrationality levels. Going forward, we plan to replicate our effects in different settings (e.g., higher stakes) and explore unexpected effects further. On the latter, we plan to explore whether competing directly with the AI system as opposed to competing with a human who is supported by an AI system, alters the observed effects.

6.2 Theoretical Background

Against the backdrop of an increasing use of AI systems in private and professional domains, initial research has investigated how humans act when they compete with an AI system. In essence, most scholars find that humans show less emotional and competitive arousal when they are pitted against machines than against humans (Adam et al., 2018; Häubl and Popkowski Leszczyc, 2019). Some scholars have researched the effect of a machine's level of human-likeness on peoples' reactions, without specifically focusing on competitive contexts. In fact, practitioners frequently design machines with human-like features to facilitate human cooperation with them (Pelau et al., 2021). Scholars demonstrate that human-like features can lead to an increased social presence and to increased emotional responses by users (Mende et al., 2019; Qiu and Benbasat, 2009). In essence, initial advances have been made to understand a human's competitive and emotional responses when directly interacting with (human-like) machines.

However, research has not yet looked at how AI systems affect competitive behavior if humans are not pitted directly against an AI system, but rather against a human who is supported by an AI system. In many practical contexts nowadays, humans do not compete directly with AI systems, but rather with other humans who are supported by AI systems. This setup is often due to ethical (Awad et al., 2018; Zhang et al., 2020) or legal (Kingston, 2016) challenges. AI systems often do not make the final decisions and humans stay in charge instead. For example, an AI system helps to diagnose a patient's medical situation, but the doctor is responsible for the final diagnosis and makes the decision on how to treat a patient. In the context of competition, two managers from different companies may be supported by

AI systems for analyses, but the managers make the final decision on the last bid for the asset that both wish to acquire. Since in practice, humans are often pitted against human opponents who are supported by an AI system, practically relevant research should investigate this competitive context.

Our paper explores a human's competitive irrationality when competing against a human opponent who is supported by an AI system. The management literature has coined the term "competitive irrationality" to describe irrational competitive behavior (Arnett and Hunt, 2002) and due to its potential impact on real-world decision making as well as its theoretical complexity, different areas of research have been investigating the paradox of competitive irrationality for decades (Güth et al., 1982; Graf et al., 2012; Häubl and Popkowski Leszczyc, 2019; Ku et al., 2005). As stakes in competitive contexts can be high, competitive irrationality – the behavioral preference for relative gains, even when winning comes at a personal loss with no strategic upside – can be extremely damaging. For example, in 2006, competitive irrationality led medical technology company Boston Scientific to acquire the device maker Guidant for 27.2 billion USD (Malhotra et al., 2008). Boston Scientific's primary motivation was to beat their opponent instead of maximizing their own gains (Malhotra et al., 2008). The acquisition would later be referred to as one of the worst deals in history by Fortune magazine. Overbidding to beat an opponent is also found in individuals playing auction games (Häubl and Popkowski Leszczyc, 2019; Malhotra, 2010). We build on this research and explore how AI system support for an opponent affects overbidding.

Our set of hypotheses is preceded by a baseline expectation that serves as a test for the robustness of the experimental setup. We deployed not only one control condition in which the human opponent is supported by another human but also a second control condition in which the human opponent receives no support. Notably, the focal human operates without support across all conditions. When the focal human is pitted against a human opponent without support compared to a human opponent with support, the perceived likelihood of winning should increase. Additionally, social comparison theory (Garcia et al., 2013) suggests that desire to win should increase as an opponent without support is more similar and comparable to oneself than an opponent with support.

Hypothesis 0 (H0): Participants will exhibit higher levels of competitive irrationality when pitted against a human without support compared to when pitted against a human with support.

Scholars have found less competitiveness in humans when they are pitted against machines than against other humans. For example, in economic games, participants display greater emotional reactions in response to unfair offers compared to fair offers, but only when their opponents are human (van 't Wout et al., 2006). In bidding games, for example, people exhibit decreased physiological arousal when bidding against a computer compared to a human (Adam et al., 2015; Adam et al., 2018). People also report lower willingness to pay for an item when the opponent in a bidding game is a machine compared to a human (Häubl and Popkowski Leszczyc, 2019). We expect the phenomenon of a human exhibiting less competitiveness when pitted against a machine compared to another human, to transfer at least partially to a new setting. Specifically, we expect a human to exhibit less irrational competitive bidding when pitted against a human who is supported by an AI system compared to a human who is not supported by an AI system. It would certainly be surprising if the focal human were to ignore the support completely and their behavior would not be (at least partially) affected by the support for the opponent.

Hypothesis 1 (H1): Participants will exhibit lower levels of competitive irrationality when pitted against a human with AI support compared to a human without AI support.

Our second hypothesis relates to the human-likeness of the AI. Machines and AI systems are frequently designed with human-like qualities to increase people's willingness to cooperate with them (Pelau et al., 2021). Human-like qualities, such as appearance and behavior, can range from physical appearance to different mental states that characterize human beings, such as engaging in reasoning or making moral judgments (Golossenko et al., 2020; Kim and McGill, 2011). Literature mostly agrees that applying human-like features to a machine (such as an AI system) increases the machine's social presence and emotional responses by a human (Mende et al., 2019; Qiu and Benbasat, 2009). In the same vein, the "computers are social actors" (CASA) paradigm assumes that humans mindlessly apply social rules and look for social cues when interacting with nonhuman agents, such as AI systems. Human-like features serve as social cues and increase the intensity of human-AI interactions, such as competitions (Nass and Moon, 2000). Notably, perceived human-likeness is a matter of degree. This is to say that humans categorize a machine as more or less human-like and not just as either human-like (or human) or not. Consequently, the reaction to the perception of human-like features is also a matter of degree (Nielsen et al., 2022). Human-like features may increase the intensity of emotional arousal in human-AI interactions, such as competitions, but human-like features of an AI will not necessarily elevate emotional arousal to the level of a human-human interaction. As argued under H1, we expect the aforementioned effects to transfer (at least partially) from a direct human-AI interaction to the setting of a focal human competing with another human, who is supported by an AI.

Hypothesis 2 (H2): Human-likeness of the AI support will attenuate the negative effect of non-human-like AI support compared to human support on a participant's competitive irrationality.

Our third hypothesis is informed by research on the relation between desire to win and competitive irrationality. Desire to win is defined as the motivation to maximize relative payoffs, even at a personal cost (Malhotra, 2010). This desire often occurs in interpersonal competitions, which fuel competitors' anticipated joy of winning (Häubl and Popkowski

Leszczyc, 2019; Malhotra, 2010). In auctions, for example, a desire to win can then drive people to bid more than an item is worth to them to win against a competitor, even when doing so provides no strategic benefit (Rubin et al., 1994).

In line with H1 and H2, we expect different levels of perceived interpersonal competition depending on the type of support for the opponent. Consequently, different levels of desire to win should emerge. Desire to win should then impact people's competitive irrationality in different contexts, such as auctions. Prior research supports this idea as desire to win is seen as the key driver for people's bidding behavior and as an antecedent of competitive irrationality (Häubl and Popkowski Leszczyc, 2019). For example, scholars have found that desire to win leads to overbidding (Malhotra, 2010) and a heightened willingness to pay (Häubl and Popkowski Leszczyc, 2019) in auctions. Taken together, we expect different levels of perceived competition (based on the type of opponent's support) to influence a person's desire to win and ultimately, their competitive irrationality (i.e., irrational competitive behavior) in a bidding game.

Hypothesis 3 (H3): Desire to win mediates the relation between the type of opponent's support and competitive irrationality.

6.3 Methods

We used oTree (Chen et al., 2016) to program the experiment and launched it through CloudResearch on Amazon's Mechanical Turk in May 2023. We used CloudResearch (formerly TurkPrime) as it provides higher-quality participants than other sample providers (Litman and Robinson, 2020). In light of limited research to base effect sizes on, we expected a small to medium effect size of d = .3 (Cohen, 2016) for our main effects. A priori power analysis with G*Power 3.1 (Faul et al., 2009) provided a required sample size of 556 participants to achieve 80% power (with $\alpha = .05$). The final sample surpassed the required sample and included complete data from 613 participants (50 participants were excluded based on pre-defined criteria, such as failing attention or comprehension checks).

Participants went through a simple three-step experimental process. Firstly, they read a short introduction to the experiment and answered attention check questions. Secondly, they read a vignette asking them to imagine the following auction scenario (Häubl and Popkowski Leszczyc, 2019; Ku et al., 2005; Malhotra, 2010): They are attending a live auction for a personally very valuable item. Prior to the auction, they had decided that they do not want to spend more than \$150. They have been actively bidding, with a most recent bid of \$145. The only other bidder just bid \$150, and now they are asked to indicate the likelihood of them placing the next bid of \$155. Thirdly, after they indicated the likelihood of placing another bid (the DV in our experiment), they concluded the study.

The experimental design featured four groups. The two control groups pitted the subjects against a human opponent (1) without any support and (2) with another human supporting the opponent. The two experimental groups pitted the subjects against a human opponent (3) with a non-human-like AI supporting the opponent and (4) a human-like AI supporting the opponent. The manipulations of the human and human-like AI support for the opponent were similar. In both, we presented the support with the same name and picture, and a speech bubble ("Hello, I'm Ash and I'm here to help your opponent use an optimal bidding strategy. Hopefully, he can beat you."). The difference was that the picture showed a human compared to a similar-looking avatar and the vignette described the support for the opponent as a "person" instead of an "AI". The non-human-like AI manipulation presented the AI without a name, picture, or personal words. Our manipulations of human-likeness are based on previous work (Mourey et al., 2017; Ochmann et al., 2020; Qiu and Benbasat, 2009).

The two most relevant dependent variables for our research question are the likelihood of placing another bid and desire to win. The likelihood of placing another bid was quantified as a percentage (0 = "definitely will not make another bid" to 100 = "definitely will make another bid"). Desire to win was measured on a 7-point scale (1 = "strongly disagree" to 7 = "strongly agree"). Measurement of both variables is adapted from previous research (Häubl and Popkowski Leszczyc, 2019; Ku et al., 2005; Malhotra, 2010). To test the success of the human-likeness manipulation, we adapted two items from previous research asking how machine-like and how person-like the AI was (Mende et al., 2019). Both items were measured on a 7-point scale (1 = "strongly disagree" to 7 = "strongly agree"). For analysis, we reverse-coded the first item and then used the average of both items.

6.4 Results

The human-likeness manipulation was successful. Ordinary least squares (OLS) regression reveals that participants perceived the human-like AI as more human-like than the non-human-like AI, $b = 1.21$, $SE = 0.18$, $t(306) = 6.81$, $p < .001$, $\eta^2 = .13$. The effect size constitutes a large effect (Cohen, 2016).

In support of *H0*, OLS regression demonstrates that participants reported a higher likelihood of bidding when pitted against an opponent without support (condition 1) compared to an opponent with support (conditions 2, 3, and 4), $b = 11.03$, $SE = 3.15$, $t(611) = 3.51$, $p < .001$, $\eta^2 = .02$. Separate comparisons of people being pitted against an opponent without support compared to people being pitted against an opponent with human-, non-human-like AI-, and human-like AI support are also in line with *H0*. The differences between conditions are significant across all three comparisons.

Counter to *H1* and *H2*, a one-way analysis of variance (ANOVA) reveals that participants reported similar levels of likelihood of bidding when they are pitted against a human who is supported by a human compared to a non-human-like AI compared to a human-like AI, $F(2, 451)$, $p = .378$.

In support of *H3,* different levels of likelihood of bidding can partially be explained by desire to win. The following mediation analysis uses a dichotomous independent variable representing a human opponent without support compared to an opponent with support. This is due to the absence of empirical support for *H2* and *H3* (no effect of conditions 2, 3, and 4 with different types of support for the opponent). Bootstrapping analysis via PROCESS with 5,000 iterations (Hayes, 2017; Zhao et al., 2010) supports a significant mediation effect from the type of opponent on the likelihood of bidding via desire to win, partially standardized IE = -.11, SE = .05, 95% CI [-.20, -.01]. Further, 32% of the total effect of the type of opponent on the likelihood of bidding can be explained by desire to win.

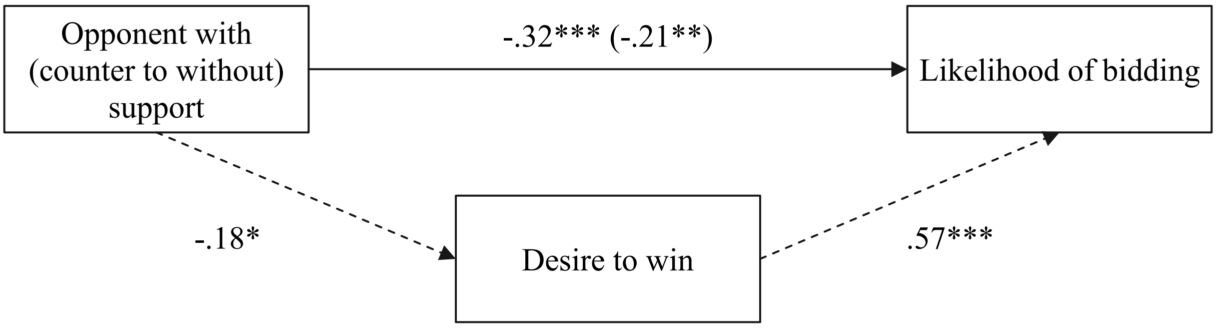

Figure 6.1. Beta coefficients for total, direct, indirect effects. * $p < .05$; ** $p < .01$; *** $p < .001$

6.5 Discussion

Our paper aimed to investigate how AI support for a human opponent affects competitive irrationality (i.e., irrational competitive behavior). In line with the baseline expectation, competing with an opponent without support compared to an opponent with support increased competitive irrationality. However, people did not demonstrate different levels of competitive irrationality depending on whether their opponent was supported by an AI system or a human. Additionally, human-likeness of the AI support for the opponent did not change this result. Lastly, desire to win mediated effects. These findings urge further exploration of how AI systems affect competitive irrationality.

Next, we plan follow-up studies to investigate the current paper's effects further. Firstly, we aim to test whether the current findings replicate in higher-stakes and more ecologically valid scenarios. For example, an endowment of real money prior to the auction could be lost in case of overbidding. Beating the opponent becomes costly in this context, which may change behavior. If this setting does not lead to a different bidding behavior, the robustness of the current results is strengthened. Secondly, we plan to test whether direct compared to indirect competition with an AI system might moderate the observed effects. The null effect in the current study may be explained by competitors mainly focusing their attention on the primary opponent, and not on the support cast. In a changed setting with direct competition between a focal human and an AI opponent, we may see the effects we initially expected.

Regarding theoretical implications, the current paper challenges existing theory on how AI systems affect competitive irrationality. Research indicates that AI systems as opponents reduce competitive arousal compared to humans as opponents (Adam et al., 2018; Häubl and Popkowski Leszczyc, 2019). However, human-like systems may elicit increased emotional, and thus competitive arousal (Mende et al., 2019; Nass and Moon, 2000). Our study suggests that neither effect seems to transfer to a setting in which AI systems support a human opponent. If this is replicated in future studies, we can infer that the effect of AI systems on humans' competitiveness depends on the setup of the competition, i.e., direct interaction with an AI compared to interaction with a human who is supported by an AI. Further, scholars may even want to explore a third scenario, in which an AI system is supported by a human.

The current paper's results caution organizations that competitive irrationality may not vanish with the implementation of AI systems. Research indicates that the use of AI systems may help people to act more rationally (Adam et al., 2018; Häubl and Popkowski Leszczyc, 2019). However, as long as AI systems act as support for humans, competitors seem to compete as irrationally as they do with only a human opponent. Future work could investigate how a competitor's attention can be shifted from full attention on the primary opponent towards attention on the primary opponent and their support. If people shift their attention from trying to only win against a human opponent to trying to win against a human with an AI system, this may change their desire to win and consequently their competitive irrationality.

Research is only in its infancy to grasp mechanisms of humans' competitive behavior when AI systems are involved. More research is thus needed to avoid costly poor decisions in practice and to ensure that the implementation of AI systems in competitive contexts is beneficial. Our paper is a first step to do so and defines next steps, that we will take on as well as further researchers may follow up on.

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6.7 Appendix

In this appendix we provide screenshots to illustrate the experimental manipulations and we provide details on the experiment's scales.

6.7.1 Screenshots of the Experiment

We deployed a 1x4 between-subjects design and conditions are illustrated by Figure 6.2.

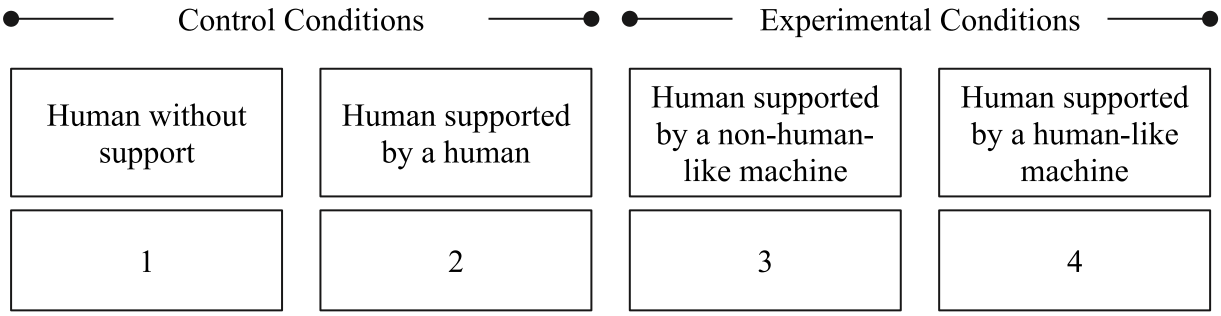

Figure 6.2. Four experimental conditions varied the type of opponent

Reading and Follow-up Questions

Please read the text below carefully to be able to answer the follow-up questions on this page and the next page. These follow-up questions will also include comprehension check questions that you need to answer correctly upon first attempt to get paid.

Auction Scenario
Imagine that you are attending a live auction and the item up for bid is something that you really, really want. It is the only item of its kind at this auction, and you don't think that you will find this item anywhere else. In fact, because you were waiting to see the item for sale one day, you made it a point to come to this auction. Before bidding began, you had decided that the most you would be willing to pay for this item is approximately $150. Of course, you'd like to pay as little as possible.

The auctioneer will end the auction as soon as about 30 seconds have passed without anybody submitting a bid. (At that point, the product will be awarded to whoever placed the highest bid.)

You have been actively bidding in the auction and your most recent bid was $145. **The only other bidder is a person who just bid $150.** You now have to decide whether you want to continue bidding. Your next bid would be $155.

Figure 6.3. Condition 1 in the experiment

Reading and Follow-up Questions

Please read the text below carefully to be able to answer the follow-up questions on this page and the next page. These follow-up questions will also include comprehension check questions that you need to answer correctly upon first attempt to get paid.

Auction Scenario
Imagine that you are attending a live auction and the item up for bid is something that you really, really want. It is the only item of its kind at this auction, and you don't think that you will find this item anywhere else. In fact, because you were waiting to see the item for sale one day, you made it a point to come to this auction. Before bidding began, you had decided that the most you would be willing to pay for this item is approximately $150. Of course, you'd like to pay as little as possible.

The auctioneer will end the auction as soon as about 30 seconds have passed without anybody submitting a bid. (At that point, the product will be awarded to whoever placed the highest bid.)

You have been actively bidding in the auction and your most recent bid was $145. **The only other bidder is a person who just bid $150. This other bidder is supported by Ash. Ash is another person, who aims to help your opponent use an optimal bidding strategy. You can see Ash below. Ash says "Hello, I'm Ash and I'm here to help your opponent use an optimal bidding strategy. Hopefully he can beat you."** You now have to decide whether you want to continue bidding. Your next bid would be $155.

Figure 6.4. Condition 2 in the experiment

Reading and Follow-up Questions

Please read the text below carefully to be able to answer the follow-up questions on this page and the next page. These follow-up questions will also include comprehension check questions that you need to answer correctly upon first attempt to get paid.

Auction Scenario
Imagine that you are attending a live auction and the item up for bid is something that you really, really want. It is the only item of its kind at this auction, and you don't think that you will find this item anywhere else. In fact, because you were waiting to see the item for sale one day, you made it a point to come to this auction. Before bidding began, you had decided that the most you would be willing to pay for this item is approximately $150. Of course, you'd like to pay as little as possible.

The auctioneer will end the auction as soon as about 30 seconds have passed without anybody submitting a bid. (At that point, the product will be awarded to whoever placed the highest bid.)

You have been actively bidding in the auction and your most recent bid was $145. **The only other bidder is a person who just bid $150. This other bidder is supported by an artificial intelligence, which aims to help your opponent use an optimal bidding strategy. You can see a grey box below, which represents the artificial intelligence.** You now have to decide whether you want to continue bidding. Your next bid would be $155.

The artificial intelligence aims to help your opponent use an optimal bidding strategy.

Figure 6.5. Condition 3 in the experiment

Reading and Follow-up Questions

Please read the text below carefully to be able to answer the follow-up questions on this page and the next page. These follow-up questions will also include comprehension check questions that you need to answer correctly upon first attempt to get paid.

Auction Scenario
Imagine that you are attending a live auction and the item up for bid is something that you really, really want. It is the only item of its kind at this auction, and you don't think that you will find this item anywhere else. In fact, because you were waiting to see the item for sale one day, you made it a point to come to this auction. Before bidding began, you had decided that the most you would be willing to pay for this item is approximately $150. Of course, you'd like to pay as little as possible.

The auctioneer will end the auction as soon as about 30 seconds have passed without anybody submitting a bid. (At that point, the product will be awarded to whoever placed the highest bid.)

You have been actively bidding in the auction and your most recent bid was $145. **The only other bidder is a person who just bid $150. Further, the other bidder is supported by Ash. Ash is an artificial intelligence, who aims to help your opponent use an optimal bidding strategy. You can see Ash below. Ash says "Hello, I'm Ash and I'm here to help your opponent use an optimal bidding strategy. Hopefully he can beat you."** You now have to decide whether you want to continue bidding. Your next bid would be $155.

Figure 6.6. Condition 4 in the experiment

6.7.2 Measures

6.7.2.1 Likelihood of Bidding

As mentioned in the main part of the paper, we followed previous research and measured likelihood of bidding on a scale from 0 to 100 (Häubl and Popkowski Leszczyc, 2019; Ku et al., 2005; Malhotra, 2010):

- How likely are you to place another bid in the auction, between **0** = "definitely **will not** make another bid" to **100** = "definitely **will** make another bid"? Click the blue bar to reveal the slider.

6.7.2.2 Comparison Concerns

To capture individuals' comparison concerns, we followed previous research to measure competition intensity, desire to win, and competitive arousal (Malhotra, 2010; Ku et al., 2005; Häubl and Popkowski Leszczyc, 2019). The items read as follows:

- How intense do you think the competition was between you and the other bidder in the auction (0 = "not at all intense" to 10 = "extremely intense")?
- How much do you agree with the following statement "I felt a strong desire to win the auction" (1 = "strongly disagree" to 7 = "strongly agree")?
- How excited did you feel about the auction (1 = "not at all" to 11 = "very much")?
- How anxious did you feel about the auction (1 = "not at all" to 11 = "very much")?

6.7.2.3 Manipulation Check

To test the success of the human-likeness manipulation, we adapted two items from previous research (Mende et al., 2019) that were rated on a 7-point scale (1 = "strongly disagree" to 7 = "strongly agree"):

- The AI was machine-like
- The AI was like a person

6.7.2.4 Perceived Objectiveness of Task

Additionally, we asked participants to rate their perception of the objectiveness of the task at hand (Castelo et al., 2019):

To answer the following question, consider these definitions:

- A **subjective** task is defined as being **open to interpretation** and based on personal opinion or intuition
- An **objective** task is defined as one that involves **facts that are quantifiable and measurable**

How subjective versus objective did the auction task seem to you, from **0 = "completely subjective" to 100 = "completely objective"**? Click the blue bar to reveal the slider.

6.7.2.5 Demographics

Final questions for the participants comprised the following demographical questions:

- How old are you (dropdown menu)?
- What is your gender (male; female; other/prefer not to say)?
- What is your level of English proficiency (1 = "very low – beginner" to 7 = "very high - native speaker")?
- Were you familiar with parts of the study (yes; no)?
- If yes, which parts of the study were you familiar with (open text field)?
- Do you have any feedback you would like to share (open text field)?

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7 Discussion and Conclusion

In an attempt to help organizations and their members realize more of the large benefits of AIs as decision support systems, the purpose of this dissertation was to investigate important antecedents of individuals' willingness to collaborate with AIs. While various companies have implemented AIs in their workflows (Chui et al., 2022; Ellingrud et al., 2023), their members often seem to fail at fully leveraging the AIs' potential because they reject helpful advice (Logg et al., 2019; Sun et al., 2021). For instance, in a major retail e-commerce company, employees frequently disregarded AI-based packing suggestions, missing opportunities for enhanced packing efficiency and reduced operational costs (Sun et al., 2021). As failing to leverage the potential of AIs can severely hurt companies and entire economies, this work aims to improve our understanding of antecedents of individuals' willingness to collaborate with AIs.

Across four research papers with five experiments and data from 3,169 participants, I tested relevant and yet understudied antecedents in four areas. Results support that (1) an individual's personality, (2) a persuasive message framing advice, (3) and historical relative AI performance in an unrelated task all distinctively affect individuals' willingness to collaborate with an AI. Lastly, I widened the scope of this dissertation to the area of competition and found that AI support for an opponent, as opposed to human support, does not affect an individual's competitive irrationality. I will briefly summarize the key findings per research paper below. This sets up subsequent parts of this discussion, in which I will discuss this dissertation's main implications for theory and practice as well as this dissertation's main limitations and future directions. I will end with concluding remarks.

The first research paper supports the idea that personality, measured by the Big Five personality model (Costa & McCrae, 1992a, 1992b; McCrae & Costa Jr., 2008; McCrae & John, 1992), is an important antecedent of an individual's use of AI advice. Consistent with my hypotheses, agreeableness and neuroticism positively correlate with use of AI advice in a previously validated forecasting task. Surprisingly, openness negatively impacts use of AI advice, with extraversion and conscientiousness showing no notable association.

The second research paper finds that framing algorithmic advice with a persuasive message enhances its use, an effect mediated by trust in the algorithm. However, contrary to expectations, personalizing the message to the user's regulatory focus (creating regulatory fit (Cesario et al., 2004; Higgins et al., 2003)) does not lead to greater use of algorithmic advice than a non-personalized message (creating non-fit).

The third research paper indicates that people consistently prefer to collaborate with an AI over a human, independent of the counterpart performance relative to the individual in a previous and unrelated task. Moreover, superior, as opposed to similar, AI performance compared to the individual in an unrelated task decreases the individual's willingness to collaborate with an AI. This effect is attributable to decreased trust in the AI's benevolence and integrity. Unexpectedly, this reluctance is also partially driven by reduced trust in the AI's competence when its performance is superior to the individual's performance.

The fourth paper broadens the scope of this dissertation, finding increased competitive irrationality against an unsupported opponent compared to one with support (human or AI). Surprisingly, the support type – whether human, non-human-like AI, or human-like AI – does not impact competitive irrationality. Consistent with predictions, desire to win partially accounts for levels of competitive irrationality.

7.1 Theoretical Implications

The current work adds to the growing literature on antecedents of the willingness to collaborate with AIs. This literature stream is growing as organizations implement AIs on a large scale and often fail to reap the benefits of AIs because individuals reject helpful advice of these powerful decision support systems (Chui et al., 2022; Ellingrud et al., 2023; Logg et al., 2019; Sun et al., 2021). While extant research has made contributions in the field, many questions remain regarding the antecedents of the willingness to collaborate with AIs (Kelly et al., 2023). In the context of this dissertation, I was able to answer some of these important questions, thereby impacting existing theory. This work's main theoretical implications are threefold.

Firstly, I generate new relevant theories for literature that improves our understanding of antecedents of the willingness to collaborate with AI systems. For example, personality traits have hitherto been underrepresented by research on antecedents of willingness to collaborate with AIs. However, the current work shows that personality (Costa & McCrae, 1992a, 1992b; McCrae & Costa Jr., 2008; McCrae & John, 1992) is an important theoretical construct to consider for literature on willingness to collaborate with AI systems: Currently researched antecedents, such as human-likeness of the AI (Qiu & Benbasat, 2009; Schanke et al., 2021) or explainability of the AI (Bauer et al., 2023; Lehmann et al., 2022), should be considered cautiously because they may vary based on the individual's personality. Another example is a new theory to mitigate the problem of algorithmic advice underutilization. Extant research has recognized the problem (Dietvorst et al., 2015, 2018; Logg et al., 2019; Meehl, 1954), but has not provided effective ideas to tackle the problem. My intervention adds to theory as it successfully increases use of advice from superior, i.e., ex-ante perfect, algorithms from previously ~51% to ~69%, which is substantially higher than the usual maximum level of ~56% from previous studies (Lehmann et al., 2022; Logg et al., 2019).

Secondly, I update existing theories regarding new relevant contexts, which increases the understanding of humans' willingness to collaborate with AI systems in current times. For example, I add to literature by showing that superior, as opposed to similar, AI performance compared to the individual in an unrelated task decreases the individual's willingness to collaborate with an AI. Existing theories indicate that increased AI performance affects willingness to collaborate with an AI positively (Choung et al., 2023; Dennis et al., 2023; Dietvorst et al., 2018), which suggests that increased relative performance may also affect willingness to collaborate with an AI positively. Since I find the opposite effect, I update existing theories and contribute to a more nuanced understanding of AI performance effect on willingness to collaborate with AIs. Further, decreased competence in trust mediates the observed effect, which updates existing theories on trust toward AI as a function of AI performance. Lastly, I add to the field of AI appreciation and AI aversion (Dietvorst et al., 2015, 2018; Logg et al., 2019) by showing AI appreciation in a new context, namely under both superior and similar counterpart performance in an unrelated task. This finding supports the theoretical robustness of AI appreciation theory.

Thirdly, generating new theories and updating existing theories regarding new relevant contexts impact literature by generating various valuable paths for future research. For example, future research may test how current personality results can be used to personalize AI systems in order to reach a better acceptance rate of AI advice. Another example is that future research may build on my intervention to increase use of AI advice and alter the intervention to reach an even higher acceptance rate of superior advice than 69%. Lastly, future research may revisit further existing theories, such as human-likeness of AIs (Qiu & Benbasat, 2009; Schanke et al., 2021), the explainability of AIs (Bauer et al., 2023; Lehmann et al., 2022), or the domain of the task at hand (Logg et al., 2019) and test them in different practically relevant contexts.

7.2 Practical Implications

This dissertation's findings aid organizations and their members in understanding and potentially mitigating the problem of rejecting helpful AI advice. Firstly, I provide relevant data for practitioners to personalize AI systems in order to reach a better acceptance rate of AI advice. More specifically, I show how the Big Five personality traits are associated with the use of AI advice. This may help practitioners personalize AI advice to the user and thus increase the use of advice. One example of how AI personalization could increase use of AI advice is beyond the scope of the current work and could be taken up by future research: Practitioners could tailor an AI to users low in agreeableness because my work suggests this trait to be of major importance for use of AI advice. People low in agreeableness often doubt and disagree (Gosling et al., 2003; Matthews et al., 2003; McCrae & John, 1992). An AI with a sophisticated chat function could address these disagreements directly, providing specific arguments to enhance user motivation and trust in the AI's advice.

Secondly, building on the previous goal of increasing use of superior AI advice, I provide and test an effective intervention that achieves this goal. In my study, persuasive messaging framing algorithmic advice led to a ~20%-point increase in use of advice. This may especially help organizations deploying AI advice systems that are usually superior to human judgment to reap more of the benefits of these powerful AIs. Notably, solely increasing use of AI advice can also backfire in settings with considerable unique human knowledge. In such cases, it is more important to decide whether to follow the human or the AI estimate. This area of complementary human-AI performance (Bichler et al., 2010; Fügener et al., 2021b; Zhang et al., 2020) is beyond the scope of the current work and could be investigated by future research.

Thirdly, I help organizations to avoid adverse effects when promoting AIs. As AIs become more multi-functional (Ko et al., 2023; Vries, 2020), practitioners may promote AIs in new tasks through proven performance relative to individuals in unrelated tasks. My results highlight that this strategy could backfire, potentially leading to organization members being less willing to work with the AI. Further, results indicate trust in the counterpart's competence, benevolence, and integrity mediate observed effects. This finding suggests a particular focus that practitioners and organizations can take to avoid the aforementioned backfiring effects. Future research may help to achieve this goal.

7.3 Limitations and Future Research

This dissertation's theoretical and practical implications should be discussed in light of their main limitations that stimulate further relevant future research. I will discuss three areas in the following paragraphs, namely (1) the limitation of solely using laboratory studies throughout this dissertation, (2) the limitations of the observed personality effects and the related personalization ideas, and (3) the limitation of the negative effect of historical superior AI performance in an unrelated task on the willingness to collaborate in a task at hand.

The four research papers in this dissertation are based on five experimental laboratory studies (including two pretests), which inherently implies a notable limitation. While experimental laboratory studies are a frequently used method of isolating causal effects (Falk & Heckman, 2009), they may incur limited ecological validity (Berkowitz & Donnerstein, 1982; Schmuckler, 2001). In other words, individuals in the real world outside the laboratory may behave differently compared to individuals in a laboratory setting. I mitigated this possibility by recruiting sample sizes based on rather conservative power analyses, isolating focal variables and their effects carefully, and collecting data from high-quality participant pools. Yet, different variables can potentially change my results outside of the laboratory. For example, members of a forecasting company may work differently with a forecasting AI than my study's participants because their line manager may pressure them to do so. Future research could deploy field studies to test the robustness of observed effects in different practically relevant contexts.

Building on the idea of considering my findings in the given context, it seems relevant for future research to investigate how an imperfect AI, which complements human performance, changes observed effects regarding Big Five personality traits and persuasive messaging strategies. While an ex-ante perfect AI system was the right choice for my specific research questions, results may change in case of an imperfect AI system. Sometimes, AI systems may not surpass human decision-making and humans may complement the AI performance with unique insights (Bichler et al., 2010; Fügener et al., 2021b; Zhang et al., 2020). In such cases, witnessing AI errors can diminish perceived usefulness (Dietvorst et al., 2015), potentially impacting my findings in two ways: Firstly, observed personality effects on use of AI advice may change. For example, the positive association between agreeableness and use of AI systems may fade. Secondly, the positive effect of persuasive messaging on use of advice may diminish, including subsequent situations in which the AI is superior, but the human's trust in the AI has faded.

Lastly, future research may detail my finding of superior AI performance in an unrelated task being associated with an individual's decreased willingness to collaborate in a task at hand. Scholars may investigate whether (1) level of performance in the unrelated task and (2) incentivization of the task at hand change observed effects.

Firstly, if an AI outperforms an individual in an unrelated task by a large margin (e.g., AI ranks 1st vs. an individual ranks 500th in a 500-player poker tournament) or an AI is displayed as highly versatile and able to perform well in multiple tasks, this may leave less room for assessing the AI's abilities negatively and consequently, affect an individual's observed willingness to collaborate positively. Consequently, this alteration may either weaken or reverse my observed finding. Secondly, if the task at hand has performance-based incentives, superior AI performance in an unrelated task may positively impact willingness to collaborate, causing observed effects to flip. In this case, detrimental emotions for collaboration that often follow upward social comparisons (Fujita, 2008; Smith, 2000; Smith & Kim, 2007) may be secondary. Instead, an individual's primary focus may be to utilize an AI as much as possible as long as this increases their performance and they can maximize incentives.

7.4 Conclusion

To conclude, I reflect more broadly on this dissertation's results. My research tests and finds important antecedents of individuals' willingness to collaborate with AI systems. Most notably, personality seems to be associated with use of AI advice, persuasive messaging increases use of superior AI advice, and historical superior AI performance in an unrelated task can decrease the willingness to collaborate with the AI in the task at hand. The latter finding can seem unintuitive at first sight, but decreased trust in three different trust dimensions helps explain the effect.

My findings advance the understanding of antecedents of individuals' willingness to collaborate with AIs, which is crucial for the success of countless organizations and entire economies. I expand existing theories on the antecedents of individuals' willingness to collaborate with AIs by unpacking the power of yet undiscovered antecedents, thus stimulating important avenues of further research. These findings bear a high practical relevance: Against the backdrop of economies continuing to transform to Industry 4.0 and many organizations failing to reap the full potential of AIs as decision support systems, this work helps these organizations to avoid costly rejection of helpful AI advice and leverage more of the AI's large potential instead. The future will be the judge of whether economies and organizations that implement AIs in their transformation to Industry 4.0 will live up to their potential.

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