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Rethinking Work in the Digital Age:

Implications of Data-driven Technologies for Work and Workers within Incumbent Firms

Amelie Lena Schmid

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Reutlingen, im August 2026 Amelie Lena Schmid

Abstract

Problem Statement: Incumbent firms face multifaceted challenges from considerable cost pressure and new market players. Implementing data-driven technologies such as data science, artificial intelligence (AI), and algorithmic management (AM) can be relevant measures to counteract. It enables organizations to rethink established approaches by digital means and to enhance efficiency and growth. However, introducing data-driven technologies in the workplace leads to profound changes in various aspects of work. We state that the present understanding of the implications for work and workers within incumbent firms needs an extension in three distinct areas. First, new insights are essential on how workers adapt their work practices in response to the changing environment. Second, it remains unclear how workers build trust in AI-based systems, given concerns about the trusting belief "reliability". Third, exploring the impact of AM on workers' efficiency, established organizational structures, and existing work relationships within traditional organizations is crucial.

Research Design: A multi-method research strategy is followed to address these research gaps. By considering the complexity of our phenomenon, we set up a multiple case study to examine the reconfiguration of work practices based on the increasing usage of data science. Moreover, we apply grounded theory methodology to investigate the trust-building process of workers in AI-based systems and the utilization of an ethical framework. Finally, we measure the potential performance effects of AM in the traditional work context, based on ~12700 manufacturing errors, using linear mixed modeling. We extend this quantitative analysis by 15 confirmatory semi-structured interviews to get a deeper understanding of AM impact and find detailed explanations.

Results: The present work provides several empirical findings. First, we illustrate how engineers reconfigure the engineering role using data science work. We identify the hybrid practice of data science work, combining engineering and data science practices. Second, we develop a process for AI implementation and operation along the five phases of the AI lifecycle. We show the dynamic interplay between building trust and the acceptance level of AI reliability. Besides, the impact of an ethical framework for trust calibration is assessed. Finally, we demonstrate that AM increases workers' efficiency and impacts existing organizational structures. In particular, human managers are essential shapers of AM and remain key supporters. Moreover, AM influences team dynamics as workers engage in collective bypassing, situational optimization, and hybrid interaction.

Contributions: We can make several contributions to theory and practice based on our results. We enhance research on data science work by providing evidence of the relevance of domain experts for shaping data science work and showing the specific characteristics of the new hybrid role. We extend trust theory by illustrating the dynamic process of building trust in AI, as workers are willing to reconfigure their expected level of reliability. Moreover, we highlight five supportive organizational measures and the utilization of an ethical framework. We contribute to the AM literature by validating the performance effects in traditional settings, considering socio-technical factors. Additionally, we explore the supportive role of human managers and the impact of AM on existing team dynamics. In practice, workers, leaders, and IT project team members can benefit from several recommendations for successfully implementing emerging data-driven technologies.

Limitations: The selected research designs create certain limitations on the results. The qualitative studies raise several concerns, such as (i) the limited generalizability of the findings, (ii) possible researcher bias, or (iii) a lack of rigor. To address the limitations, we employ data triangulation, select the multiple-case study approach, and follow systematic coding procedures. Furthermore, there are limitations related to the quantitative study as manufacturing data is collected over a limited period of nine months. Finally, we must acknowledge general limitations regarding the organizational setting for the present work. Given that all conducted studies rely on data collected from a single international supplier operating in the automotive industry, it is crucial to consider that our findings might be heavily biased by this context.

Future Research: The present work foresees three potential areas of future research. There might be a specific interest in investigating the impact of emerging data-driven technologies such as generative AI. Generative AI has the potential to overtake tasks that previously needed human involvement. Hence, it is reasonable to analyze its impact on work and workers within incumbent firms. Additionally, a detailed study on the negative outcomes of AM in the traditional work context could complement our findings, as – within the present work – we primarily focus on the positive effects. It could further enhance our understanding of human management to overcome AM-related challenges within incumbent firms. Finally, future research could provide additional information on the overall digital transformation process and examine aspects beyond digital transformation. A compelling study area in this context involves the contrasting attributes between incumbent firms and digital natives.

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List of Abbreviations

AM	Algorithmic management
AMCIS	Americas conference on information systems
BISE	Business & Information Systems Engineering
CIP	Continuous improvement process
CNOW	Changing nature of work
D	Detectability
DOI	Digital object identifier
ECU	Electronic control unit
EI	Ethical impact
FM	Failure mode
FMEA	Failure mode and effects analysis
GTM	Grounded theory methodology
IDC	Internal defect costs
IS	Information systems
IT	Information technology
N.A.	Not available
N.R.	Not ranked
O	Occurrence
P	Publication
PCB	Printed circuit board
QM	Quality management
R&D	Research & development
RQ	Research question
S	Severity
SD	Standard deviation
SIG	Special interest group
TWC	Traditional work context
VHB	German academic association for business research
WI	Internationale Tagung Wirtschaftsinformatik

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Part A

1 Introduction

"Digital transformation is not a technical issue – it is a human challenge."

(member of the board of management of Robert Bosch GmbH)

This quote from a top manager of Robert Bosch GmbH illustrates that digital transformation heavily depends on workers' ability to cope with the introduction of new technologies at the workplace. It is not just about the technological aspects but also involves adapting to new ways of working and changing established managerial mechanisms. In the present work, we aim to investigate the implementation of data-driven technologies within incumbent firms and analyze related implications for work and workers.

1.1 Motivation

Incumbent firms – as companies within the manufacturing industry – are founded on a mission to deliver innovative, high-quality products that spark enthusiasm and enhance the overall standard of living and quality of life. Such strong brands are proud of their immense technical expertise and the leading market position they have gained over the last few decades. In recent years, disruptive business models (e.g., electronics manufacturing services), new players on the market (e.g., Amazon or BYD), and advanced product innovations (e.g., autonomous driving or vehicle platforms) are transforming the core markets and the corresponding business models (Skog et al., 2018). Due to the growing international competition, incumbent firms must increase the speed of their internal development cycles and adapt their internal processes accordingly. Moreover, the high-cost structure of the manufacturing industry results in significant cost pressure, which creates serious challenges for companies to retain their profitability. As a countermeasure, incumbent firms must focus on manufacturing efficiency and reducing internal defect costs to ensure future profitability. Jan Becker (President, CEO, and Co-Founder of Apex.AI) succinctly sums this up in the current Megatrend report of an international automotive supplier: *"Companies that do not continually improve their efficiency will go under."* (Heinke, 2024).

As a result, digital transformation is the highest priority on the global agenda, and leaders throughout incumbent firms have a high expectation that data-driven technologies enhance their competitive position (Carroll, Conboy, et al., 2023). While digital transformation might not be a new topic, its importance within organizations is growing due to rapid technological development. Therefore, implementing data-driven technologies such as data science, artificial intelligence (AI), and algorithmic management (AM) can be considered as essential measures.

It enables organizations to rethink established approaches by digital means as they heavily influence value creation and drive efficiency and growth within incumbent firms (Vial, 2019). It is not surprising that in 2023, digital transformation is among the top three priorities in companies worldwide, as 74 % of all companies engage in digital transformation initiatives (Flexera Software, 2023).

However, the implementation of data-driven technologies in the course of digital transformation is suffering from a lack of esteem due to its high failure rate and many unsuccessful initiatives (Carroll, Conboy, et al., 2023). Various studies indicate that over 80 % of digital transformation efforts ultimately fail (Oludapo et al., 2024; Wade & Shan, 2020). Achieving measurable value upon implementing new data-driven technologies is the main issue among companies in 2023 (PwC, 2023). For example, workers struggle to exploit the full potential of data due to insufficient data availability, poor data quality, and a lack of data governance. Thus, data analysis highly depends on manual effort, e.g., extensive data collection and exchange or the creation of reference tables for data governance (Kayabay et al., 2022). Consequently, various internal initiatives deteriorate to small, local pilot projects lacking a holistic approach, as only single, local problems are solved. Furthermore, incumbent firms face challenges in adapting their traditional processes accordingly. Therefore, the full potential of advanced data-driven technologies is not unleashed, as existing organizational structures make seamless incorporation of the technologies complicated to achieve (Kaganer et al., 2023; Vial, 2019).

Besides these challenges, introducing data-driven technologies in the workplace leads to profound changes in various aspects of work. The field of information systems (IS) has consistently aimed to investigate changes in work that can be ascribed to information technology (IT). In the early stages, computerization led, e.g., to automation and the streamlining of specific tasks, resulting in changes to traditional job requirements and roles (Brynjolfsson & McAfee, 2016; Pinsonneault & Kraemer, 1993). Further technological advancements established, among others, the global distribution of work (Cascio, 2000), open access to information resources (Puranam et al., 2014), and enhanced tools for remote collaboration (Eckhardt et al., 2019). Today, the digital age shapes a dynamic work environment characterized by the integration of machine learning and generative AI (Fabri et al., 2023) or completely new work forms, as in the gig economy (Wood et al., 2019). Consequently, 70 % of the workers in Germany feel that digitalization has a considerable influence on their work (EY, 2021).

In the present work, we focus on the implications of implementing data-driven technologies in the workplace. In more detail, we want to enhance our understanding of the related changes in various aspects of work and examine how workers cope with the introduction of data-driven technologies on different levels. For example, knowledge workers, e.g., engineers, are confronted with using data science within their daily work. They must shape a hybrid practice, which requires further insights related to the design of the new role (van den Broek et al., 2021). Besides, building trust is a prerequisite for successful usage of data-driven technologies. While the trusting beliefs and implications for trust in general technology are already well understood, the current body of knowledge needs an extension related to advanced technologies such as AI (Glikson & Woolley, 2020). A deeper understanding of trust in AI is relevant due to the complex and indeterminate nature of AI behavior, coupled with the perceived risks (Ferràs-Hernández, 2018; Strich et al., 2021). In this context, the trusting belief "reliability" needs particular attention, as workers might struggle to evaluate the reliability of AI-based systems (Hoff & Bashir, 2015). Finally, data-driven technologies create new forms of management as algorithms increasingly take over managerial tasks and activities (Möhlmann et al., 2021). Given the opportunities to enhance organizational processes and performance, AM is increasingly being transferred from the gig economy to traditional workplaces (Cameron et al., 2023). Here, AM only partially replaces human managers but mediates the interaction between workers and managers (Benlian et al., 2022; Jarrahi et al., 2021). Consequently, it is highly relevant to investigate the performance effects and implications of AM in an incumbent firm.

1.2 Research Questions

The present work aims to deepen our understanding of the effects of data-driven technologies on work and workers within incumbent firms in the digital age. We consider three data-driven technologies as the drivers for the digital transformation process: (i) data science, (ii) AI, and (iii) AM. For each technology, we raise one research question, as different aspects and implications need to be examined. The following paragraph outlines the motivation and contextualization of each research question.

To understand the impact of data science within incumbent firms, it is vital to study the individual role of workers comprehensively. In particular, for domain experts and knowledge workers, data science has a significant impact (Lebovitz et al., 2021). Existing research suggests that domain experts are asked to provide their domain knowledge and share their know-how in a way that the data scientists can make use of it in the further development process (Lebovitz et al., 2021; S. Park et al., 2021; Sambasivan & Veeraraghavan, 2022). Moreover, current studies consider the evolvement of hybrid practice predominantly from the perspective of data scientists (van den Broek et al., 2021). Consequently, domain experts often find themselves in a passive role, primarily responsible for providing and sharing domain knowledge with data scientists (S. Park et al., 2021). To solve these issues, it is mandatory to involve domain experts actively in the context of work transformation and to overcome the knowledge boundary between data scientists and domain experts (Waardenburg et al., 2022). Hence, we raise the following research question:

***RQ1**: How do engineers perform data science work?*

A significant challenge for embedding data-driven technologies within organizations represents the generation of trust (Söllner, Hoffmann, & Leimeister, 2016). This is, in particular, the case for AI, as the unpredictability and lack of transparency in the behavior of AI-based technologies create issues for workers in quantifying uncertainties (Thiebes et al., 2021). Therefore, the second research question aims to analyze the AI trust development of organizations, which is stated as follows:

***RQ2:** How do organizations build trust in AI-based systems?*

To generate a comprehensive understanding of the trust-building process in AI-based technologies of workers within incumbent firms, we analyze two distinct aspects: (i) the role of reliability and (ii) the usage of an ethical framework. Due to the limited visibility of AI, it is hard to judge the performance and reliability of the AI-based system (Hauptman et al., 2022). The goal of the first sub-question is, therefore, to consider the role of reliability in the AI trust-building process. Second, we examine the increasing importance of ethical frameworks in this context (Fjeld et al., 2020). Hence, the second sub-question aims to analyze how an ethical framework can foster proper trust calibration of workers in practice. It results in the following two research sub-questions:

***RQ2.1:** How do organizations build trust in AI-based systems, given the important role of reliability?*

***RQ2.2:** How do organizations use ethical frameworks to calibrate trust in AI-based systems?*

Finally, we want to shed light on the emerging concept of AM, which is already well-established in the gig economy. Traditional organizations increasingly utilize this data-driven technology to manage their permanent workers, given its excellent business opportunities for incumbent firms (Cameron et al., 2023). However, in the traditional work context, the usage of

AM requires a different approach. In contrast to the platform-based work context, AM does not entirely replace human managers but is incorporated into existing organizational structures. While the great benefits of AM in the platform economy are well known, insights into the effects of this data-driven technology in organizations with traditional business models are still rare (Benlian et al., 2022; Lippert et al., 2023). Therefore, we formulate our third research question:

RQ3*: What impact does AM have within traditional organizations?*

More specifically, several research gaps are addressed. First, current AM research primarily focuses on workers' subjective experiences, while empirical evidence on the objective performance effects of AM is missing (M. Liu et al., 2024). Second, relevant socio-technical factors that impact workers' efficiency require further analysis (Parent-Rocheleau & Parker, 2022). Third, current research on AM in traditional organizations is dominated by the logistics sector and the prime example of Amazon warehouses, which demands further research from different perspectives, as AM is increasingly permeating traditional settings (Alizadeh et al., 2025; Keegan & Meijerink, 2025). Finally, there is a growing need to understand how AM is shaping existing work relationships, e.g., among co-workers or with human managers, as established organizational structures are heavily influenced by AM (Krzywdzinski, Schneiß, & Sperling, 2024).

Hence, the following two research sub-questions are considered:

RQ3.1: *What performance impact does AM have in the traditional work context, and what are the relevant influencing factors?*

RQ3.2: *How does AM impact the efficiency of workers and existing work relationships within traditional organizations?*

1.3 Structure

The present work consists of three parts. In part A, the first chapter provides an overall motivation for the topic and introduces the guiding research questions of the present work. Afterwards, the conceptual background (Chapter 2) and the overall research approach (Chapter 3) are described, illustrating the applied methodologies and the research context. Part B comprises five peer-reviewed papers published in the context of the present work. The first three publications (P1, P2 & P3) are of an exploratory nature and examine the redesign of workers' roles (Chapter 4), the trust-building process in AI (Chapter 5), and the related effects of an ethical framework (Chapter 6). It is followed by a quantitative analysis (P4) to measure the performance effects of the changing work, as well as several moderating effects (Chapter 7). Finally, a mixed methods study combines the quantitative investigation with confirmatory semi-structured interviews to examine the implications of AM on workers' efficiency and established work relationships (Chapter 8). In part C, the results are summarized (Chapter 9) and discussed within the broader research context (Chapter 10). Moreover, implications for theory and practice (Chapter 11), limitations (Chapter 12), and further research directions (Chapter 13) are provided. The present work is completed and finalized by the conclusion (Chapter 14).

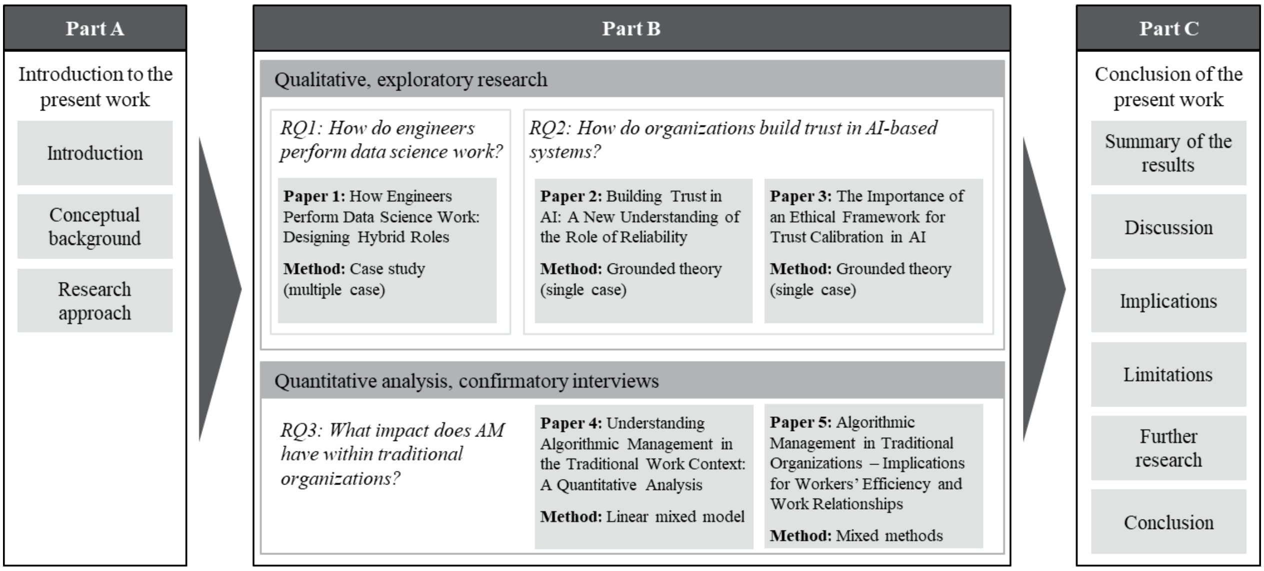

Figure 1: Structure of the present work

The following paragraph briefly summarizes each publication embedded in the present work. For each paper, we describe the research problem, the methodological approach, and the main contribution.

P1: How Engineers Perform Data Science Work: Designing Hybrid Roles (Schmid & Wiesche, 2023b). In the first publication, we investigate the work transformation of engineers. Engineers represent domain experts who are increasingly affected by the digital transformation process within incumbent firms in the manufacturing industry. We conduct an exploratory analysis utilizing 30 semi-structured interviews with engineers of an international automotive supplier. The three distinct cases reveal that engineers actively incorporate the data science perspective into their existing roles. Thus, we contribute to the literature by demonstrating the evolvement of hybrid data science work, combining both the engineering and data science perspectives.

P2: Building Trust in AI: A New Understanding of the Role of Reliability (Schmid & Wiesche, 2023a). This study aims to analyze the building of trust in AI, considering the importance of reliability. Due to the characteristics of AI, we claim that workers face challenges in judging the reliability of AI-based systems compared to other technologies. We analyze the dynamic process of an AI implementation and operation based on 17 interviews. Our results highlight that workers accept a lower level of reliability without a negative impact on the process of building trust. Hence, we contribute to the current literature on trust in AI by developing a dynamic process of building trust while also considering the interplay with AI reliability and further organizational measures.

P3: The Importance of an Ethical Framework for Trust Calibration in AI (Schmid & Wiesche, 2023c). In this publication, our primary focus is investigating an ethical framework as a robust measure to foster proper trust calibration of workers during the verification and validation phase of the AI-based system. We conduct an exploratory analysis due to the sensitive nature of the research object. Utilizing 17 interviews, we evaluate the effectiveness of the applied ethical framework and show how it enables trust calibration in practice. Hence, our primary contribution is the illustration of an ethical framework based on the FMEA approach in practice. Furthermore, we highlight the significance of focusing on AI reliability and AI safety during the verification and validation phase of the AI lifecycle.

P4: Understanding Algorithmic Management in the Traditional Work Context: A Quantitative Analysis (Schmid & Wiesche, 2024). Within this publication, we explore the implications of AM in the traditional work context while focusing on the increased significance of its application for managing permanent workers in incumbent firms. AM is implemented into pre-existing organizational structures to enhance performance by partially replacing human managers. While there is already extensive research on the implications of AM in the platform-based context, the effects of AM in the traditional work context still need to be better understood. Using linear mixed modeling, we examine a dataset of ~12700 error records to analyze the utilization of AM within an international automotive supplier. Our findings indicate that AM improves work performance by reducing error resolving time. Thus, we make a valuable contribution to the ongoing discussion of AM in the traditional work context. Moreover, we enhance the understanding of this topic by providing insights into relevant boundary criteria such as workforce involvement, task complexity, or time of work.

P5: Algorithmic Management in Traditional Organizations – Implications for Workers' Efficiency and Work Relationships (Schmid & Wiesche, 2026). In this final study, we examine the impact of AM in traditional organizations. Utilizing mixed methods research, we extend the quantitative analysis of ~12700 error records by 15 confirmatory interviews with affected workers, managers, and project leaders within an international automotive supplier. Socio-technical factors such as task complexity and worker engagement are considered, given the heterogeneous environment and the strong connection permanent workers maintain within traditional organizations. The results provide objective evidence that AM significantly improves efficiency within traditional organizations. The interviews further reveal that human managers retain a supporting role in this hybrid organizational setting. Moreover, established work relationships among co-workers are influenced by AM in several ways, e.g., by adding new dimensions of collective bypassing, situational optimization, and hybrid interaction. Finally, we offer insights into the collaborative dynamics among workers, human managers, and AM within traditional organizations.

Table 1: Embedded publications

No.	Authors	Title	Outlet	Type
P1	Schmid, Wiesche	How Engineers Perform Data Science Work: Designing Hybrid Roles	WI 2023	Conference (VHB-Rating: B; Impact factor: N.A.)
P2	Schmid, Wiesche	Building Trust in AI: A New Understanding of the Role of Reliability	AMCIS 2023	Conference (VHB-Rating: C; Impact factor: N.A.)
P3	Schmid, Wiesche	The Importance of an Ethical Framework for Trust Calibration in AI	IEEE Intelligent Systems *(published 2023)*	Journal (VHB-Rating: N.R.; Impact factor: 6.4)
P4	Schmid, Wiesche	Understanding Algorithmic Management in the Traditional Work Context: A Quantitative Analysis	WI 2024	Conference (VHB-Rating: B; Impact factor: N.A.)
P5	Schmid, Wiesche	Algorithmic Management in Traditional Organizations – Implications for Workers' Efficiency and Work Relationships	BISE *(published 2026)*	Journal (VHB-Ranking: B; Impact factor: 10.4)
Note: VHB = German Academic Association for Business Research N.A. = Not available N.R. = Not ranked				

2 Conceptual Background

This section introduces the primary theoretical concepts relevant to the present work. We provide a broad overview of various data-driven technologies and delineate the three leading technologies of the present work in more detail. Moreover, we illustrate the characteristics of incumbent firms and the traditional work context as they represent our overall research context and provide an overview of the various characteristics of work and workers. We introduce the critical role of trust and AM as a new form of management in the digital age. The chapter concludes by showing the relevant positive and negative outcomes of the digital transformation process.

2.1 Overview of Data-driven Technologies

Various data-driven technologies exist, resulting in multifaceted consequences for work and workers (Figure 2). In the following, we will provide an overview of data-driven technologies and related consequences within an organizational setting. We substantiate the overview with suitable examples and briefly describe each branch. Generally, technologies can be classified based on whether they change *individual tasks and activities* or transform *interaction with organizational members* and whether these technologies *replace* or *support* both aspects (Bughin, 2018; Ghawe & Chan, 2022; McAfee, 2006; Vimalkumar et al., 2021).

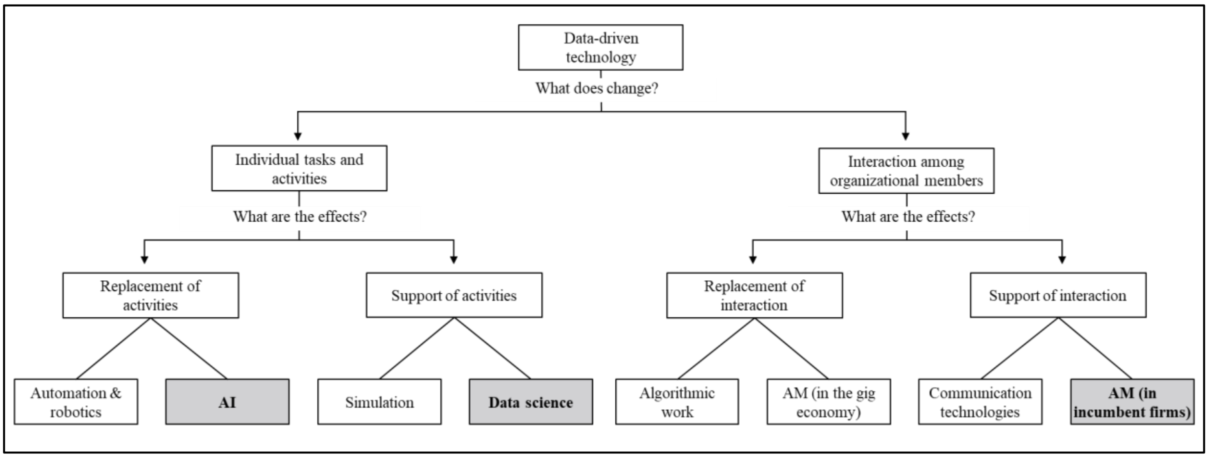

Figure 2: Overview of data-driven technologies

Individual tasks and activities can either be replaced or supported by data-driven technologies. Having the ability to interact with the environment, *AI* is increasingly replacing non-routine tasks such as predicting future events or decision-making (Agrawal et al., 2019; Y. Li & Hahn, 2022). Moreover, the rise of *robots and automation* replaces routine jobs, e.g., production or logistics (Vries et al., 2020). Nevertheless, data-driven technologies also support individual tasks and activities. In this context, *data science* uses big data, e.g., to continuously improve the efficiency and overall decision-making of individuals (Provost & Fawcett, 2013). In contrast, *simulation* enhances the execution of stand-alone tasks, e.g., by using statistics on demand (McAfee, 2006).

The interaction among organizational members can also be replaced or supported by data-driven technologies. On the one hand, data-driven technologies can replace the relationship between leaders and their employees. Such a data-driven human-management relationship is called *AM* (Möhlmann & Henfridsson, 2019). Here, managerial tasks such as work allocation, performance evaluation, or incentivizing are taken over by an algorithm (Möhlmann et al., 2021). Moreover, the interaction between co-workers can be replaced, also described as *algorithmic work*. In this case, algorithms act as co-workers and knowledgeable peers (Tarafdar et al., 2022). On the other hand, the interaction among organizational members can be assisted by data-driven technologies. For managerial tasks, *AM* can support the human-management interaction, e.g., by complementing and mediating the established relationship between managers and employees (Benlian et al., 2022; Jarrahi & Sutherland, 2019). Besides, data-driven *communication technologies* support the interaction among co-workers, e.g., via conferencing tools or e-mails (Ghawe & Chan, 2022).

The briefly presented data-driven technologies focus on the consequences within an organizational setting. Therefore, we do not take into account the external effects of data-driven technologies, such as changing customer relationships (e.g., chatbot communication) (H. Jiang et al., 2022) or digitized product innovation (e.g., Internet of Things (IoT)) (Rahmati et al., 2021).

In the present work, we focus on three technologies: (i) data science, (ii) AI, and (iii) AM (in incumbent firms). We selected the specific technologies to cover various dimensions and aspects of the presented overview of data-driven technologies. The relevant technologies for the present work will be illustrated in more detail in the following. *Data science* involves analyzing extensive data using methods from fields like machine learning or natural language processing (Passi & Sengers, 2020). Recent technological developments such as smart devices and sensors represent an increasing source for data collection (Kayabay et al., 2022). Hence, the growing availability of data helps identify new opportunities concerning an organization's internal operations based on extracting knowledge from data. Additionally, data science is of great importance in improving decision-making and enhancing the efficiency of processes

(Provost & Fawcett, 2013). The massive amount of data fuels the development of *AI,* a technology capable of interacting with the environment (Y. Li & Hahn, 2022). While the term AI was mentioned in the 1950s, utilizing AI has seen various highs and lows (Duan et al., 2019). Currently, we are facing real AI hype as various application areas within organizations and society emerge (Slota et al., 2020). Today, AI-based systems can collect and interpret information, recognize patterns and rules, generate results and decisions, or evaluate results and decisions to accomplish specific goals (Ferràs-Hernández, 2018; Strich et al., 2021). Consequently, an important application area is the industry where AI is used, e.g., to establish smart factories (Javaid et al., 2022). Incumbent firms are increasingly subject to the transformative effects of *AM*. Emerging from the platform economy, AM is also being integrated into the pre-existing structure of organizations with a traditional work context (Benlian et al., 2022). Here, it is supporting the human-management relationship, e.g., by enhancing the coordination of workers or increasing decision-making efficiency (Kellogg et al., 2020).

2.2 Incumbent Firms and the Traditional Work Context

We focus specifically on incumbent firms, representing organizations already well-established within a specific industry and market. In contrast to start-ups, incumbent firms can rely on optimized processes, mature technologies, and experienced personnel (Ghawe & Chan, 2022). Nevertheless, incumbent firms must consistently strive to develop and implement data-driven technologies to enhance their internal processes and retain their competitive position in the market. To achieve this, emerging data-driven technologies are not only aligned with the existing organization (cf. "IT-enabled transformation"). Instead, these technologies fundamentally reshape the value proposition and identity of the incumbent firm (Wessel et al., 2021). Hence, digital transformation can be understood as the comprehensive integration of data-driven technologies across all aspects of a business, leading to significant changes in its operations and organizational mechanisms (Vial, 2019). Although digital transformation is not a new topic, it is increasingly vital for incumbent firms due to the emergence of recent data-driven technologies (Carroll, Conboy, et al., 2023).

The present work examines various aspects of work and workers in incumbent firms, a domain that is significantly influenced by the integration of data-driven technologies. Our focus on incumbent firms, which adhere to a traditional business model, allows us to closely examine work and workers within the traditional work context. This work context, as we explore, can be distinguished from the non-traditional context across six key dimensions (Table 2) (Guevara & Ord, 1996).

First, *work practices* in the non-traditional context are often highly standardized, resulting in a high focus on single tasks (Wood, 2021). Hence, workers fulfill their tasks on an individual basis, even without any contact with a human supervisor (Möhlmann et al., 2021). On the contrary, workers within the traditional work context possess a greater understanding of the impact of their work practices on the achievement of overall organizational goals and vision. This fact is closely linked to the second aspect of *organizational culture*. Within traditional companies, workers feel a sense of belonging to their work unit and a strong identification with the overall organization (Olkkonen & Lipponen, 2006). Contrarily, workers in the non-traditional work context – such as gig workers – tend to have a weaker sense of belonging to their company. Instead, they identify themselves as independent and rather self-employed (Möhlmann et al., 2021).

Table 2: Traditional vs. non-traditional work context (adapted by Guevara and Ord (1996))

Attributes	Traditional work context	Non-traditional (platform) work context	Illustrative references
Work practices	Jointly; focus on overall and superior goals; team-centric; intrinsic skill use	Distributed; focus on individual activities; task-centric; standardized	(Karanović et al., 2021; Olkkonen & Lipponen, 2006)
Organizational cultures	Strong identification with the company; a sense of belonging	Isolated; reduced organizational identity	(Möhlmann, 2021; Petriglieri et al., 2019)
Rules and procedures	Transparent task allocation; office work outweighs remote work; no individual tracking	Non-transparent task allocation; remote work outweighs office work; tracking of worker data	(Davis, 2016; Eckhardt et al., 2019; Karanović et al., 2021; Wibowo et al., 2022)
Organizational structures	Hierarchical; stable organization; closed organizational boundaries	High job autonomy; isolated workers; open organizational boundaries	(Gulati et al., 2012; Lippert et al., 2023; Wibowo et al., 2022)
Management styles	Human management	Algorithmic management	(Benlian et al., 2022; Lippert et al., 2023)
Pay and rewards	Direct employment with permanent contract; high job security	Self-employed workers; no permanent contract; less secure jobs	(Ashford et al., 2018; Cascio, 2000)

Third, there is a significant difference in the *rules and procedures* between traditional and non-traditional work contexts. For example, while the allocation of tasks within incumbent firms is highly transparent to all team members, workers within the non-traditional work context often experience dissatisfaction related to unclear task allocation schemes (Karanović et al., 2021). Moreover, tracking workers' performance and evaluating individual productivity is a common method used by platform companies (Möhlmann & Henfridsson, 2019). In contrast, traditional companies emphasize establishing virtual trust rather than relying on extensive performance tracking (Eckhardt et al., 2019). However, the *organizational structure* within the traditional work context is characterized by a strict hierarchy with closed organizational boundaries. This includes, e.g., a hierarchical separation of roles and a differing degree of responsibility among workers. Moreover, the membership within the company is essentially closed, which means that external workers need approval from internal members to enter the firm. Such a closed membership does not exist within non-traditional companies, such as platforms. In addition, the non-traditional work context builds on more flexible boundaries and a less hierarchical order (Gulati et al., 2012). Consequently, workers in different work contexts experience varying *management styles* highly dependent on the specific setting. While workers in the traditional work context interact with human managers, workers in non-traditional settings constantly exchange with algorithms as a substitute (Lippert et al., 2023).

The final differentiation between the traditional and non-traditional work context can be made based on *pay and reward*. Workers within the non-traditional work context do not have a permanent work contract and are often self-employed. It results in high job insecurity, varying compensation, and financial instability. In contrast, the traditional work context offers high job security to workers, including permanent job engagement (Ashford et al., 2018).

2.3 Characteristics of Work and Workers

In the following, the characteristics of work and workers are explained in more detail. Table 3 provides an overview of the three main types of work relevant to the present work: Engineering work, IT work, and production work. Engineering and IT work can be categorized as knowledge work. Knowledge work is characterized by a low level of standardization and highly complex and ambiguous tasks (Pyöriä, 2005). Such tasks involve knowledge creation (e.g., the detection of new patterns and relationships), knowledge retrieval (e.g., using various data sources), knowledge sharing (e.g., providing information within the proper context to enhance adaptive learning), and knowledge application (e.g., utilizing domain expertise and apply it across different organizational processes) (Benbya et al., 2024). Hence, knowledge work needs extensive communication and coordination across team members who jointly solve problems.

Table 3: Characteristics of work: engineering work, IT work & production work

Characteristic	Engineering work	IT work	Production work
Type of work	Knowledge work (Alvesson, 2004)		Manual work (Yan et al., 2011)
Workers	Engineers, technicians, manufacturing experts (Bechky, 2003)	Data scientists, software engineers, machine learning experts (M. Jiang et al., 2024)	Manufacturing workers, assemblers, operators (Bechky, 2003)
Work content	Designing and developing physical products	Developing and managing IT products	Manufacturing physical products
Working approach	Waterfall (Thesing et al., 2021)	Iterative, agile (Salmela et al., 2022)	Continuous improvement process (CIP) (McLean et al., 2017)
Skills & expertise	Problem-solving skills, specialized domain knowledge (Sheppard et al., 2006)	Continuous learning mentality, cope with constant change, data knowledge (Muller et al., 2019; Riemenschneider & Armstrong, 2021)	Processual expertise, expert machine knowledge (Bechky, 2003)
Assumptions and beliefs for work	Driven by conceptuality; use physical approaches to generalize results (Anderson et al., 2010; Sheppard et al., 2006)	Driven by rationality, objectivity, and neutrality; diminish human bias (Agarwal & Dhar, 2014; Jones, 2019; Power et al., 2019)	Driven by structure and concrete instructions (Bechky, 2003)

Knowledge workers are highly qualified individuals who use their intellectual and symbolic skills for work (Alvesson, 2004; Pyöriä, 2005). Typical examples of knowledge workers are engineers and IT workers such as data scientists or software engineers. While engineers are responsible for designing and developing physical products, data scientists or software engineers are developing IT products (Bechky, 2003; M. Jiang et al., 2024). Consequently, the engineering work approach follows the classical waterfall process and not the iterative, agile methods of IT work (Salmela et al., 2022; Thesing et al., 2021). The required skills and expertise in engineering and IT work differ significantly. Engineers use their specialized technical domain knowledge to solve real-world problems. They proceed conceptually and use physical approaches to generalize results (Anderson et al., 2010; Sheppard et al., 2006). On the contrary, IT professionals such as data scientists must continually update their knowledge due to the ever-changing work environment (Riemenschneider & Armstrong, 2021). Their work approach is driven by rationality and objectivity, with the goal of diminishing human bias and finding truth in data (Agarwal & Dhar, 2014; Jones, 2019; Power et al., 2019). Overall, the underlying assumptions and work practices of engineering and IT work differ greatly, although both represent ambiguous and uncertain knowledge work (Lebovitz et al., 2021).

In contrast to knowledge workers, manual workers such as blue-collar workers or operators on the production floor use their manual skills to fulfill their daily tasks (Drucker, 1999; Yan et al., 2011). Manual workers follow continuous improvement initiatives to improve processes in a structured way for manufacturing physical products. It is based on manufacturing approaches such as total quality management or lean manufacturing (McLean et al., 2017). Manual workers in the manufacturing industry need processual expertise and machine knowledge on the shop floor. Moreover, they are driven by structure and concrete instructions of the task, which provide clarity and precision of their work (Bechky, 2003).

2.3.1 Hybrid Work

Introducing data-driven technologies in the workplace constantly changes the characteristics of work. New work practices evolve over time as technologies modify rather than completely replace existing jobs (Bughin, 2018; Huysman, 2020). For example, Nelson and Irwin (2014) illustrate that librarians change their work as a reaction to the emerging internet. Moreover, Vaast and Walsham (2005) report that sales agents transform their work practices with increasing IT use. In addition, several scholars describe work adaptations based on AI or big data, e.g., within accounting (Leitner-Hanetseder et al., 2021), the consulting industry (Strich et al., 2021), medicine (Jussupow et al., 2021) or manufacturing (Tao et al., 2018). Consequently, the impact of data-driven technologies on individual professions is leading to the evolvement of new hybrid work. Such hybrid work roles are already well understood at the intersection of managerial and professional roles (Croft et al., 2015; McGivern et al., 2015). However, new hybrid practices combine established domain knowledge and new IT expertise as data-driven technologies increasingly impact work. The characteristics of hybrid practices still need to be fully understood (van den Broek et al., 2021).

2.3.2 Professional Role Identity

The concept of professional role identity is closely linked to work, shaping how workers define their work practices and themselves (Vaast & Pinsonneault, 2021). Data-driven technologies are significantly impacting workers, either threatening or renewing their professional role identity (Nelson & Irwin, 2014). The professional identity varies across different work types. While data scientists have an uncertain identity in an evolving work environment (Vaast & Pinsonneault, 2021), engineering identity has a long-standing history (Morelock, 2017; Rodriguez et al., 2018). Recently, the concept of IT identity is gaining popularity, representing "the extent to which individuals view use of an IT as an integral part of the self" (Carter & Grover, 2015). In this context, IT workers such as data scientists possess the unique characteristic that IT both facilitates and threatens their identity simultaneously (Vaast & Pinsonneault, 2021). Conversely, IT represents a minor aspect of the professional identity of engineers (Sheppard et al., 2006).

2.4 Trust in Data-driven Technologies

Trust is a crucial success factor for the acceptance and sustainable adoption of data-driven technologies within organizations (Salam et al., 2021; Söllner, Hoffmann, & Leimeister, 2016; Thiebes et al., 2021). The most recognized definition of trust describes that trust is "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer et al., 1995). Trust can be classified into two stages: initial and knowledge-based trust (McKnight et al., 2011). Initial trust is based on the trustor's assessments before having any experience or interaction with the other party (McKnight et al., 1998). In contrast, knowledge-based trust develops over time. This means that the trustee has to get to know and experience the trustor and be able to predict particular behavior (Lewicki & Bunker, 1996). Over the last 25 years, the phenomenon of trust has been of great interest within various disciplines like psychology, management, computer science, and IS. Literature on trust research can be clustered into four trust relationships, namely trust (i) between people, (ii) between people and organizations, (iii) between organizations, and (iv) between people and technology (Söllner, Benbasat, et al., 2016). As data-driven technologies are at the center of the present work, we focus on the research stream of trust between people and technology, also called "trust in technology" (McKnight et al., 2011).

Trust in technology is built based on distinct trusting beliefs, which can be human-like or system-like (Lankton et al., 2015). Human-like trusting beliefs are similar to general expectations about trust in other people. Hence, trust is built based on (i) integrity (= trustee follows principles that the trustor accepts), (ii) ability (= skills of the trustee are considered as powerful within a domain) and competence (= capability of trustee to accomplish trustor's goals), as well as (iii) benevolence (= trustee acts in trustor's interest) (Lankton et al., 2015; Mayer et al., 1995; McKnight et al., 2011; Thiebes et al., 2021). In contrast, system-like trusting beliefs are directly connected with technology. These trusting beliefs are (i) reliability (= belief that the technology will operate consistently), (ii) functionality (= belief that the technology can fulfill the trustor's needs), and (iii) helpfulness (= belief that the technology offers sufficient help) (Lankton et al., 2015; McKnight et al., 2011; Söllner, Hoffmann, & Leimeister, 2016; Thiebes et al., 2021).

While the trusting beliefs and implications for trust in general technology are already well understood, the current body of knowledge needs an extension related to advanced technologies such as AI (Glikson & Woolley, 2020). As already mentioned, AI is characterized by advanced abilities such as the identification of patterns and rules as well as the generation and assessment of results (Ferràs-Hernández, 2018; Strich et al., 2021). The complex and indeterminate nature of AI behavior, coupled with the perceived risk, necessitates a deeper understanding of trust in AI. For example, Glikson and Woolley (2020) add tangibility as a new dimension for trust in AI. Tangibility is the ability to perceive or touch the AI technology, e.g., robotic AI. Moreover, Thiebes et al. (2021) identify beneficence, non-maleficence, autonomy, justice, and explicability as new dimensions for trustworthy AI.

Besides these new aspects, examining the existing system-like trusting beliefs in the context of advanced AI technologies is necessary. The trusting belief helpfulness is rather connected to the beneficence of AI, meaning AI usage that is beneficial to humans by respecting human rights and ethics (Allen et al., 2006; Thiebes et al., 2021). Hence, helpfulness, as initially defined, is not at the center of trust in AI research. The trusting belief transparency needs to be considered for trust in AI. Clear and comprehensive explanations of AI functionalities enhance transparency and are also understandable for workers without a technological background (Adadi & Berrada, 2018). Therefore, the implications and effects are straightforward for building trust in AI and not in our focus. Considering the unique characteristics of AI, it stands out that the reliability of AI is tough to evaluate (Adadi & Berrada, 2018; Hoff & Bashir, 2015). Even offering a consistent measure of reliability does not guarantee that workers perceive or understand the information (Faltaous et al., 2018). The reasons lie in the fact that learning algorithms and machine intelligence lead to autonomous and unpredictable AI behavior.

Consequently, the relationship between AI reliability and trust-building is complex (Glikson and Woolley, 2020). For these reasons, we examine the implications and mechanisms of reliability for generating trust in AI.

2.5 Algorithms – A New Form of Management

Algorithms increasingly take over managerial tasks and activities. This so-called AM refers to collecting and utilizing vast amounts of data on a platform to develop learning algorithms that execute functions traditionally performed by human managers (Möhlmann et al., 2021). AM consists of two components: algorithm and management. On the one hand, the word *algorithm* refers to a set of predefined computational procedures utilizing digital data to generate quantitative output (Christin, 2017). On the other hand, *management* is a set of operational and managerial tasks usually performed by humans (Tarafdar et al., 2022). Consequently, AM can take over various tasks, depending on the area of application and specific industry. One of the most relevant fields for AM is platform-based work in the gig economy. Here, online labor platforms such as Uber or Upwork use AM for two managerial tasks: controlling and matching (Möhlmann 2021). Algorithmic control is defined as managers' endeavor to use algorithms to influence workers' behavior and align it with organizational targets (Cram & Wiener, 2020). That means in more detail that managers can utilize AM to influence workers' decisions by restricting access to information and recommending preferred choices. In addition, managers can assess workers' performance by recording their behavior and rating their individual performance. Besides, AM is enforced to discipline workers by replacing the unfavored ones and dynamically rewarding preferred actions (Kellogg et al., 2020). In contrast, algorithmic matching coordinates demand and supply (Möhlmann et al., 2021). Based on worker and customer data, the algorithm calculates the best fit between customer demand and the available workforce (Lippert et al., 2023).

The impact of AM is diverse, affecting both workers and organizations in various ways. AM significantly reduces workers' freedom to make their own decisions within their work, as predefined rules limit their autonomy. This work setting often leads to demotivation, dissatisfaction, or anxiety (Gagné et al., 2022; Leclercq-Vandelannoitte, 2017). Besides, workers might face an increase in workload while at the same time being rewarded based on performance, with non-monetary or monetary incentives (Kellogg et al., 2020; Parent-Rocheleau & Parker, 2022). Therefore, algorithms create power asymmetries and heavily constrain the actions of workers (Kinder et al., 2019; Wood, 2021). On the organizational side, AM implies positive effects such as access to a cost-effective, on-demand workforce, as well as increasing efficiency and enhanced decision-making (Kellogg et al., 2020; J. Taylor & Joshi, 2018). Furthermore, organizations can achieve the highest possible level of economic value by, e.g., dynamic pricing strategies (Möhlmann et al., 2021).

Given the opportunities to enhance organizational processes and performance, AM is increasingly transferred from the gig economy to traditional workplaces (Cameron et al., 2023). In human resource management, AM augments and executes personnel-related managerial decisions such as recruitment or performance judgments (Meijerink & Bondarouk, 2023). In sales, algorithms recommend future customer sales opportunities and extract an action list for account managers (Pachidi et al., 2021). In the warehouses, AM assigns picking and packing tasks (Wiggin, 2025) or monitors workers' performance (M. Liu et al., 2024; Morse, 2022). However, AM in a traditional organizational setting slightly differs from the observations of platform-based work in the gig economy, as it complements existing structures and processes. AM does not entirely replace human managers but mediates the interaction between workers and managers (Benlian et al., 2022; Jarrahi et al., 2021). Consequently, it is highly relevant to investigate the performance effects of AM within an incumbent firm and evaluate socio-technical influencing factors that could help organizations cope with challenges in the new work setting. Moreover, there is a growing need to understand how AM is shaping existing organizational structures, given that AM is implemented later in the organizational history (Jarrahi et al., 2021). Hence, we want to evaluate how AM impacts established work dynamics, the role of human managers, and the interactions among existing organizational actors (Keegan & Meijerink, 2025; Krzywdzinski, Schneiß, & Sperling, 2024).

2.6 Expected Outcomes of Digital Transformation

The impact of digital transformation within incumbent firms is multifaceted, including positive and negative effects. Obviously, the overall expectation of digital transformation in incumbent firms is to generate positive outcomes (Ghawe & Chan, 2022). For example, organizations highlight the improvement of operational efficiency and internal performance as the primary goal. By leveraging data-driven technologies and utilizing the power of data, incumbent firms can reduce costs and optimize their operations in order to retain their competitive position in the market (Vial, 2019). In this context, automation can take over highly standardized and repetitive tasks, allowing workers to focus on utilizing their unique creative skills (Willcocks, 2020). Additionally, leaders within the organization can take advantage of the data-driven decision-making process. It is based on rising data availability and business analytics. Consequently, management benefits from increased productivity, enhanced information quality, deep analytical insights, and, thus, overall firm performance (Brynjolfsson et al., 2011; Sharma et al., 2014). Besides, digital technologies also enable new business models, such as the platform business. Hence, incumbent firms are able to expand their traditional business model and deliver new, innovative digital products or services to their customers, generating additional value (Hanelt et al., 2021; Hodapp et al., 2022).

However, large platform companies might cannibalize the core market of incumbent firms. Thus, the platform business is an excellent example of the dual nature of incumbent firms' digital transformation, as it presents enormous opportunities and threats. Reasons can be attributed to the fact that incumbent firms fail to adapt to new business models and cannot understand platform principles (Hodapp et al., 2022). Consequently, incumbent firms might be replaced by new businesses (Trittin-Ulbrich et al., 2021).

Beyond the business context, additional negative outcomes also exist in a broader perspective. Generally, incumbent firms are confronted with unsuccessful transformation efforts and poor target achievement of digital transformation projects. Hence, many firms struggle to generate significant business value from digital transformation projects (Carroll, Conboy, et al., 2023; Mikalef et al., 2019; Oludapo et al., 2024). Besides these performance-related aspects, some dark sides for workers within an organization should be considered. First, if management follows data-driven decisions without a knowledge base related to the underlying algorithms and data sources, it can potentially result in incorrect decisions. This risk arises mainly when they completely relinquish their decision authority (Giermindl et al., 2022). Second, workers within a digital work environment might suffer from poorer working conditions. For example, digital sensors or algorithmic control mechanisms constantly observe workers' activities, monitor workers' performance, and, thus, generate individual feedback. Moreover, AM generates a relatively isolated work environment in which underlying work rules are not transparent to the worker (Cram et al., 2022; Wood, 2021). Consequently, workers suffer from work exploitation, short-term employment, or even complete job loss (Ashford et al., 2018; Trittin-Ulbrich et al., 2021). Third, digital transformation poses challenges in terms of ethical, legal, and societal aspects. For example, users must keep in mind the lack of control and traceability over the data utilized to train an AI-based system. Therefore, biased data can lead to biased AI-generated content and results, which are neither objective nor neutral (Marabelli et al., 2021; Slota et al., 2020). It is, therefore, essential to consider ethical issues as well as security aspects during the digital transformation process (Oludapo et al., 2024).

3 Research Approach

3.1 Multi-Method Research

Multi-method research is applied to study the implications of data-driven technologies on work and workers within incumbent firms. The multi-method research approach has various advantages for multidisciplinary disciplines such as IS, as it provides a deeper understanding and a comprehensive view of reality (Fischer & Riedl, 2017; Mingers & Brocklesby, 1997). It combines qualitative and quantitative research methods in order to generate deep insights into various aspects of the phenomena (Mingers, 2001). In the present work, grounded theory methodology, case study (qualitative), and linear mixed modeling (quantitative) are applied as the primary research methods. The combination of qualitative and quantitative approaches supports the development of a complementary understanding from different perspectives to overcome the methodological weaknesses of a single method (Reis et al., 2022; Venkatesh et al., 2013).

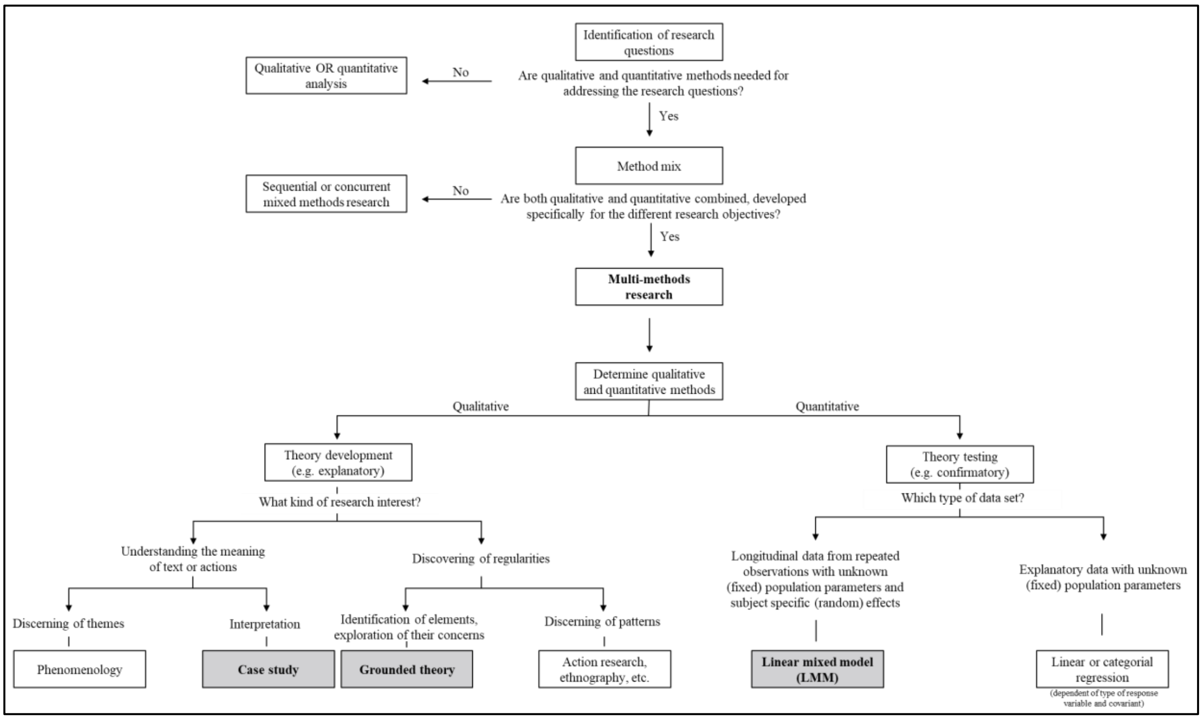

Figure 3: Decision tree for research method and data analysis (Fahrmeir et al., 2013; Miles et al., 2020; Mingers, 2001; Tesch, 2013; Venkatesh et al., 2016)

The essential characteristics of the two research directions differ to a large extent. While the overall goal of quantitative research is to test and confirm theories, qualitative research seeks to answer open questions to generate theory (Döring & Bortz, 2016; Miles et al., 2020). Moreover, quantitative research achieves external validity through statistical representativeness, while qualitative approaches seek to understand a phenomenon in depth and provide thick descriptions (Patton, 2009). The selection of both qualitative and quantitative methods has to be taken based on several criteria. Figure 3 shows the decision tree, which is applied. Detailed insights into the selection of each method are provided in the following paragraphs.

3.2 Research Methods

3.2.1 Grounded Theory Methodology

Grounded theory methodology (GTM) was introduced in the 1960s by Glaser and Strauss (1967) and is, as of today, one of the most relevant methods for qualitative research in social sciences (Morse, 2009). The overall goal of GTM is to build an inductive theory based on observations of particular phenomena, categorizing underlying elements, and examining their connections (Miles et al., 2020). As the inductive development of theory is closely linked to the data generation and research process itself (Glaser & Strauss, 1967; Patton, 2009), GTM is a highly suitable method for research areas with limited or no existing research (Urquhart, 2013). For such exploratory research, GTM has also been increasingly used in IS (Matavire & Brown, 2013) to study, e.g., the transformation of (IT) work (Möhlmann et al., 2021), technology-based changes in decision-making (Lebovitz et al., 2021) or socio-technical and organizational aspects (Kaganer et al., 2023).

GTM is characterized by a highly iterative approach (Figure 4), which does not follow a predefined sequential scheme. In contrast, the research process involves recurring alternation among data collection, data analysis, and theory development (Mruck & Mey, 2009). There is no unique set of GTM procedures generally accepted to guide the entire research process. Consequently, it is necessary to continuously make decisions that affect the course of the research project. Scholars can select appropriate approaches for data collection and data analysis out of a variety of procedures such as (i) theoretical sampling, (ii) substantive coding (= open, axial, and selective coding), (iii) theoretical coding, (iv) memoing, as well as (v) constant comparison (Holton, 2007; Wiesche et al., 2017). Theoretical sampling describes the process of data selection based on the analysis of previously collected data and the emerging theory. That means researchers continuously decide what new data should be collected while existing data is analyzed in parallel (Glaser & Strauss, 1967). Hence, theoretical sampling aims to select cases capable of replicating or expanding upon the emerging theory (Eisenhardt, 1989). In substantive coding, it is necessary to work directly with the data by applying three procedures: open, axial, and selective coding (Holton, 2007). Open coding represents the initial step of the coding procedure and refers to the first identification of concepts within the data (Miles et al., 2020; Strauss & Corbin, 1998). It is followed by axial coding, which is the detailed analysis of one category and the connection to subcategories around its "axis" (Strauss, 1978; Strauss & Corbin, 1998). Finally, the existing categories are further combined and developed through selective coding to identify the core categories (Glaser, 1978). If necessary, theoretical coding may be used to conceptualize the substantive codes of the previous coding steps and further develop theory (Glaser, 1978; Hernandez, 2009). Moreover, memoing can be applied to write down the most relevant statements and ideas during the entire data collection and analysis process (Glaser, 1978; Wiesche et al., 2017).

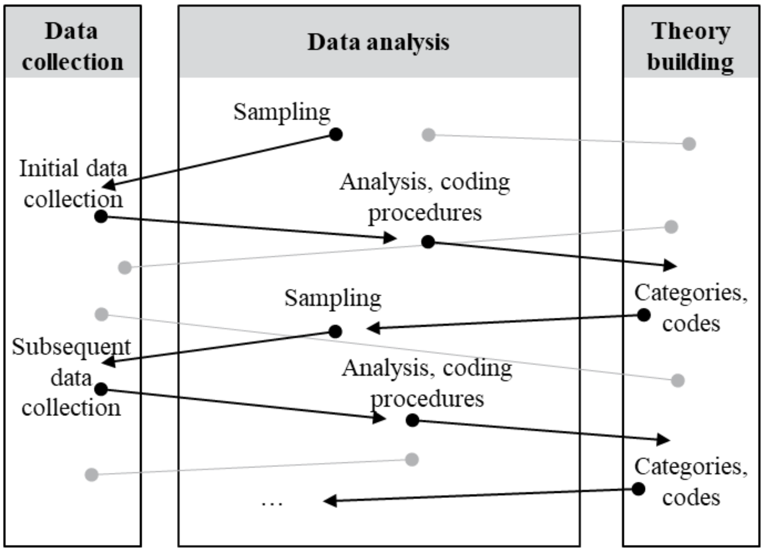

Figure 4: Iterative research approach (Mruck & Mey, 2009)

Constant comparison is often described as the core of GTM, as it refers to the process of constantly comparing data in a specific category with other data instances (Urquhart, 2013). It guides the entire data analysis process, integrating the systematic coding procedures and the theory development (Glaser & Strauss, 1967). The overall goal of GTM is to generalize the empirical results to build theory. Therefore, researchers should refrain from forcing predetermined concepts on data but focus on the emergence of categories (Seidel & Urquhart, 2013). A researcher's ability to conceptualize a theory that emerges from the data is also called theoretical sensitivity (Glaser & Strauss, 1967). Ultimately, causal relationships can be derived, leading to the discovery of explaining theory (Seidel & Urquhart, 2013). It must be noted that GTM does not offer a clear break between data collection and data analysis. Hence, researchers must persist in data collection and analysis until theoretical saturation is achieved (Döring & Bortz, 2016; Suddaby, 2006).

In the present work, we utilize GTM to gain a profound understanding of the impact of data-driven technologies on work and workers within incumbent firms. This is particularly relevant as such traditional companies are characterized by highly complex environments (Urquhart, 2013). Moreover, existing scholarship argues that GTM represents a relatively neutral method with no explicit epistemology and is considered to be neither positivist, interpretive, critical realist, nor constructivist (Bryant & Charmaz, 2007; Orlikowski, 1993). Even though others claim that no method can be totally neutral (Charmaz, 2014), GTM still serves as an extremely usable research method (Urquhart & Fernández, 2013). We apply GTM in the first, second, and third publications embedded in the present work; however, we vary the extent to which it is used. Within the first publication, we partially adopt grounded theory methods by utilizing memoing and substantive coding procedures for data analysis. However, we integrate these methods into a multiple-case study (Chapter 3.2.2), as this combination provides a rigorous and reliable approach to generating knowledge and an emerging theory in IS research (Arshad et al., 2013; Halaweh et al., 2008). In the second and third publications, we fully apply GTM and use the methodology to theorize the trust-building process in AI, focusing on AI reliability (P2) and the role of an ethical framework (P3).

3.2.2 Case Study

A case study represents another common qualitative method suitable for rather complex social phenomena (Yin, 2010). It allows one to . Case data need to be collected for each case of the study and include, e.g., interview data, observations, documentation, and records or contextual information (Patton, 2009). Generally, case studies can be differentiated into four different types: (i) single-case holistic design, (ii) single-case embedded design, (iii) multiple-case holistic design, and (iv) multiple-case embedded design (Figure 5). Single-case designs are suitable when observing so-called “critical cases”. These cases contribute significantly to knowledge and theory-building due to their strategic importance in addressing the overarching problem. Additionally, single cases may be chosen if they represent an extreme or unique case. Here, researchers might lack alternative cases but find it worthwhile to analyze the existing – although unusual – case. Lastly, the presence of a representative or typical case can also justify the application of a single case study (Flyvbjerg, 2006; Patton, 2009; Yin, 2010). Researchers generally prefer multiple-case designs rather than single-case designs, as the analytical conclusions from multiple case studies are typically more powerful and robust. The careful selection of cases should follow the so-called “replication logic” and either (i) replicate the findings or (ii) extend the emergent theory. On the one hand, cases that replicate the emergent relationship enhance confidence in the validity of the results (= literal replication). On the other hand, cases that yield contrasting results for predictable reasons offer the opportunity to refine the emergent theory (= theoretical replication) (Eisenhardt, 1989; Miles et al., 2020; Yin, 2010). For both designs, either holistic or embedded case studies might be selected. While a holistic case study does not involve any subunits, an embedded case study involves more than one unit of analysis, which cannot be pooled across cases (Yin, 2010).

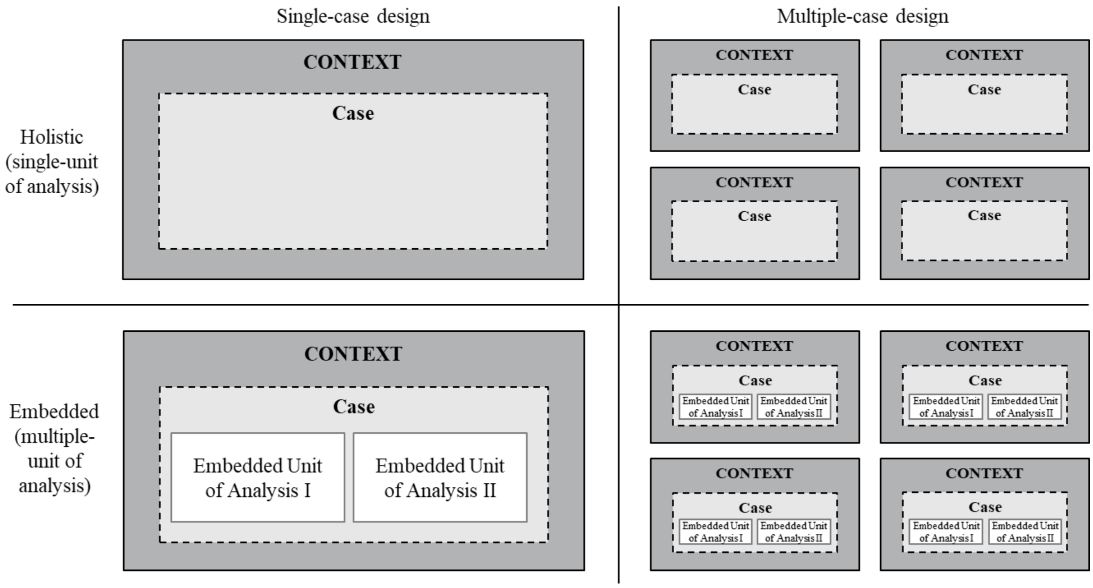

Figure 5: Overview of case study types (Yin, 2010)

For case studies, various data analysis approaches exist. The overall goal of the different procedures is to go beyond initial impressions and derive an accurate theory that fits close to the data (Eisenhardt, 1989). According to Yin (2010), standard techniques for analyzing case studies are (i) pattern matching, (ii) explanation building, (iii) time-series analysis, (iv) logic models, and (v) cross-case analysis. The pattern matching technique compares empirically generated patterns with predicted ones, which can be derived from rival theoretical explanations (Sarker & Lee, 2001; Sarker et al., 2018). When utilizing this approach, researchers should identify additional indications for the same pattern while remaining open to challenging the existing one (Miles et al., 2020). A sub-type of pattern matching is explanation building, predominantly applied within explanatory case studies. The overall goal is to build an explanation of a case in an iterative manner (Paré, 2004; Yin, 2010). Time-series analysis helps to investigate changes over time. Here, it is highly relevant to analyze “why” and “how” questions as they examine operational links and the relationship between events (Benbasat et al., 1987; Yin, 2010). The logic model illustrates complex cause-and-effect relationships, e.g., about individuals or organizations. It should be defined before data collection, as it is "tested" during data analysis by tracing the actual events over time (Yin, 2010). While the four presented data analysis approaches can be applied for single- and multiple-case study designs, the cross-case analysis is only suitable for multiple-case designs. Cross-case analysis can be highly insightful, as it deepens understanding and provides an explanation beyond the specific case. Researchers can contrast and compare the identified insights to previous cases. Moreover, clusters or families can be derived and sorted along specific dimensions (Miles et al., 2020).

The literature proposes several criteria for evaluating the quality of research designs, which mainly apply to case studies (Yin, 2010). First, researchers must consider *construct validity* by demonstrating that the selected measures of the concepts being studied indeed reflect the specific changes of the phenomenon. During data collection, it can be ensured through the use of multiple sources of evidence and the establishment of a chain of evidence. Moreover, it might be helpful to have the draft case study report reviewed by the primary informants. Second, it is recommended that *internal validity* within explanatory or causal case studies be increased during data analysis. Here, researchers must determine causal relationships between conditions by carrying out pattern matching, explanation-building, addressing rival explanations, and using logic models. Third, it is necessary to examine *external validity,* which refers to the generalizability of the findings beyond the immediate case study. Even though generalization is challenging, it can be reached using theory (in single case studies) or replication logic (in multiple case studies). The final quality criterion represents *reliability*, which refers to the fact that the researchers must ensure that a repetition of the study by other scholars would lead to the same results. In this way, any biases or errors within the study should be minimized. Researchers can achieve reliability by profound documentation of the data collection process, e.g., by using study protocols or developing a case study database (Miles et al., 2020; Yin, 2010).

Within publication 1, we apply a multiple-case holistic design to understand the data science work of domain experts. In more detail, we select three distinct groups of engineers in different contexts related to R&D departments, manufacturing sites, and external suppliers. We successfully construct three cases for our study by gathering a significant amount of raw data, including interviews, observations, and documentation (Patton, 2009).

3.2.3 Linear Mixed Model

Within the building set of quantitative methods, regression analysis is the most common statistical methodology for exploring empirical problems in social sciences. Sir Francis Galton (1822-1911) is considered the pioneer of the methodology, as his analytic study on heredity served as the initial inspiration and baseline for regression analysis (Fahrmeir et al., 2013; Galton, 1886; Stanton, 2001). After that, Karl Pearson (1857-1936) formalized and extended this work, combined with Gauß' work on astronomical data using the least squares method. Today, the regression analysis is applied in almost all scientific disciplines. Many variations have been developed, such as several linear regression models, the logit model for binary response variables, or mixed models (Fahrmeir et al., 2013).

The general goal of the regression analysis is to describe on an analytical basis the relationship between a variable of primary interest y (= response variable) and a set of regressors $x_1, \dots, x_k$ (= explanatory variables). More precisely, we want to estimate the explanatory variables' impact on the response variable's mean value. Whereas the response variable is also called the "dependent variable", the explanatory variables are additionally defined as "independent variables" or "covariates". The decision to use a specific regression model is primarily based on the independent and dependent variables, which can be continuous, binary, or categorical.

Generally, the most common standard model of the multiple linear regression is given by

$$y_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_k x_{ik} + \varepsilon_i, \qquad i = 1, \dots, n \tag{1}$$

where:

- y_i is the i^{th} observation of the dependent variable,
- x_{ij} is the i^{th} observation of the j^{th} independent variable ($j = 1, \dots, k$),
- β_0 represents the intercept,
- β_j is the j^{th} slope coefficient ($j = 1, \dots, k$),
- ε_i is the i^{th} error term,
- n represents the number of observations.

The errors $\varepsilon_i, \dots\ \varepsilon_n$ are independent of the covariates and identically distributed, such that

$$\mathrm{E}(\varepsilon_i) = 0 \quad \text{and} \quad \mathrm{Var}(\varepsilon_i) = \sigma^2, \tag{2}$$

where:

- E is the expected error,
- σ is the standard deviation.

It holds that the expected value of the error term is zero, with a constant variance σ^2 across all errors ε_i. Latter is also called homoscedasticity, and it means that the variance of the residuals is constant across the entire range of the independent variable.

In addition, the linear regression relies on further key assumptions such as the (i) linearity of covariate effects, (ii) normality of residuals, and (iii) uncorrelated errors. First, the linearity of covariate effects refers to a linear relationship between the response variable and the covariate. Second, it is mandatory to verify that the residuals follow a normal distribution, e.g., by plotting the residuals. Finally, the residuals should not be autocorrelated, which might happen when the regression model is incorrectly specified. Violating these assumptions can lead to biased estimates, a loss of information, and incorrect conclusions from the regression analysis (Fahrmeir et al., 2013).

We plan to use the regression analysis within P4 and P5 to analyze AM in the traditional work context, considering ~12700 manufacturing errors. As our tests reveal skewed data, we transform it. This is done by calculating the natural logarithm of our dependent variable in order to generate a symmetric distribution and hence fit the data within the scope of the linear model (West, 2022).

Moreover, our dataset is characterized by longitudinal data, which includes repeated observations from 22 different error numbers and nine manufacturing lines. In this case, extending the multiple linear regression model by subject-specific (random) effects is essential using the so-called linear mixed model (LMM). In contrast to the fixed effects (unknown population parameters), random effects are subject-specific and can also be described as grouping factors (McCulloch & Searle, 2000; Schielzeth et al., 2020). The overall goal of including subject-specific effects is to enhance the estimation of the fixed effects (Fahrmeir et al., 2013). Additionally, the LMM is generally robust to violations of the model assumptions, such as in our case, related to the skewed data (Schielzeth et al., 2020).

The LMM is given by

$$y_{ij} = \beta_0 + \beta_1 x_{ij1} + \cdots + \beta_k x_{ijk} + \gamma_{0j} + \varepsilon_{ij}, \qquad i = 1, \dots, n_j, j = 1, \dots, m \tag{3}$$

where:

- y_{ij} is the i^{th} observation of the dependent variable for the j^{th} combination of the 22 error numbers and nine manufacturing lines,
- $x_{ij1}, \dots, x_{ijk}$ are the i^{th} observations of the independent variables for the j^{th} combination of the 22 error numbers and nine manufacturing lines,
- β_0 represents the fixed population intercept,
- $\beta_1, \dots, \beta_k$ are the fixed population slope parameters of covariates $x_1, \dots, x_k$ that are common across all combinations of the 22 error numbers and nine manufacturing lines,
- γ_{0j} represents the random intercept, which is the individual (random) deviation from the population intercept β_0, for each combination of the 22 error numbers and nine manufacturing lines,
- ε_{ij} represents the i^{th} error term of the j^{th} combination of the 22 error numbers and nine manufacturing lines,
- n_j represents the number of observations for the j^{th} combination of the 22 error numbers and nine manufacturing lines,
- m represents the number combinations between the 22 error numbers and nine manufacturing lines.

For the random errors ε_{ij}, a similar assumption (cf. equation 2) holds, e.g., that they are independent of the covariates and identically distributed.

3.3 Research Context

The content of the present work refers to various empirical studies carried out within the organizational framework of a leading international Tier 1 supplier of technology and services with its headquarters in Germany. In particular, the present work is linked to one specific business sector of the organization that primarily operates within the automotive industry. This specific division supplies in a B2B business automotive systems to original equipment manufacturers (OEMs).

We select a company within the automotive industry in Germany as it serves as a fitting example for an incumbent firm with a traditional work environment (Hofmann et al., 2017;

Svahn et al., 2017). Looking at the past decades, it is evident that the company has a well-established operating model. Besides, workers within the company are part of a stable work environment with transparent organizational structures and hierarchies. Despite its well-established position, the company is confronted with significant challenges to sustain its competitive position due to changing market conditions, increasing cost pressure, and the rapid pace of product innovation. Consequently, it is necessary to implement and utilize data-driven technologies to secure a competitive advantage in the market. Based on several studies within this company, we will observe and analyze the implications for work and workers within the incumbent firm.

Part B

4 How Engineers Perform Data Science Work: Designing Hybrid Roles (P1)

Title	How Engineers Perform Data Science Work: Designing Hybrid Roles
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Publication[a]	18. Internationale Tagung Wirtschaftsinformatik (WI) 2023, Paderborn, Germany A preliminary version of the paper has been presented at the 12th SIG-CNOW pre-ECIS Workshop "Exploring critical challenges for the changing nature of work" (2023), Kristiansand, Norway
Status	Published
Individual contribution	The author of the present work has significantly contributed to the problem definition and study design. She has been responsible for data collection and analysis. Further, she significantly contributed to the creation of this manuscript.

Figure 6: Fact sheet publication 1

Abstract. As of today, organizations are still struggling to derive consistent value from data science projects. The basic relevance of domain knowledge for data science work can be considered as common sense. Engineers, in particular, offer a unique view of emerging data science work based on their critical role within traditional industries. As a constraint, current studies on data science work consider domain experts as rather passive, and engineering-related studies are rare. To further explore these challenges, the present study analyzes the data science work of 30 engineers at an international automotive supplier. By investigating three cases, the evolvement of hybrid data science work can be derived by combining two perspectives: engineering and data science. Thus, engineers actively incorporate the data science perspective, particularly when development activities involve minimal participation of data scientists. This contribution significantly enhances existing knowledge by demonstrating how engineers embrace the data scientists' perspective and perform hybrid data work.

Keywords: Data science work, data scientists, engineers, hybrid practice, transformation of work.

[a]Due to space constraints in the outlet, the content of the original publication is condensed. We added Chapter 4.7 to the present work to provide deeper insights into the results and contribution.

4.1 Introduction

During the last years, data science projects have gained significant importance as an essential approach for organizations to leverage the vast amounts of available data. However, organizations often face major challenges with data science projects like long project cycles, never-ending pilots, or even failed projects (Joshi et al., 2021). This results in the inability to extract meaningful insights and create consistent business value (Günther et al., 2017). One of the key issues lies in the existence of an expertise gap between data scientists and domain experts, with their specialized knowledge in a specific domain (Kayabay et al., 2022). In this context, it is already acknowledged that a close collaboration between data scientists and domain experts is a success factor for data science implementation as well as for the performing of data science work, respectively (van den Broek et al., 2021). It can be explained by the fact that – in contrast – a forced technology implementation might generate a feeling of fear, which leads to a rejecting attitude among the domain experts (Pachidi et al., 2021; Tams, 2022). This holds particularly true for highly educated groups like engineers, who might react negatively to a new technology, if they feel attacked by it (Anthony, 2018).

However, current studies regarding the collaboration of domain experts and data scientists consider the role of domain experts as rather passive, with only limited specific contributions towards the emerging data science work. Instead, domain experts are asked to simply provide their domain knowledge and share their know-how in a way that the data scientists are able to make use of it in the further development process (Lebovitz et al., 2021; S. Park et al., 2021; Sambasivan & Veeraraghavan, 2022). As a consequence, the resulting data science work is predominantly performed by the data scientist.

In-depth, the current insights regarding the data science work of domain experts are predominantly grounded on studies within business-related areas like in HR (van den Broek et al., 2021), sales (Pachidi et al., 2021), or consulting (Strich et al., 2021). However, the professional group of engineers is of particularly high relevance, as they represent a key subject for the ongoing digital transformation within traditional industries while facing at the same time fundamental changes with respect to their existing tasks and roles (Azmi et al., 2018; Muhuri et al., 2019). Furthermore, the special characteristic of engineers within organizations, e.g., being conceptually driven as well as their critical contribution towards product development and innovation, request to take a differentiated look at this group of domain experts (Bechky, 2003; Menzel et al., 2007).

Considering the relevance of domain knowledge for successful data science work (van Giffen & Ludwig, 2023), the present work aims to expand the existing perspective of data scientists by focusing on the unique role of engineers. Thus, the following research question is answered:

How do engineers perform data science work?

The data science work of engineers is analyzed based on 30 semi-structured interviews within an international automotive supplier. The evolvement of a hybrid work practice, which is predominantly performed by the domain experts, is illustrated. Finally, the interconnection of the given work practices of engineers and the incorporation of new work practices of data scientists is discussed.

4.2 Theoretical Background

4.2.1 Data Science Work and Engineering Work

Recently, data science has gained increasing attention within organizations, as it can be used to gather new insights and create additional value from data (Günther et al., 2017). So far, no consistent designation for data science and its work practices exists. The used terms and definitions within information systems (IS) research range from naming a specific method like the usage of AI (Strich et al., 2021), big data (Provost & Fawcett, 2013), machine learning (Meyer et al., 2014) or robotics (Willcocks, 2020). Moreover, these specific fields are summarized, and only generic terms like data-driven work (Brynjolfsson et al., 2011) or data work (Parmiggiani et al., 2022) are applied. In order to frame the scope of our study, we refer to data science as the practice of analyzing large-scale data to get a glimpse into decision-making and taking action (Abbasi et al., 2016; Crisan et al., 2021; Passi & Sengers, 2020). Basically, the work of a data scientist is characterized by the detection of correlations and patterns within a defined dataset. The overall goal of their work is to reveal insights based on data, even though these might not be generalizable due to the missing direct link to the underlying reasons and causalities (Provost & Fawcett, 2013). Thus, *data science work* is driven by rationality, objectivity, and neutrality. The behavior of data scientists is evidence-based, with the goal to diminish human bias (Agarwal & Dhar, 2014; Davenport, 2018; Jones, 2019; Power et al., 2019).

In contrast, an exact understanding of the specific problem is of great importance for *engineering work*. That means that engineers apply their specific domain knowledge to generate solutions and use, e.g., physical approaches to generalize their results (Anderson et al., 2010; Sheppard et al., 2006). Moreover, the behavior of engineers is rather conceptual, having the goal of designing, e.g., new products (Bechky, 2003). Engineers apply different strategies to guide others towards a particular meaning during the development process. Thus, engineers might want to utilize data to support an intended preference (Barley et al., 2012). It can be concluded that the basic approach and goal of data science work differs from engineering work to a large extent.

4.2.2 Transformation of Knowledge Work

It is already well known that work practices change based on increasing technological usage (Vaast & Walsham, 2005). Also, data science offers tremendous new opportunities and creates different demands for the work of any domain expert (Leitner-Hanetseder et al., 2021). In the present study, work is defined as "the use of human, informational, physical, and other resources to produce products/services" (Alter, 2013). Especially in the knowledge work context, data science has a major impact (Lebovitz et al., 2021).

In general, it is usually assumed that the transformation of knowledge work does not originate from the domain experts themselves. Instead, work transformation might be triggered by a forced IT system implementation (Soh et al., 2003; Vaast & Walsham, 2005) or activated by an external market change (Nelson & Irwin, 2014). In both cases, domain experts face numerous challenges. The negative effects of a forced work transformation are already well known: research on forced IT system implementations gave evidence on issues like decreasing job satisfaction due to less job control on the side of the employee (Bala & Venkatesh, 2013) or challenges regarding workarounds and unintended use (Boudreau & Robey, 2005). Prior studies have additionally focused on work transformation, where external market change caused an adaptation of the working mode without any alternative. For example, Nelson and Irwin (2014) illustrate how librarians have to change their work as a reaction to the emerging internet. The so-called "paradox of expertise" leads to the fact that they refrain from integrating the new technology into their working mode by themselves, although the capabilities are available.

Moreover, current studies consider data science applications that are predominantly developed by data scientists and not by domain experts (Strich et al., 2021; van den Broek et al., 2021; Waardenburg et al., 2022; Z. Zhang et al., 2020). One reason is the lack of capability of domain experts to apply data science, especially in business professions with limited data-related understanding (Oberländer et al., 2020). Instead, data scientists are requested to closely align their developing activities with the domain experts in order to integrate the specific knowledge into the technology, as domain-specific knowledge is a crucial success factor for data science work (Lebovitz et al., 2021; van den Broek et al., 2021). However, during the collaboration of domain experts and data scientists, additional challenging effects, such as limited or even lacking communication between the two groups, occur. Maintaining a common motivation and consistently following joint goals represent further issues that hinder successful collaboration and data science work (Mao et al., 2019). As a consequence, domain experts might not be able to interpret and evaluate the outcome of the developed algorithms, as the internal logic is unknown (Z. Zhang et al., 2020).

All the mentioned challenges might be tackled by granting domain experts an active role in the development of data science. Therefore, it is essential to overcome the knowledge boundary between data scientists and domain experts (Waardenburg et al., 2022). In the IS context, the active participation in workforce advice networks during an IT system implementation serves as a first example of that. Such high employee interaction at the workplace during the implementation phase has a positive influence on job performance (Sykes et al., 2014). However, most studies consider the formation of data science work from a data scientist's point of view and leave domain experts with the passive attitude of providing and sharing domain knowledge only (S. Park et al., 2021).

To conclude, it remains unclear how domain experts perform data science work independently from the strong influence of data scientists. This holds especially true if the development of data science applications takes place by engineers themselves, e.g., due to the given data and understanding of engineering. Thus, it is necessary to focus on data science work based on engineers' application of data science.

4.3 Methodology

In this research, we choose a qualitative research approach to examine data science work performed by the domain expert instead of the data scientist. Specifically, we analyze data science work by engineers within three cases. We find the qualitative approach particularly helpful, as it allows us to adapt a research process towards the evolving research context in an iterative manner (Charmaz 2014; Corbin and Strauss 2015). Thus, it enables the answering of "how" questions (Langley, 1999; van de Ven & Huber, 1990).

4.3.1 Data Collection and Immersion into the Field

The analysis is based on a study of an international automotive supplier within the automotive industry, which is developing and manufacturing semiconductors and sensors as well as electronic control units (ECUs) at 40 plants and locations worldwide. We chose the automotive industry because it is a strategically relevant showcase for the complex digitalization process of incumbent firms and related engineers. The analysis includes frequent visits to the field over the course of 12 months (Walsham, 1995). Thereby, we involve ourselves deeply in the context in order to truly understand the ecosystem (Johns, 2006).

We choose three cases within the organization, as the analytical conclusions of multiple-case designs are generally more powerful and robust compared to single-case designs (Miles et al., 2020; Yin, 2010). Case similarity and case variability serve as guiding principles for the selection of cases (Kirsch, 1997; Orlikowski, 1993). To ensure case similarity, we choose the organizational area related to the production of ECUs as the overall context of the study. The utilization of data science plays a major role in this entire area, as it is increasingly applied at different points along the entire ECU value stream. Thus, the environmental conditions and the availability of data can be considered common ground. However, the cases vary in terms of involved engineers, departments, functions, specific tasks, stakeholders, and localization.

Table 4: Overview of the three cases

Characteristics	Case 1: Supplier	Case 2: R&D	Case 3: Manufacturing
Traditional work design	Manual claim management of each individual material; shipment of the broken part to the supplier; discussion with supplier ex-post, based on the physical product.	Product development by using domain knowledge; decision-making based on the experience of the employees, as well as analytical models, basic statistics/ simulation.	Manufacturing problems are solved by reacting to emerging issues; evaluation of the situation by an operator at the line; non-systematic quality management.
Work design with data science application	Claim management based on manufacturing data from production lines; no shipment of broken parts; exchange of data.	Data-driven product development; decision-making based on data models by using manufacturing data as well as field data.	Systemized problem analysis and solving using manufacturing data and visualization; data-driven quality assurance.

Table 4 represents an overview of the three selected cases: (1) supplier, (2) research & development (R&D), and (3) manufacturing. Each case is selected based on a specific purpose within the overall research (Yin, 2010). Case 1 is chosen as it involves engineers who closely interact with external suppliers. The engineers selected from the R&D departments of case 2 bring in the perspective of highly educated employees having scientific backgrounds in physics, chemistry, and material science. Case 3 serves as a good field of investigation, as it is related to the core process of the company, and the involved engineers need to meet the highest quality standards.

In order to generate a profound picture, we sample 30 engineers across all three cases from different hierarchical levels, a varied degree of data science knowledge and working experience, as well as a mixture of backgrounds and work roles (Patton, 2009). Data is collected using semi-structured interviews (Miles et al., 2020). Within these interviews, our primary goal is to elaborate on the emerging data science work practice. For that purpose, in the first step, we ask the participants to describe their current tasks in detail. Subsequently, this is followed by the elaboration of the new work practices with a focus on recent changes based on increasing data availability. The preliminary interview guideline (Table 19; Appendix B) is further optimized by follow-up questions as data collection progresses (Miles et al., 2020). The duration of the interviews is ~54 minutes.

Even though interviews are the primary data source, we collect further qualitative data to enhance the fundamental understanding and to receive a clearer picture of the phenomenon (Walsham, 1995). The data include different documentation of the reported data science use cases, which have been created for internal management reviews. Additionally, current data science projects are elaborated and discussed in a two-day workshop with our attendance and representatives of the relevant functions.

4.4 Data Analysis

To obtain a profound overview of the key messages during the data collection process, we apply memoing and write a short summary with the most relevant statements after each interview (Glaser 1978). These memos help to further remember all relevant data during the data collection process. Consecutively, we are able to get back to the raw data during the data analysis. We transcribe all interviews, resulting in 482 pages of qualitative data, which serves as the primary data of this study.

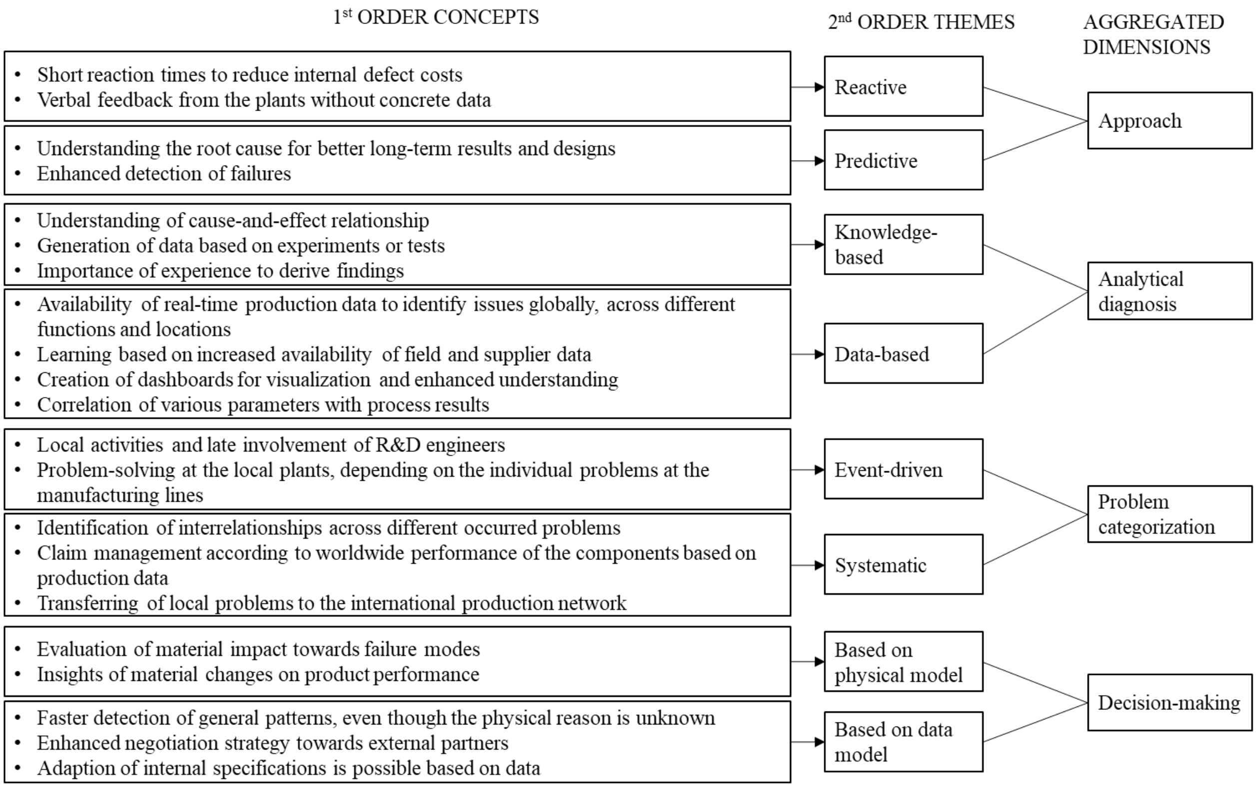

Figure 7: Illustration of the coding process

The data analysis follows an iterative procedure. Qualitative data analysis software (MAXQDA) is used to gather, organize, and analyze the data in a clear and transparent manner. We code all interview transcripts systematically, applying grounded theory methodology (Corbin & Strauss, 2015; Sarker et al., 2018). In the first step, open coding is used to assign appropriate labels to the interview passages, which summarize the key message in a short phrase (Miles et al., 2020). Here, we identify the general work characteristics in applying data science. During the data analysis process, the persistence of the former engineering work practices is evident. That is why we use axial coding for the identification of connections between the subcodes (Strauss, 1978). We can map the former engineering work practices as well as the new data science work practices to each work element. Finally, we apply selective coding to further develop and combine the dimensions, resulting in the final consolidation (Figure 7) (Glaser, 1978). The whole coding process follows an iterative procedure through several rounds of reviewing and rewriting (Miles et al., 2020).

4.5 Results

The present work targets on a deeper understanding of data science work performed by engineers. As a result, a hybrid data science practice is presented, illustrating that engineers combine elements from their established work practices and the new work practices of data scientists. The characteristics of the hybrid role can be detailed by the following four relevant work elements: (i) approach, (ii) analytical diagnosis, (iii) problem categorization, and (iv) decision-making (Figure 8). Each of these categories and the respective characteristics of the two roles are elaborated in the following.

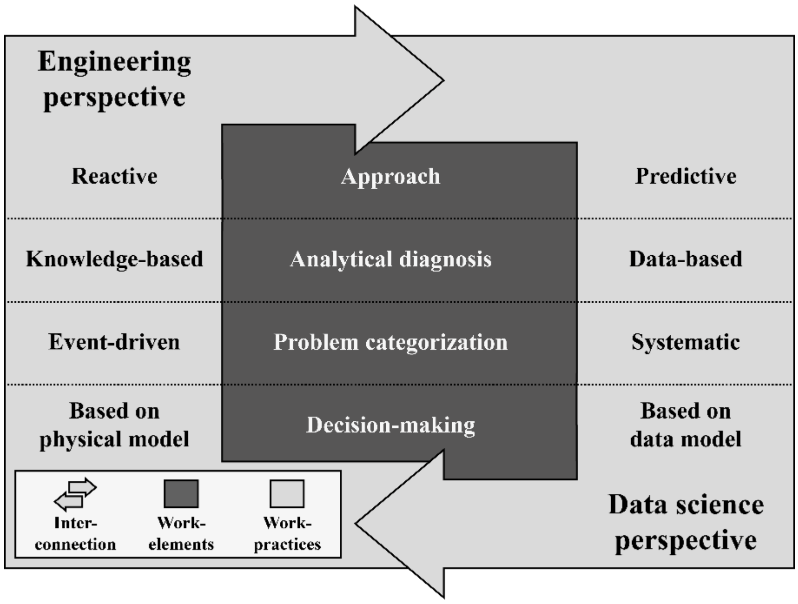

Figure 8: The hybrid practice of data science work

Combining a reactive and a predictive approach. Both the reactive and predictive aspects are highly relevant for engineers' data science work within all three cases. On the one hand, the *reactive* work practices are well established since engineers need to support problem solving during the manufacturing process. Short reaction times are needed, as internal errors cause high internal cost. The collaboration between R&D and manufacturing requires staying reactive under specific circumstances:

> *"The major pain point is that we get a lot of verbal feedback from the plants regarding their problems. They are saying: […] last night we had ten failures pieces, please support us." (#28; Table 15)*

Nevertheless, identifying such incidents is an important baseline to learn for the future. Here, the application of data science is essential. Thus, the reactive working approach is strengthened by the *predictive* perspective. The proactive usage of data tremendously increases the speed of product development and failure detection. Additionally, the adaptation of current operational processes can improve the quality of future work. As a result, plants can trigger improvements, such as machine settings with reference to identified errors. All in all, this targets to prevent reoccurring issues based on the same root cause.

In addition, by means of the explorative identification of similar error structures, future issues can be avoided. Such an early warning system helps to keep the operations running within defined control limits, as potential issues are detected in advance. The roll-out and the proactive integration of the developed solution into future products by the workers from R&D ensures a reduction or even elimination of specific failures. Such a mindset of forward-thinking in R&D helps to introduce fundamentally new ideas:

> *"With much more detail, we can clearly identify the root cause in comparison to a hypothesis […]. And now, we can understand: 'Ok, if I do this, it will make this happen, and at the end of the line, we will have a good result because I understand what is happening in between.' […] And this also allows the team (…) to make better designs from scratch." (#27; Table 15)*

Analytical diagnosis based on knowledge and data. Engineers have acquired profound domain knowledge during their studies, and several years of working experience complement the knowledge level to a great extent. Hence, *knowledge-based* diagnosis is of great importance for certain operations. One respondent highlights the benefits of knowledge application, like an intense and autonomous analysis of any problem. For that purpose, a deeper involvement in the field is necessary to deal with the situation and to deduce a solution simply based on domain knowledge.

> *"The bottom line of my work is to build up knowledge. And I believe that this will remain the same and that you will continue to need the expertise, the experience." (#22; Table 15)*

However, in some situations, the exact identification of failures and error patterns is complex. This can even lead to an entire lack of understanding of relevant topics or occurring issues. To address this issue, data science is essential for conducting a complementary *data-based* analysis. Facts and figures enhance the problem diagnosis in various ways. In the first step, a detailed visualization of the manufacturing data can help to get a general feeling for the respective circumstances:

> *"Even the development who is very, very far away from production can check and see that: 'ok, we have a problem at this and this station and that press fit force has been increased for the past two hours.' […] And then […] I see: 'ok, the force increase is caused by this supplier batch of the pins.' And this is making it much easier to detect the root cause of the problem." (#26; Table 15)*

Additionally, the data richness of the visualization is a key driver for high transparency and thus creates a deeper understanding of the current operations. Observing and controlling internal processes on a regular basis can help to detect anomalies. In this way, specific questions can be answered fast:

> *"You know, for example, did the control systems that stimulates the control units have a problem or was it due to individual control units or due to which signals?" (#13; Table 15)*

This is valid if visualizations of relevant information are continuously available and always up to date. Using real-time data enables the constant tracking of manufacturing processes. In this way, the influence and effects of individual activities of workers from R&D or manufacturing can be identified immediately:

> *"But for such regular queries, I created a Tableau dashboard. [...] There you see nicely: after we made the change here, that we got a nice improvement. From B/C to mainly A, but also a little bit of B still there. And to track that effectiveness, I just quickly made a dashboard." (#13; Table 15)*

Considering case 2, it can be concluded that the application of data science even leads to a systematic verification of already existing knowledge-based assumptions. In this context, the scope of the current work within R&D can be expanded since it is now possible to investigate relevant aspects by means of available data. In the past, models were built up, and – in some cases – no clear explanation could be found. Today and in the future, data science application offers the possibility to check and calibrate these already existing models based on the data. Thus, so far, open questions, e.g., regarding the maximum storage time of printed circuit boards (PCBs), can now finally be answered:

> *"What is the right storage time of PCBs [Printed Circuit Boards]? That is very difficult to check on the development side. We try to anticipate the aging process, like calculating how much oxide growth I have. But in the end, you can also say: 'Hey, the truth is in the field, right?' Let's see how old the PCBs are, whether we see a correlation, for example, that PCBs which are one year old have a higher defect rate than completely fresh PCBs." (#30; Table 15)*

Using event-driven and systematic problem categorization. Our data reveal that problem categorization is another important component, which is a relevant data science work practice.

As already indicated, in the context of problem solving, the established work practices of engineers are rather *event-driven*. Case 3 shows that single, specific events must be analyzed in order to define a solution for the specific problem. In particular, this holds if the occurring issue needs to be solved fast. Timing is another crucial factor which explains an apparently randomized way of working:

> *"The difficulty is: I always have the problems in the plants at different points in time. That's tricky, because today plant A calls, tomorrow plant B calls." (#09; Table 15)*

This event-driven way of working results in work being categorized as single issues. Local on-site teams are set up and start to work jointly on the specific issue. High efforts within the organization and upon coordination will be created, and critical resources will not be used in a targeted manner. Wort-case, this traditional working mode causes double work and could even lead to unproductiveness:

> *"So, in production, there is a problem, and practically they try to solve it on their own. This is the process: First, they look at it. If they cannot solve it, they contact the development. Of course, there is the development and then some contacts from the development. How does it work with the calendars? They need to search for an appointment. They need to tell the guys from development what issues they are facing and what problem solving they have tried. And they start to work together on this." (#27; Table 15)*

Such an event-driven procedure has to be guided by a *systematic*, all-time solution to the problem. As one key aspect, data science shifts the perspective and generates the required holistic view. It needs to be taken care that single events at specific local plants are excluded from the data to prevent those local effects from distorting the overall picture. Such local events are, among others, incorrect machine settings or local environmental conditions that are not design-related or linked to the specific component.

As an essence, the systematic problem categorization focuses on the global perspective and distinguishes between real global pain points and specific location-dependent effects. The availability of manufacturing data offers the opportunity to detect the root cause of a problem at any line in a structured way. The priority of local effects is decreased, and the focus is set on global incidents, which can be solved with much more effectiveness. In this way, it is possible to identify interrelationships of a different order, which can cause further possible issues. Thus, it fundamentally changes the problem categorization with respect to the claim management procedure. Even the work with external partners is changing, as the systematic usage of data provides a new basis for collaboration. This can be illustrated by the following example of case 1, that describes how the work practice with external suppliers is adapted:

> *"It is possible to make a claim of the performance of the components based on production data. This means that not only individual cases can be claimed, but also the global performance of different plants as well as differences in the performance of different suppliers." (#29; Table 15)*

The systematic problem categorization can also help to implement continuous improvement methods within the international production network. In this way, problems are not only solved at that single point in time but are also faster detected in case of similar occurrences at different locations:

> *"We share all information in an international lesson learned network so that everyone in the organization can make use of a holistic approach and transfer it to their cases." (#03; Table 15)*

Decision-making grounding on physical model and data model. In daily work, engineers have to make countless decisions using physical and data models as a combination. Decisions *based on physical models* do not necessarily require a large amount of data for verification. Instead, engineers build a basis for the decision through the application of models which are referring to physical laws. These physical models are available for every engineering topic, such as mechanics, hardware, or manufacturing development. They serve as an important baseline for decision-making in the R&D area, like the selection of the appropriate material in the product design:

> *"If I change the material from copper to iron, I would like to know if this has an influence on my failure mode, e.g., the temperature cycling performance. My physical model tells me that stress and strain can cause cracks in the solder joint [...] and that iron promotes this more than copper, as the coefficient of thermal expansion is more critical. I have not recorded a single data point; I have derived analytically from physical models that this is going in the wrong direction." (#02; Table 15)*

The analytical derivation of the cause-and-effect relationship based on the physics of failure enables this verification without the application of data science. In contrast, data and, thus, the application of data science is the fundamental prerequisite for deriving decisions based on data models. This holds for decisions within all three cases, such as the selection of a supplier (case 1), product development decisions (case 2), or decisions regarding the right way to solve occurring problems (case 3). By using the data model approach, it is possible to identify issues that cannot be explained solely by a physical model. Instead, it is possible to see further indications which might cause an issue. One example is the correlation between the results and a certain supplier, which enables insights into their respective performance and creates a better basis for negotiation:

> *"Based on the data, we can try to change the specification for the PCB [Printed circuit board] shrinkage for the PCB (reflow) cycles. It is hard work, but based on our statistic regression, we see that the range of the currently defined specification is too big, and we can reduce it." (#28; Table 15)*

However, the accuracy of decision-making based on data models is strongly dependent on their granularity and level of detail. It is important to have a comprehensive description, leading, in the best-case scenario, to a digital twin that contains any relevant element of the real world. At the final stage, the algorithm is even able to develop and recognize its own patterns with a huge amount of data. It is important to mention that the examples of the decision-making aspects illustrate how the two perspectives of the physical model and data model approach interact with each other. At first glance, decisions by data models based on probabilities can be taken, which do not require any domain knowledge. However, the physical reason behind these failures is still unclear. Digging deeper into the topic shows that results from the data model are not enough and, hence, have to be explained by a physical reason:

> *"Of course, based on the data, we would only see that the workpiece carrier is causing the issue, and when we check it physically, we know this is being caused by the loose screw." (#26; Table 15)*

Combining engineering and data science work practices towards an interconnected hybrid practice. To sum up, engineer perform data science work by integrating data science practices into their existing role. Depending on the phenomenon, it can be necessary to apply sophisticated engineering work practices. However, the merger with data science leads to the creation of a new hybrid practice. As a result, the feedback loop can be closed by the interconnection of both work practices:

> *"Particularly regarding our manufacturing, we can close this circle because, at the end of the day, we always view our work as CIP. And if we include the feedback, we can look at how we can improve." (#20; Table 15)*

Finally, it can be recognized that both perspectives are strongly interwoven and in constant interaction. The traditional approach serves even as a baseline for fueling the data science perspective. For example, the generated data from event-driven issues within case 3 are an important prerequisite for further enhancing the R&D process:

> *"We have developed an IDC [internal defect cost] reduction cycle. Here we have both the backward integration to existing products and forward integration for new products." (#02; Table 15)*

4.6 Discussion

The scope of the present study is to understand the design of data science work by engineers. Integrating data science into the existing work of the domain expert leads to the evolvement of hybrid data science work. Hence, the content of the current literature is expanded in two ways. First, it is introduced that the domain experts are the drivers of their data science work. Second, we show that engineering domain experts embed data science into their existing work, resulting in the hybrid practice.

4.6.1 Theoretical and Practical Contributions

For data scientists, it is already well known that they utilize data to construct new ways of working (Muller et al., 2019). In contrast, domain experts are so far considered as being passive in the sense of performing data science work (Jung et al., 2022; van den Broek et al., 2021). In the present work, we broaden this limited view and illustrate a new work setting that engineers themselves create. Consequently, data science work is performed by domain experts, which leads to the fact that engineers question their existing border criteria. Moreover, the workers even calibrate and verify their established work results by means of data science.

Among others, this can be emphasized, e.g., in the sense of decision-making. Here, the sole application of data science results in uncertainty and missing underlying explanations (Lebovitz, 2019; Lebovitz et al., 2022; Provost & Fawcett, 2013). Nonetheless, work practices of engineering, like the understanding of physical causalities, remain relevant. As a result, the combination of engineering and data science allows for a profound understanding, which provides further evidence of the relevance of hybrid work practices. Prior studies have already emphasized the importance of creating hybrid systems in the context of machine learning, as

AI can only partially solve problems (Z. Zhang et al., 2020). Within the present work, we illustrate such a hybrid approach in the context of data science and provide, for the first time, a detailed explanation of the hybrid practice that is demanded. In addition, it serves as a detailed example of an emergent evolvement of digital transformation, as domain experts continuously realize value from the adjustment of their work (Koch et al., 2021).

The findings further extend recent studies investigating the impact of technology on work (van den Broek et al., 2021; Willcocks, 2020). As an example, Strich et al. (2021) show that the old tasks of consultants are eliminated by an AI system. However, we demonstrate that domain experts do not discard the existing work practices. Instead, data science complements the established work, and it becomes part of the existing job. In this way, we contribute to research that recognizes that technology will rather modify than completely replace existing jobs (Bughin, 2018; Huysman, 2020) as well as research on the evolvement of an "IT identity" (Carter & Grover, 2015). We extend this body of knowledge by illustrating two underlying success criteria concerning domain experts: First, the stronger contribution compared to the data scientists, and second, the capability to perform new data science work by themselves.

As an outcome, we derive contributions to practice from this study. First, it provides a more differentiated view on the establishment of new data roles within organizations. Major aspects of domain experts should be kept to a large extent, instead of pushing for a strict transformation from classical engineers towards data scientists. This procedure helps to overcome obstacles and convince additional domain experts to go in the same direction. Second, the results of this study reveal that the commitment to data science application plays a crucial role in the successful implementation. It is, therefore, important to share the success story within the company to influence others.

4.6.2 Limitations and Future Research

The present study is subject to some limitations. The qualitative approach and the selective sample size result in restrictions on the overall generalizability of the results, as the data collection is limited to the domain-specific context with a focus on the automotive industry. An effort is spent to counteract this obstacle by selecting three different cases within the overall context. However, further research could seek to widen this perspective and compare the results with domain experts from different industries.

Finally, our work focuses on the specific characteristics of the created hybrid data science work while disregarding the respective transformation process towards that hybrid practice. It might be interesting to see how the transformation path works and whether the well-known “Model of Institutionalizing“ (Reay, T., Golden-Biddle, K., & Germann, K., 2006) also holds in the data science context.

4.7 Conclusion

During the last years, it has already been strikingly titled that big data and, thus, data science will “transform how we live, work, and think“ (Mayer-Schönberger & Cukier, 2013). Researchers indicate that it results in a hybrid practice (van den Broek et al., 2021), combining domain knowledge and data science knowledge. However, the detailed characteristics of this hybrid role remain open. Moreover, despite recognizing the relevance of domain knowledge in data science work, numerous studies still consider engineers in a passive role, limited to providing and sharing domain knowledge with data scientists. To address these challenges, the present work analyzes the design of hybrid data science work, based on 30 semi-structured interviews with engineers of an international automotive supplier. The identified hybrid data science work reveals four work elements and the respective work practices from the engineering and data science perspectives. For example, data science work practices are essential and offer various benefits for decision-making. Moreover, engineers integrate the data science perspective to question established assumptions related to their work. All in all, this contribution advances current knowledge by showcasing how engineers actively adopt the practices of data scientists and engage in hybrid data science work.

5 Building Trust in AI: A New Understanding of the Role of Reliability (P2)

Title	Building Trust in AI: A New Understanding of the Role of Reliability
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Status	Published
Individual contribution	The author of the present work has significantly contributed to the problem definition and study design. She has been responsible for data collection and analysis. Further, she significantly contributed to the creation of this manuscript.

Figure 9: Fact sheet publication 2

Abstract. It is well known that trust represents a crucial success factor for the adoption of a technology. Among others, the reliability of the technology has a direct impact on the process of building trust. In the present paper, it is claimed that there is a contradiction related to the impact of reliability on building trust between former technologies and AI with its specific characteristics. Moreover, the static relationship between the process of building trust in AI and the corresponding measures, as reported in the literature, requires a new approach. To close this gap, an analysis of an AI implementation and operation of an international automotive supplier is conducted. Based on 17 interviews – as the main outcome – workers accept a lower level of reliability without a negative impact on the process of building trust. In order to explain and understand this finding, the importance of organizational measures for trust calibration is discussed.

Keywords: Artificial intelligence, trust, reliability.

5.1 Introduction

Artificial intelligence (AI) is a new driver in the field of technology and has a major impact on business success (Davenport & Dasgupta, 2019). This is mainly related to the massive growth in data, an increasing automation of common processes, and the possibility of scaling across networks. As an outcome, AI is impacting various aspects within an organization, e.g., the way organizational decisions are made and knowledge management (Brynjolfsson & Mitchell, 2017). To unleash the full potential of AI, as a prerequisite, a high degree of trust in the emerging technology is mandatory. However, the lack of trust represents one of the main reasons preventing workers from taking full advantage of AI (Gillath et al., 2021).

The role of trust in AI within organizations is highly critical, and hence, the process of building trust represents an important research stream in Information Systems (IS). There are numerous factors that influence building trust. The positive effect of performance-related aspects on trust in IT systems is already well known (Söllner, Hoffmann, & Leimeister, 2016). It has to be pointed out that the *reliability* of the IT system serves as an important baseline for building trust in technology. Reliability refers to the confidence of the user that the technology will operate in a suitable and consistent way (McKnight et al., 2011). In contrast, AI is often described as a “black box”, which is basically caused by the fact that it is difficult for workers to completely understand the algorithm with its underlying rules and the logic behind it (Adadi & Berrada, 2018; Hoff & Bashir, 2015; Y. Li & Hahn, 2022). As a result, workers feel faced with a non-transparent decision-making process for AI and thus have to tackle challenges regarding the right interpretation of AI output (Buttazzo, 2022; Danks & London, 2017). Based on that, it is claimed that the current assumptions regarding the impact of reliability on building trust in technology need an extension towards AI-based systems.

In the past, as a basic understanding, a rather static relationship between the influencing aspects of trust and workers’ trust-building in technology was assumed. However, in the context of AI, it is already known that the process of building trust in AI needs to be continuously maintained during its development and implementation (Hengstler et al., 2016). So far, there is no clear understanding of the dynamic process of building trust in AI during AI implementation or the underlying organizational measures.

Thus, the major goal of the present study is to investigate the evolvement of trust during AI implementation, as well as the role of reliability in building trust in AI systems and related organizational measures. Hence, this research seeks to answer the following research question:

How do organizations build trust in AI-based systems, given the important role of reliability?

An exploratory analysis is carried out to tackle the research question. Based on 17 semi-structured interviews within one of the biggest automotive supplier companies, we explore the process of building trust in AI over time and the important role of reliability. The lower degree of reliability, as well as the decisive measures and phases behind embedded AI implementation and operation, are considered and studied. As a result, the trust-building process and the evolvement of the degree of AI reliability within an organizational context are discussed.

5.2 Literature Review

5.2.1 Artificial Intelligence

AI is defined as a new generation of technologies that is able to interact with the environment (Glikson & Woolley, 2020; Y. Li & Hahn, 2022; Niehaus & Wiesche, 2021). In this context, the capabilities of AI include (i) the collection of information from the outside, (ii) information interpretation like recognition of patterns and rules, (iii) generation of results like answering questions or providing instructions to other systems, and (iv) the evaluation of the results and decisions in order to achieve a specific objective (Ferràs-Hernández, 2018). In general, two classifications exist: strong and weak AI (Russell & Norvig, 2010). Strong AI refers to machines with superintelligence that actually operate like humans. It has to be confessed that these types of systems do not exist today. This is the reason for focusing our efforts on weak AI, specifically on systems that are capable of stimulating intelligent behavior. Such simulated human intelligence is defined as the ability to perform human tasks, like face recognition or visual inspections (Glikson & Woolley, 2020; Hengstler et al., 2016). Nevertheless, AI goes far beyond the pure automation of repetitive human tasks based on pre-programmed rules (Parasuraman & Riley, 1997). It is empowered by the increasing availability of large amounts of data, as well as high-performance computing and immense storage capacity (Willcocks, 2020). Thus, the application of AI becomes a crucial success factor for the competitive position of firms (Haenlein & Kaplan, 2019; Hengstler et al., 2016), resulting in a real AI hype within society and organizations (Slota et al., 2020).

Despite the potential benefits of AI, most organizations have not yet successfully leveraged its capabilities, and the integration of AI within organizations represents one of the biggest challenges (Alsheibani et al., 2022). Some researchers are already indicating that the implementation process within organizations needs to be oriented toward the nature of the AI lifecycle to tackle this. The AI lifecycle is dynamic and follows five different phases, namely:

(1) requirements engineering, (2) design, (3) implementation, (4) verification and validation, as well as (5) operation (Q. Lu et al., 2022).

5.2.2 Trust in Technology

It is well known that the implementation of trust represents a crucial success factor for the acceptance and sustainable adoption of technology within organizations (Salam et al., 2021; Söllner, Hoffmann, & Leimeister, 2016; Thiebes et al., 2021). The phenomenon of trust is complex and is of great interest within various disciplines like psychology, management, computer science, or IS. The basic definition of trust is displayed by the willingness of an individual to depend on another person and to be vulnerable to the actions of that person caused by the lack of control over the other party (Mayer et al., 1995). Generally, trust can either be defined in terms of "trust in people" or "trust in technology", which are built by differing trusting beliefs (McKnight et al., 2011). Trust in people refers to trust in a specific person or an organization. Here, trust is built based on competence, benevolence, and integrity (Mayer et al., 1995; McKnight et al., 2011; Thiebes et al., 2021). In contrast to that, trust in technology refers to a specific IT artifact. In this case, the trusting beliefs are connected with the technological performance of the IT system and are closely linked to high reliability (McKnight et al., 2011; Söllner, Hoffmann, & Leimeister, 2016; Thiebes et al., 2021). That means if workers cannot trust the reliability of the IT system, they might deny its application (Lankton et al., 2015).

5.2.3 Trust in AI

In the context of AI, fundamental trusting beliefs related to technological aspects, such as reliability, become challenging to comprehend. The reasons for this difficulty can be connected to the distinct features of AI, which result in a limited understanding of the underlying algorithms and a challenging interpretation of the technology's output for workers (Adadi & Berrada, 2018; Hoff & Bashir, 2015). Only providing a continuous measure of reliability does not necessarily indicate that workers perceive or comprehend this information (Faltaous et al., 2018). It must be noted that in contrast to former technologies like traditional automation, the behavior of an AI-based technology is unknown, as it is lacking in predictability (Glikson & Woolley, 2020; Im et al., 2023). Thus, workers might not be capable of adequately quantifying the uncertainties of AI models by themselves. It creates tension, which slows down or even stops the process of building trust in AI (Thiebes et al., 2021). In addition, the limited visibility of AI makes it hard to judge the performance and reliability of the AI-based system (Hauptman et al., 2022). Nevertheless, the trust-building process in AI forces workers to calibrate their level of trust according to the reliability of AI (X. Li et al., 2022). During this process of trust calibration, over-trust (trust that surpasses AI's reliability) or under-trust (trust that falls behind AI's reliability) should be avoided to allow a positive impact on successful human-AI cooperation (Okamura & Yamada, 2020; Thiebes et al., 2021).

Numerous studies are considering different aspects of the trust calibration process in AI. As a common ground, these studies consider a rather static relationship between the influencing aspects and the trust development during implementation: Hengstler et al. (2016) report the general importance of proactive communication, stakeholder alignment, and operational and data security. Calisto et al. (2022) highlight the relevance of security and perceived risk for building trust in AI recommendations. So far, the dynamic phases of the aforementioned AI lifecycle have not been taken into account to tackle the challenges related to AI trust (Q. Lu et al., 2022). To consider the complex phenomenon of trust, the current perspective on the trust evolvement process and its underlying mechanisms needs to be extended. Adding the aforementioned complications regarding reliability in the context of AI causes a gap that will be closed by the present work. Thus, it is necessary to study the role of reliability in the context of AI in more detail and identify dynamic countermeasures based on the new approach.

5.3 Methodology

In the present paper, the process of building trust during AI implementation within a global production network is investigated. In this context, special attention is paid to the role of reliability. Due to the sensitive nature of the phenomenon of trust in AI, it is essential to select an appropriate methodology for the evaluation (Y. Li & Hahn, 2022). An exploratory research strategy is applied to consider this, as it allows the adaptation of the research process towards the evolving research context in an iterative manner (Miles et al., 2020).

5.3.1 Data Collection and Immersion into the Field

The analysis is based on a study of an international supplier in the automotive industry. In this context, an AI-based system is considered to serve as a quality gate in manufacturing. The selected organization is developing and manufacturing semiconductors and sensors as well as ECUs at 40 locations worldwide. To improve the high-quality standards further, AI-based visual inspection is implemented in the running operations of more than 200 manufacturing lines in seven international plants. Such AI-based inspection technologies have the highest impact compared to different areas of AI application in firms (Boer et al., 2022). In the present study, the investigation of the evolvement of trust within the organization and its underlying mechanisms during AI implementation represents the main research object.

In order to gather a deep understanding of the ecosystem, we involve ourselves deeply in the context. During data collection and analysis an iterative approach is followed by using grounded theory methodology (Glaser & Strauss, 1967). This is appropriate since traditional companies within the automotive sector are characterized by an environment of high complexity (Urquhart, 2013). The sensitive research setting of embedded AI gave further indication for selecting a qualitative approach (Y. Li & Hahn, 2022). Primarily, data is collected using semi-structured interviews. We recruit the participants based on conceptually-driven sequential sampling and start with initial informants of the central project team (Miles et al., 2020). All participants are selected based on three criteria: (i) role in the AI project team, (ii) function, and (iii) location. Beyond that, workers with insights into different phases of implementation are considered to investigate the phenomenon from different perspectives. This allows us to make comparisons along different phases of AI implementation and operation. All in all, 17 participants are chosen from four plants and the central team (Table 5). First, we ask the participants to give a detailed description of their role during the implementation process. Second, their concerns and challenges during that process, as well as the supporting measures, are elaborated. Here, we additionally capture the individual's feelings regarding reliability. Third, we gather their impressions regarding the AI operation as well as their overall opinion on the AI-based process. The preliminary interview guideline is instantly optimized by follow-up questions if data collection progresses (Miles et al., 2020).

While interviews are the primary data source of the present study, we collect further qualitative data to deepen the fundamental understanding and capture the phenomenon more clearly (Walsham, 1995). For the sake of transparency, the project folder with detailed internal documentation of all activities of the entire project team, as well as the respective plants, is accessible to everyone. We utilize the project folder to further investigate data such as (i) presentations for management reviews, (ii) documentation of the new process release, (iii) several checklists and best practices provided as informational material for the implementing plants, (iv) AI performance dashboards, (v) results of team internal workshops, and (vi) the AI model training process. Additionally, we have the chance to visit one location on-site to obtain our perception of the AI-based system.

Table 5: Overview of the sample

#	Position	Function	Location	Role in the AI implementation	Phase(es)
1	Project leader	Manufacturing	Plant A	Main project leader	1-5
2	Expert	Manufacturing	Plant B	Domain expert, AI training data	5
3	Expert	R&D	Central team	Engineering support	4
4	Director	Quality mgmt. (QM)	Plant C	Process release, ensure quality standards	2
5	Director	R&D	Central team	Engineering support	4
6	Director	Manufacturing	Plant A	Management persuasion	5
7	Executive director	Manufacturing	Plant A	Project representation on management level	5
8	Expert	Manufacturing	Plant A	Data pipeline, tech. support	2
9	Project leader	Manufacturing	Plant D	Local project leader, AI implementation on site	3
10	Director	Digitalization	Central team	Internal consulting	1
11	Director	QM	Plant D	Quality assurance	2
12	Expert	Digitalization	Central team	AI training, coordination with domain experts	5
13	Team leader	Manufacturing	Plant A	Digitalization coordinator	4
14	Expert	Digitalization	Central team	Data pipeline support	2, 5
15	Expert	Digitalization	Central team	Data pipeline support	2, 5
16	Expert	Manufacturing	Plant A	Former main project leader	1-3
17	Expert	Assistant	Central team	Organizational support	1

5.3.2 Data Analysis

To acquire a profound overview of the key messages during the data collection process, we write a short summary with the most relevant statements after each interview (Glaser, 1978). These memos help us to recall all relevant data during the data collection process. Consecutively, we can go back to the raw data during data analysis. Based on grounded theory, we use open, axial, and selective coding to analyze the interview transcripts (Corbin & Strauss, 2015). In the first step, open coding is applied to assign appropriate labels to the interview passages, which summarize the key message in a short phrase (Miles et al., 2020). During this initial step, we identify general mechanisms that support trust calibration. However, during the data analysis process, we noticed various mechanisms during the different phases of AI implementation and operation. That is the reason why we continue with axial coding to cluster the mechanisms accordingly. Furthermore, we are able to determine workers' expectations regarding AI reliability. It results in the five organizational measures along the AI lifecycle and reveals the high relevance of trust calibration within the fourth phase. In selective coding, we further develop and combine the dimensions, resulting in the final consolidation. It has to be noted that the results presented below should be viewed as "tendencies", as our research is of empirical interpretative nature (Walsham, 1995).

In the course of the study and the analysis, further data is generated, e.g., interview notes, reports, and organizational documentation (Wiesche et al., 2017). This triangulation across data sources (multiple interview partners with different backgrounds and positions, written documents) and data collection methods (interviews, observations, reports) helps to further enhance and strengthen the identified concepts (Miles et al., 2020).

5.4 Results

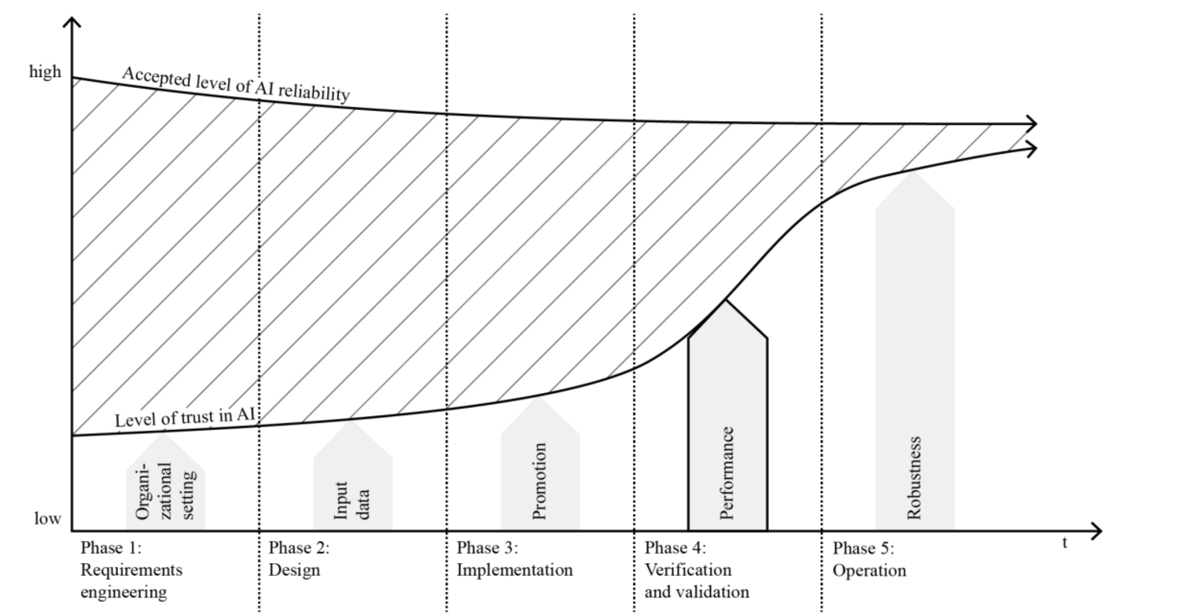
The main target of the present work is to generate a deeper understanding of the process of building trust in AI-based systems, given the important role of reliability and the dynamic nature of the AI lifecycle. Trust calibration, as well as the evolvement of reliability, is studied along the previously mentioned five phases of the AI lifecycle (Q. Lu et al., 2022): (1) requirements engineering, (2) design, (3) implementation, (4) verification & validation and (5) operation. As a result, a process model is developed that is oriented toward the AI lifecycle within an organization (Figure 10). In the following section, the results are presented.

Three main findings can be deduced:

(i) The accepted level of reliability by the workers and the development of the level of trust

(ii) The major impact of trust calibration during AI validation and verification

(iii) The corresponding measures for building trust within each phase



Note:
The black frame shows the immense influence of AI verification and validation. The five grey arrows show the supportive measures towards the level of trust. The phases of the AI lifecycle are separated by a dashed line.

Figure 10: Process of AI implementation and operation

The accepted level of AI reliability and the level of trust change dynamically over time during AI implementation. At the beginning of the implementation, the workers seek a very high degree of reliability while – at the same point in time – there exists a low level of trust. This is caused by the fact that the workers are not willing to accept any deviation from the AI model with respect to reality, which is also clearly communicated as a requirement to the AI development team.

> *"In the beginning, they [the AI developers] always came to us and presented us some kind of key figures. Then they told us: 'Now we have [...] a slip through of 1, 2 or 3 %.' Then I said: 'You can forget that. We demand 0 % slip through from our machines, and now we are suddenly supposed to allow 1%.' And then I said: 'That's not going to happen, it won't work.'" (#02; Table 5)*

However, the results show that in the course of the implementation, the workers are willing to deviate from that initial requirement, which means that they accept a lower degree of reliability than their original statement. This finds entry in the project plan, e.g., by the adaption of the reliability requirement from 100 % towards a lower level. Strikingly, this optimization of the reliability target has no negative effect on the level of trust, which is nonetheless still increasing. At this point in the AI lifecycle, trust calibration has a considerable impact during AI verification and validation, which will be discussed in the following subchapter. In conclusion, one of the primary key findings drawn from our study is that the workers' trust in AI has reached a significant level, to the point where they interact with the technology almost naturally. This can be confessed even though the level of reliability has to be adjusted and lowered.

> *"We could insist and say: 'It has to be perfect.' But if reality itself is not perfect, then we have to make a compromise." (#12; Table 5)*

Various underlying measures can be observed and will be discussed in detail in the following subchapter.

5.4.1 Measures for Building Trust

The trust-building process is dynamic; consequently, the same holds true for the underlying measures and mechanisms. Five focus areas for underlying mechanisms, targeting different objectives along the AI lifecycle, are identified. They are illustrated by grey, thick arrows in Figure 10: (i) Organizational setting, (ii) Input data, (iii) Promotion, (iv) Performance, and (v) Robustness.

The identified mechanisms during the first phase are mainly related to the overall **organizational setting**. What can contribute to the trust calibration in this phase is (i) a high internal reputation of the AI development team or (ii) the overall strategic focus of the organization on AI topics as well as, (iii) the comprehensive announcement of corresponding management decisions.

> *"For our organization, AI has been of great strategic importance for many years. It got a great push through the foundation of the corporate internal AI campus." (#05; Table* 5*)*

Considerable responsibility is assigned to the workers in the second phase with respect to the **input data**. As an example, they are requested to name an individual domain expert who has to define a test dataset that can be used as a baseline for the AI training. By this involvement, the responsibility of the workers regarding the input data becomes clear. It, therewith, helps to enhance the understanding of the technology and the relevance of high-quality input data. As one outcome, the workers, e.g., invented the label "unknown" for input data they could not even classify by themselves. Thus, the workers have to admit that they cannot provide the previously claimed high reliability standard themselves.

> *"The information, what data they want to use, from what time periods, on what lines, what products, that's up to the plant [the workers] to decide." (#16; Table 5)*

In this phase, it is also important to emphasize what kind of input data and, thus, which parts are not covered by the AI model. In the provided documents, it is evident that precise documentation is made even for "out-of-scope packages". It describes the underlying reasons for the exclusion, e.g., due to the bad quality of input data. Consequently, workers are starting to learn about the boundaries of the AI-based system.

The relevant measures within the third phase are targeting **promotion**. It is essential to share the knowledge of the initial project teams with the extended user group, e.g., further plants. During the exchange and training meetings, the workers are educated on the different failure modes. In this way, they are able to deal with errors and find ways to fix them. Consequently, the workers themselves are able to explain the new AI technology to outside parties.

> *"I am very busy making sure that we bring this topic out of the project phase and into the normal process. This means that knowledge must be built up at the plant." (#01; Table 5)*

The measures within the fourth phase have the largest lever to build trust. The major trust increase in that phase is achieved by providing clarity on the AI **performance**. In order to achieve that, the workers developed a risk comparison tool that gives evidence of the reliability of AI compared to the previous process without AI. Based on that, a risk evaluation is carried out, which specifies the potential risks of the different failure modes and provides a systematic analysis of the potential impact of the new AI-based system. The common ground of this tool is the "Failure Mode and Effects Analysis" (FMEA). It is a commonly used methodology within manufacturing to identify potential failure modes and to evaluate their impact on the system. Thus, the FMEA methodology serves as a risk comparison tool and provides a systematic analysis of the potential impact of the new AI-based system. As a result, the adaptation of the FMEA by the workers towards the AI-based systems provides the opportunity to quantify the remaining uncertainties of the AI model. It supports developing a deeper understanding of AI and its related pitfalls.

> *"Together with the R&D department, we developed a tool that always takes into account the probability of occurrence, the detectability, the severity, and frequency of every error, according to the FMEA method. […] This analysis is mandatory for the release process." (#01; Table 5)*

Further supportive measures can be identified, like (i) the creation of a glossary, which includes the performance-related figures and their interpretation, or (ii) the implementation of appropriate risk management. Different strategies for risk management need to be provided, like a detailed reaction plan including containment and corrective actions. It includes profound documentation of different levels of countermeasures, e.g., how to switch off the AI or how to exclude certain parts from AI.

> *"So, the most important thing is that we have immediate measures to prevent the error from persisting, and then we have to somehow eliminate it in the long term." (#08; Table* 5*)*

After the successful completion of the fourth phase, the workers are confident enough to scale the technology even with the constraint of a slightly lower level of reliability. One of the major key findings is that the measures in the fourth phase concentrate on analogous patterns regarding AI reliability, which ensures proper trust calibration.

The AI implementation develops towards AI operation within phase five, supported by mechanisms regarding **robustness**. This includes, e.g., the constant adaptation of the model to new products. The workers must understand that the AI model needs constant improvement and training in order to keep it running. Moreover, the model needs to remain robust in terms of security and safety aspects.

> *"There are changes regarding the products, new components, etc., so this results in subsequent effort. This is not just a one-time process." (#03; Table 5)*

5.5 Discussion

5.5.1 Theoretical and Practical Contributions

Our research builds on studies that investigate trust in technology (McKnight et al., 2011; Söllner, Hoffmann, & Leimeister, 2016) in combination with studies specifically focusing on trust in AI (Glikson & Woolley, 2020; Y. Li & Hahn, 2022). The present study adds to the ongoing discourse on the significance of reliability, emphasizing that lower reliability discourages the application of the technology by workers (Lankton et al., 2015), while enhanced reliability promotes greater confidence in AI-based systems (Forster et al., 2018). We took the non-transparent characteristics of AI as a starting point to investigate this connection further. It turns out that the workers are willing to accept a lower level of reliability, whereas, in contrast, this has no negative impact on the process of building trust. This is a major finding which extends the current body of knowledge and is in contraction to previous literature. Here, it is stated that workers might refuse the application of the technology if they cannot trust its reliability (Lankton et al. 2015).

The reasons lay in the implementation of various measures for trust calibration. While the relevance of human involvement during both the development and the training process of algorithms for building trust is already stated (Jago, 2019), current literature on the dynamic interplay between trust calibration, AI reliability, and the corresponding measures along the entire AI lifecycle is limited. Up to now, it has been reported in the literature that continuous maintenance of the process of trust calibration during the AI lifecycle is mandatory (Hengstler et al., 2016; Q. Lu et al., 2022). In the present work, we take a deep look at these findings and provide more details concerning the correlation of reliability and the measures for trust calibration.

The results indicate that the initial high expectations of the workers related to reliability support the process of building trust. It can be seen as a baseline for starting to deal with the new technology, regardless of workers' limited technological understanding (Im et al., 2023). Particularly during the AI verification and validation phase, the creation and utilization of a risk comparison tool can significantly increase trust, as it offers transparency on the otherwise complex interpretation of AI performance (Thiebes et al., 2021). It is quite obvious that the increasing understanding regarding AI can fully counterbalance the decreasing level of reliability. Thus, the current body of knowledge is extended by the findings regarding this interplay, as it shows how the provision of analogous patterns on AI performance supports the trust calibration and the reconfiguration of workers' expectations (Calisto et al., 2021).

We further extend the current body of knowledge by elaborating on the dynamic nature of this process. Whereas various researchers assume a rather static relationship between the measures and the process of building trust (Glikson & Woolley, 2020), the present study reveals the important connection between the dynamic phases of the AI lifecycle and the measures along these different phases. At first glance, the necessity of a dynamic relationship between trust calibration and the respective measures along the AI lifecycle is evident.

As an outcome, we derive some contributions to practice from this study. First, a more differentiated view on the role of reliability in the process of building trust in AI can be deduced. Organizations dealing with an AI implementation should be aware that they can equalize a lower level of reliability by the implementation of adequate measures. Second, the present work gives deep insights and profound explanations of what these measures should look like. In the course of the AI implementation and operation process, it is important to focus on several targets. It must be noted that a systematic risk evaluation during AI validation and verification represents the most important aspect of proper trust calibration. Our recommendation is to focus especially on the generation of analogous patterns for AI reliability within that phase. In order to tackle this, organizations need to provide understandable references and parameters for AI performance. In this way, workers can interact with the complex technology naturally and further enhance their confidence.

5.5.2 Limitations and Future Research

The present study is subject to some limitations. The qualitative approach and the selective sample size result in restrictions on the overall generalizability of the results, as the data collection is limited to the domain-specific context with a focus on the automotive industry. In order to level that out, 17 interview participants are selected, considering various positions, working experience, and hierarchies. Basically, this can be extended by a future large-scale survey with the target of verifying the generalizability of the presented process model. Further research, e.g., by investigations regarding the threshold of using AI (Glikson & Woolley, 2020), could also expand our process model. It might be reasonable to connect the threshold of use with the investigated measures and map it towards the derived phases. This would allow us to connect our started discussion regarding reliability with it.

5.6 Conclusion

AI is increasingly important in our lives and within organizations (Davenport and Dasgupta 2019). In this study, we investigate for the first time the dynamic process of building trust in AI, considering the important role of reliability. We assign reliability this high importance, as from our point of view, the basic assumptions regarding the role of reliability in enhancing trust in technology do not hold in the context of non-transparent AI systems. Thus, the present study aims to investigate the dynamic underlying measures that might counteract these issues during AI implementation and operation. An AI project of an international automotive supplier is examined based on 17 interviews. The present paper provides two main outcomes concerning trust calibration: First, organizational measures lead to a major increase in the workers' trust. This is due to the fact that they are tailored towards the critical phase of AI verification and validation. Second, it turns out that workers are willing to tolerate a lower level of AI reliability due to their increasing experience with the AI-based system.

6 The Importance of an Ethical Framework for Trust Calibration in AI (P3)

Title	The Importance of an Ethical Framework for Trust Calibration in AI
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Individual contribution	The author of the present work has significantly contributed to the problem definition and study design. She has been responsible for data collection and analysis. Further, she significantly contributed to the creation of this manuscript.

Figure 11: Fact sheet publication 3

Abstract. The transformative power of artificial intelligence (AI) raises serious concerns about ethical issues within organizations and implicates the need for trust. To cope with that, numerous ethical frameworks are generally published, but only on a theoretical level. Furthermore, proper trust calibration in AI is highly relevant to workers. Up to now, only limited studies have been conducted to investigate how an ethical framework can foster proper trust calibration of workers in practice. To close this gap, an ethical framework is investigated which ensures trust calibration by targeting AI reliability and AI safety. Finally, the effectiveness of the applied framework is evaluated based on 17 interviews within an international automotive supplier. As a result, this ethical framework leads to a major increase in trust. This is a groundbreaking outcome since workers are willing to accept a lower level of AI safety and AI reliability at the same time.

Keywords: Artificial intelligence, ethics, calibration, reliability, safety, organizations, manufacturing, trusted computing.

6.1 Introduction

Artificial intelligence (AI) is one of the main drivers in the field of technology and has a major impact on organizations and society. Its transformative power to improve life and business comes along with serious ethical concerns. AI is often described as a "black box", which is caused by the fact that it is difficult for workers to understand the algorithm with its underlying rules and the logic behind it (Holzinger & Muller, 2021). This leads, in the following, to the fact that workers feel they are faced with a non-transparent decision-making process of AI. Subsequently, challenges related to the explainability and robustness of the AI model have to be tackled (Holzinger, 2021). This can be overcome by the introduction of ethical frameworks, which are of increasing importance. Up to now, numerous ethical frameworks containing fundamental ethical principles have been developed by researchers, organizations, and governments (Fjeld et al., 2020).

However, these frameworks typically maintain a high level of abstraction, lacking specific guidance on their practical implementation and operationalization. These findings highlight a compelling need to explore the implementation of an ethical framework within an organizational context. Furthermore, to unleash the full potential of AI within organizations, a high degree of trust in the emerging technology is required as a prerequisite. However, lacking trust is one of the main reasons workers cannot take full advantage of AI. To compensate for the lack of trust and to ensure business success, special attention needs to be paid to the process of building trust, also called "trust calibration". Trust calibration targets the avoidance of over-trusting or under-trusting AI. The former might lead to serious safety issues and the latter to a prevention of AI usage (Okamura & Yamada, 2020).

Both impact factors mentioned above are governed by numerous influencing factors that specifically depend on the research stream and its perspective. User-related studies in information systems exhibit that the reliability of the AI system serves as an essential baseline for proper trust calibration. Reliability refers to the confidence of the worker that the technology will operate in a suitable and consistent manner (X. Li et al., 2022; McKnight et al., 2011). In contrast, in computer science, it is evident that AI *safety* represents an important pillar within ethical frameworks. It is straightforward that AI safety is closely related to reliability since AI safety requires as a prerequisite that the AI system has to be reliable (Fjeld et al., 2020; Jobin et al., 2019). Thus, both terms can even be considered as synonyms.

Since AI safety and AI reliability can be used as synonyms, it is obvious that both influencing factors have, in contrast, a direct impact on both AI ethics and AI trust. Following this logic in a literature review, it turns out that only limited studies have been carried out to investigate how an ethical framework can foster the proper calibration of workers' trust in practice. Thus, the following research question will be answered:

How do organizations use ethical frameworks to calibrate trust in AI-based systems?

The research question is approached by a two-part exploratory analysis using 17 semi-structured interviews. First, the applied ethical framework within an international automotive supplier is illustrated. Second, the effectiveness of this implementation is analyzed. The process of trust calibration in AI as a function of time is evaluated in combination with the underlying ethical framework and further measures.

6.2 Background

6.2.1 AI Trust

It is well known that trust is a crucial success factor for the acceptance and sustainable adoption of AI (Salam et al., 2021; Thiebes et al., 2021). To reach that goal within organizations, workers have to calibrate their level of trust according to the reliability of the AI system (X. Li et al., 2022). During the process of trust calibration, over-trust (trust that surpasses AI's reliability) or under-trust (trust that falls behind AI's reliability) should be prevented to avoid a negative impact on successful human-AI cooperation (Okamura & Yamada, 2020; Thiebes et al., 2021). It must be noted that in contrast to former technologies like traditional automation, the behavior of AI-based technologies is relatively unknown (Glikson & Woolley, 2020). These so-called "black box" models result in a limited understanding of the generated decisions and a lack of explainability (Holzinger, 2021). Moreover, workers might not be capable of adequately quantifying the uncertainties of AI models by themselves. It creates tension regarding the actual robustness of the AI model, which slows down or even stops the process of trust calibration (Thiebes et al., 2021).

Designers can facilitate a proper trust calibration by providing instant feedback concerning the reliability of the AI system towards the worker. This feedback from the designers includes, e.g., the explanation of factors that affect AI reliability or further information regarding task performance (Hoff & Bashir, 2015). In addition, an iterative and human-centered AI design process can further enhance explainability and robustness, strengthening the implementation of trustworthy AI (Holzinger, 2021). However, best practices and deeper insights into the dynamics behind the trust calibration in AI, need to be included. This raises the demand for a profound understanding concerning the dynamic process of trust calibration in AI within organizations, as well as the role of reliability, explainability, and robustness.

6.2.2 AI Ethics and the AI Lifecycle

For many years, AI ethics has been a controversial topic, which can be explained by the rapid technological development and a high degree of complexity, e.g., in software for automated and autonomous driving. The purpose of AI ethics is to serve as a fundament for ethical decision-making by machines and computers. Such ethical frameworks give guidance to software developers as well as workers and ensure the ethical behavior of AI (Allen et al., 2006). So far, researchers, organizations, and governments have proposed various ethical frameworks, including their underlying ethical principles. All of these frameworks are limited to a theoretical level, and all of these make use of generic principles for AI ethics, such as transparency, justice, responsibility, privacy, or accountability (Fjeld et al., 2020; Jobin et al., 2019; Zhou et al., 2020).

In practice, the application of AI systems follows different stages of the AI lifecycle: (1) requirements engineering, (2) design, (3) implementation, (4) verification, and (5) operation (Q. Lu et al., 2022). In contrast, ethical frameworks predominantly focus on AI in general and, apart from that, neglect the existence of different phases. This is explained by the high degree of complexity of AI, which obviously makes it hard to implement suitable ethical frameworks in practice. It results in one of the most fundamental challenges within organizations, namely, to deal with remaining potential ethical risks.

As a countermeasure, we propose a new, practical approach for the first time by integrating the concept of trust calibration into the context of AI ethics. This connection can be established as the ethical principle of “safety” and is closely linked to the important dimension of “reliability” for trust calibration. Moreover, both characteristics – AI safety and AI reliability – are of striking importance for the verification and validation as part of the AI lifecycle. In this fourth phase, it is checked whether the AI system fulfills the requirements and meets its purpose in the intended way (Q. Lu et al., 2022). The demand for a tailored ethical framework that specifically addresses AI reliability and safety becomes evident, emphasizing the importance of proper trust calibration in practice.

6.2.3 Research Setting

The entire analysis is based on a comprehensive study of an international automotive supplier. In this context, an AI-based system is considered to serve as a quality gate in manufacturing. The selected organization is developing and manufacturing semiconductors and sensors as well as ECUs at several locations worldwide. To improve the high-quality standards, AI-based visual inspection is implemented in the running operations at more than 200 manufacturing lines in seven international plants. Ensuring a high-quality manufacturing process is crucial, as the goods are used for safety-critical applications within vehicles whose failures or malfunctions might cause serious injury to people or severe damage to equipment, property, or environmental harm. As a matter of fact, ethical aspects are highly relevant to internal quality gates.

6.3 Applied Framework

Within the organization, an ethical framework is applied with the purpose of considering the safety criticality of the different failure modes in manufacturing (Figure 12). This approach leads, in the end, towards a quantitative assessment of the overall ethical impact with a special focus on AI safety and AI reliability. The common ground of this framework is the "Failure mode and effects Analysis" (FMEA), an automotive standard according to IATF 16949. It is a commonly used methodology within manufacturing to identify potential failure modes and to evaluate their impact on the system. In the software context, the FMEA methodology gains increasing attention in front of the verification and validation of AI systems and contributes to ensuring AI safety and understanding possible ethical failures and risks, respectively (Ebert & Weyrich, 2019; Q. Lu et al., 2022). In the present practical context, the FMEA methodology serves as a risk comparison tool and a systematic analysis of the potential ethical impact of the new AI-based system.

The applied ethical framework consists of four elements: (i) Failure modes (FMs), (ii) Occurrence (O), (iii) Detectability (D), and (iv) Severity (S) of the respective failure mode. In the framework, the ethical impact of the different failure modes is represented by the product of elements O, D and S.

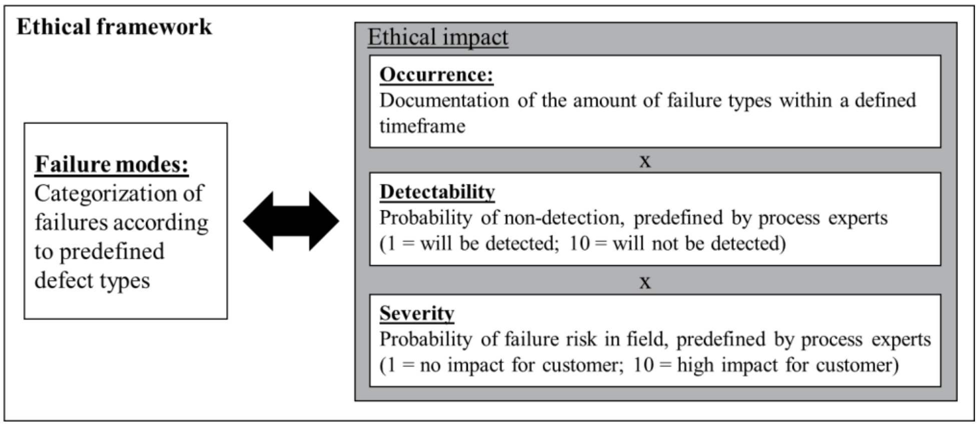


Figure 12: An illustration of the ethical framework based on FMEA

To quantify the ethical impact, the following procedure is used: First, an adequate timeframe is selected for the evaluation. During that timeframe, the Occurrence (O) of the different failure modes is documented. Second, the respective values for Detectability (D) and Severity (S) are determined, and their merits are set according to the FMEA systematic between 1 and 10. In this context, a small number represents a high probability of being detected by the AI system and a low impact for customers in case of non-detection. A high number represents a low probability of being detected and a high impact on the customer in case of non-detection, respectively. Finally, the individual scores of the different failure modes are summed up over all defect types, resulting in an overall risk number for the AI-based system. This represents the overall ethical impact (EI), which, in short, is calculated by equation 4.

$$\mathrm{EI} = \sum_{i=1}^{n} \mathrm{EI}_i(\mathrm{FM}_i) = \sum_{i=1}^{n} (\mathrm{O}_i * \mathrm{D}_i * \mathrm{S}_i) \tag{4}$$

In this way, the result of the new AI-based system can be compared to the previous method without the usage of AI.

6.4 Empirical Evaluation

An empirical study is conducted to investigate the effectiveness of the applied ethical framework and the respective trust calibration during the entire AI lifecycle within the global production network. In this context, the role of AI reliability and AI safety represents the focal point. Due to the sensitive nature of trust calibration in AI, selecting an appropriate methodology for the evaluation is essential. To consider that, an exploratory research strategy is selected by using grounded theory methodology (Glaser & Strauss, 1967).

6.4.1 Data Collection

Primarily, data is collected using semi-structured interviews. To investigate the ethical framework as well as the trust calibration from different perspectives, 17 workers from different organizational roles and hierarchical levels are selected. Among others, the project leader of the AI project, representatives of quality management and engineering, and the corresponding leaders who released the new AI-based process are considered for the interviews. Moreover, we choose workers from different international plants who have made differing progress along the AI lifecycle. By doing this, we can make comparisons between the different phases. It is well noted that all data is collected with the informed consent of all participants. During the entire data collection and analysis process, special attention is paid to respect the participants' confidentiality and anonymity. As a consequence, identifiable details are obscured, and only selected sanitized parts of the data are shared (Hoda, 2022).

We collect further qualitative data to deepen the fundamental understanding and to capture the phenomenon with more clarity. Thus, numerous data such as presentations for management reviews, documentation of the new process release, several checklists and best practices provided as informational material for the implementing plants, AI performance dashboards, results of team internal workshops, and the AI model training process are investigated.

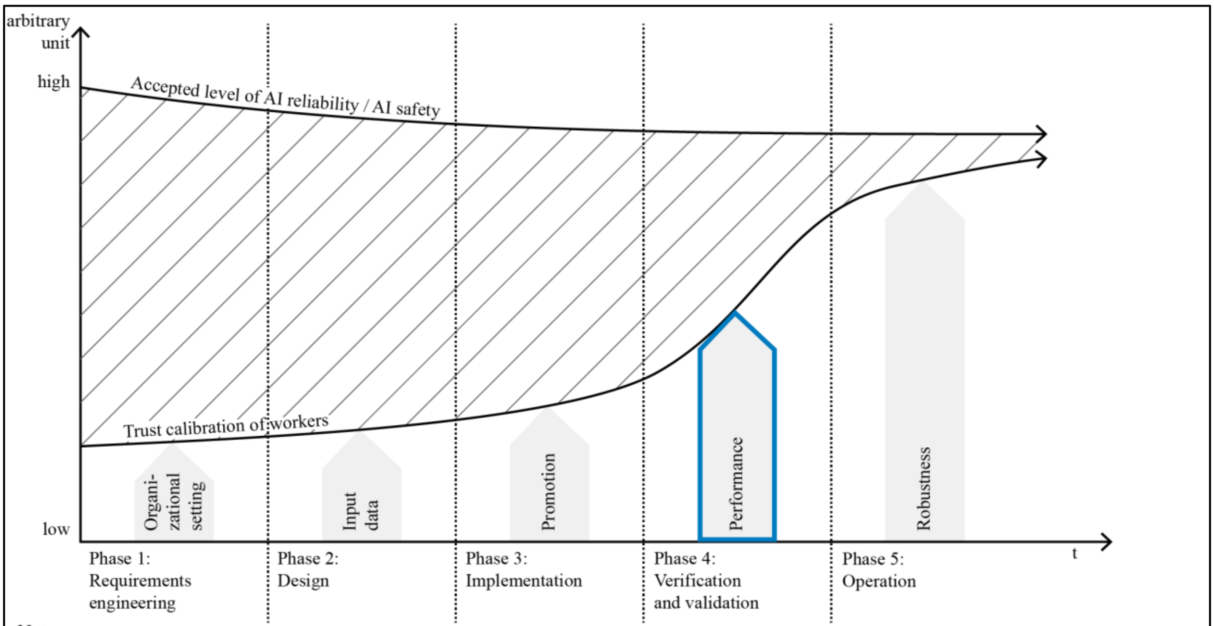
6.4.2 Data Analysis

To obtain a profound overview of the key messages during the data collection process, a short summary with the most relevant statements is written after each interview (Glaser & Strauss, 1967). These memos help to recall all relevant data during the data collection process (Hoda, 2022). Consecutively, we are able to get back to the raw data during the data analysis process.

Based on grounded theory, we use open, axial, and selective coding to analyze the interview transcripts. In the first step, open coding is applied to assign appropriate labels to the interview passages, which summarize the key message in a short phrase. The emerging main categories are still closely linked to the raw data. However, the generic expectations of the workers regarding AI reliability and AI safety along the five predefined phases of the AI lifecycle can be deduced. In the second step, axial coding is applied to interlink the categories and identify subcategories in a systematic way. Besides, the underlying mechanisms of trust calibration are elaborated. During the data analysis process, we realize varied mechanisms at the different phases of the AI lifecycle. That is the reason why we use selective coding to cluster the mechanisms accordingly and to synthesize the data regarding trust calibration. Finally, we apply constant comparison to further develop and combine the dimensions, resulting in the final consolidation (Glaser & Strauss, 1967; Hoda, 2022).

6.5 Results

The main target of the present work is to investigate the implementation of an ethical framework in practice and to analyze its effectiveness towards trust calibration. Trust calibration, as well as the evolvement of AI reliability and AI safety, is studied along the previously mentioned five phases of the AI lifecycle (Q. Lu et al., 2022): (1) requirements engineering, (2) design, (3) implementation, (4) verification, and (5) operation. As a result, an iterative, human-centered process model is developed, which is oriented along the AI lifecycle within an organization. The major contribution of the model is the interplay between trust calibration, the ethical framework, as well as AI reliability and AI safety (Figure 13).



Note:
The blue frame shows the immense influence of ethical framework during the AI verification and validation. The five grey arrows show the supportive measures towards the levelof trust. The phases of the AI lifecycle are separated by a dashed line.

Figure 13: Trust calibration among the AI lifecycle and the impact of the ethical framework during the fourth phase

Three major findings can be deduced from the process model:

(i) The trust calibration of the workers along the five phases of the AI lifecycle

(ii) The major impact of the ethical framework during AI validation and verification

(iii) The development of the accepted level of AI reliability and AI safety

As a constraint, it must be noted that the illustration does not show any defined values but rather the general progression and tendency of the different aspects.

6.5.1 The Ethical Framework for Effective Trust Calibration

An ethical framework is used to support trust calibration and to overcome ethical concerns related to the AI-based system. In particular, the framework puts special focus on the concerns regarding AI reliability and AI safety since these are of great importance for trust calibration. Based on that, the ethical framework applies predominantly during the fourth phase, AI verification and validation.

The accepted level of AI reliability and safety, as well as the level of trust, changes dynamically as a function of time during the AI lifecycle. At the beginning of the implementation, the workers seek a very high degree of reliability and safety while – at the same point in time – there exists a low level of trust. This is caused by the fact that the workers are not willing to accept any deviation from the AI model with respect to reality which is also clearly communicated as a requirement to the AI development team.

> *"In the beginning, they [the AI developers] always came to us and presented us some kind of key figures. Then they told us: 'Now we have [...] a slip through of 1, 2 or 3 %.' Then I said: 'You can forget that. We demand 0 % slip through from our machines and now we are suddenly supposed to allow 1 %.' And then I said: 'That's not going to happen, it won't work.'" (#02; Table 16)*

However, the results show that during the AI lifecycle, the workers are willing to deviate from that initial requirement. This means that they are willing to accept a lower degree of reliability and safety than to their original statement. This finds entry in the project plan, e.g., adapting the reliability requirement from 100 % to a lower level.

Strikingly, this optimization of the reliability targets has no negative effect on the level of trust, which is nonetheless still increasing. At this point in the AI lifecycle, the ethical framework has a considerable impact, as it helps workers enhance their understanding of the AI-based system. This results in the largest leap regarding trust calibration in this fourth phase.

> *"The AI classifies in the background, and you can check: What does the AI say? What does the operator say? Is there a mismatch, and what is the impact?" (#03; Table 16)*

The ethical framework provides a simple comparison pattern to give evidence of AI reliability and AI safety as compared to the previous process without using AI. Based on that, a risk evaluation is carried out, which specifies the possible ethical impact of the different failure modes.

"I would say the most important tool that we provide for the plants to monitor the functioning of the AI on a day-to-day basis is a comprehensive dashboard." (#08; Table 16)

It can be concluded that the ethical framework during AI validation and verification is crucial for developing a deeper understanding of the AI-based system and its related pitfalls. After the successful completion of the fourth phase, the workers are confident enough to scale the technology even with the constraint of a slightly lower level of reliability and safety. The ethical framework concentrates on AI reliability and safety, which ensures proper trust calibration. Thus, the trust in AI exceeds to such a high extent that the workers engage with AI nearly in a kind of natural manner. This can be confessed even though the level of reliability and safety has to be adjusted and lowered.

"We could insist and say: 'It has to be perfect.' But if reality itself is not perfect, then we have to make a compromise." (#12; Table 16)

During the evaluation of the ethical framework, we detect further underlying measures for trust calibration, which are discussed in the following chapter.

6.5.2 Supportive Measures along the AI Lifecycle

The trust-building process is dynamic, and as a consequence, the same holds for the underlying measures and mechanisms. Besides the impact of the ethical framework, five additional focus areas for underlying mechanisms are identified. These are targeted toward different objectives along the AI lifecycle and are illustrated by grey, thick arrows in Figure 13: (i) Organizational setting, (ii) Input data, (iii) Promotion, (iv) Performance and (v) Robustness.

The identified mechanisms during the first phase are mainly related to the overall **organizational setting**. What can contribute to the trust calibration in this phase is (i) a high internal reputation of the AI development team or (ii) the overall strategic focus of the organization on AI topics, as well as (iii) the comprehensive announcement of corresponding management decisions.

"For our organization, AI has been of great strategic importance for many years. It got a great push through the foundation of the corporate internal AI campus." (#05; Table 16*)*

Considerable responsibility is assigned to the workers in the second phase with respect to the **input data**. As an example, they are requested to define an individual domain expert who has to define a test dataset, which is used as a baseline for the AI training. By this involvement, the responsibility of the workers regarding the input data becomes clear. It therewith helps to enhance the worker's understanding of the technology and the relevance of high-quality input data. As one outcome, the workers, e.g., invented the label "unknown" for input data, which they could not even classify by themselves. Thus, the workers have to admit that they cannot provide the previously claimed high reliability standard themselves.

> *"The information, what data they want to use, from what time periods, on what lines, what products, that's up to the plant [the worker] to decide." (#16; Table 16)*

In this phase, it is also important to emphasize what kind of input data and, thus, which parts are not covered by the AI model. In the provided documents, it is evident that precise documentation is made even for "out-of-scope packages", including the underlying reasons for that, e.g., due to the bad quality of input data. Thus, the workers are starting to get to know the boundaries of the AI-based system.

The relevant aspect within the third phase is **promotion**. It is essential to share the knowledge from the project teams and pilot workers with the extended user group, e.g., further plants. During the exchange and training meetings, the workers are educated in understanding the different failure modes. In this way, the workers are enabled to deal with errors and find ways to fix them. Consequently, the workers themselves are able to explain the new AI technology to outside parties.

> *"I am very busy making sure that we bring this topic out of the project phase and into the normal process. This means that knowledge must be built up at the plant." (#01; Table* 16*)*

During the fourth phase, it is stated that the ethical framework makes a major contribution towards fundamental trust calibration. Further supportive measures regarding AI **performance** can be identified, like (i) the creation of a glossary, which includes the performance-related figures and their interpretation, or (ii) the implementation of appropriate risk management. Nevertheless, some ethical risks of potential issues remain. Different strategies for risk management need to be provided, like a detailed reaction plan including containment and corrective actions. It includes profound documentation of different levels of countermeasures, e.g., on how to switch of the AI or how to exclude certain parts from AI.

> *"So, the most important thing is that we have immediate measures to prevent the error from persisting, and then we have to somehow eliminate it in the long term." (#08; Table* 16*)*

The AI implementation develops towards AI operation within phase five, supported by mechanisms regarding **robustness**. This includes, e.g., the constant adaptation of the model to new products. The workers must understand that the AI model needs constant improvement and training in order to keep it running. Moreover, the model needs to remain robust in terms of security and safety aspects.

> *"There are changes regarding the products, new components, etc., so this results in subsequent effort. This is not just a one-time process." (#03; Table 16)*

6.6 Discussion

Our research builds on studies focusing on ethical frameworks for AI (Fjeld et al., 2020; Jobin et al., 2019; Q. Lu et al., 2022) in combination with studies specifically focusing on worker's trust calibration (McKnight et al., 2011; Okamura & Yamada, 2020). For the first time, the common ground of AI reliability and AI safety is justified, and both perspectives are brought together. As an outcome, we investigate an ethical framework that is tailored to AI validation and verification in an organizational context for proper trust calibration. It turns out that workers are stepwise aware of the lower reliability and safety. Nonetheless, they do not refuse; rather, they engage and even promote the technology in the organization. Thus, the ethical framework leads to a major increase in trust, which comes along with a willingness of the workers to accept a lower level of AI reliability and safety. This major finding extends the current body of knowledge and clearly contrasts with previous literature. There, it is stated that workers might refuse the application of the technology if they cannot trust its reliability and safety to the fullest extent (Lankton et al., 2015).

The current body of knowledge is further extended by the findings regarding the iterative interplay between ethical frameworks, trust calibration as well as AI reliability and safety. Up to now, it has been reported in the literature that continuous trust calibration during the AI lifecycle is mandatory. It can be achieved by following an iterative and human-centered design (Hengstler et al., 2016; Holzinger, 2021; Q. Lu et al., 2022). In this study, a practical example that tackles such a continuous trust calibration is provided for the first time. We can confess that the adoption of an ethical framework enhances both the explainability and robustness of AI models. This is highly relevant as both factors of explainability and robustness contribute to promoting reliability and, thus, trust in AI-based systems (Holzinger, 2021). The reasons lay in the fact that the provision of analogous patterns on AI reliability and safety supports this trust calibration. For workers, the cause-and-effect relationship of the results becomes clear as the explainability is enhanced (Holzinger & Muller, 2021). Moreover, the ethical framework serves as a systematic risk management in practice that tackles ethical concerns in a structured manner (Chen, 2020; Thiebes et al., 2021).

Finally, the illustrated human-centered AI design process serves as the first practical example of the hybrid approach that is demanded in AI development. It combines the benefits of data-driven machine learning with human domain knowledge (Holzinger & Muller, 2021). In this way, it is possible to ensure that humans retain control. As a consequence, the full advantage of AI is realized, and AI further contributes to discovering previously hidden connections.

6.7 Limitations and Future Research

The present study is subject to some limitations. The qualitative approach and the selective sample size result in restrictions on the overall generalizability of the results, as the data collection is limited to the domain-specific context with a focus on the automotive industry. To level that out, 17 interview participants are selected, considering various positions, working experience, and hierarchies. Basically, this can be extended by a future quantitative approach with the target of verifying the generalizability of the presented results.

Future research could expand our process model by integrating further factors for trust calibration. It might be reasonable to focus on other phases of the AI lifecycle and investigate suitable ethical frameworks for later phases, such as operation.

6.8 Conclusion

It is well known that AI is increasingly important in our lives and within organizations. In the present study, for the first time, we investigate the implementation of an ethical framework for the dynamic process of trust calibration in AI and develop a practical human-centered design process. To combine the two perspectives of AI ethics and AI trust, we use AI reliability and AI safety as a common ground. Based on 17 interviews within an automotive supplier, the effectiveness of the ethical framework is evaluated.

The present paper provides two main outcomes with respect to trust calibration by means of an ethical framework: First, it leads to a major increase of workers' trust. This is due to the fact that it is tailored towards the critical phase of AI verification and validation. Thus, the presented measures enable workers to explain and understand AI-generated decisions (Holzinger, 2021).

Second, it turned out that workers are willing to tolerate a lower level of AI reliability and safety as a function of their increasing experience with the AI-based system.

7 Understanding Algorithmic Management in the Traditional Work Context: A Quantitative Analysis (P4)

Title	Understanding Algorithmic Management in the Traditional Work Context: A Quantitative Analysis
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Figure 14: Fact sheet publication 4

Abstract. Algorithmic management (AM) is increasingly transferred to the traditional work context (TWC) and is applied to support the management of permanent workers. AM only partially replaces human managers here, but the core elements of AM remain similar. Hence, AM is implemented into pre-existing organizational structures to enhance processes and performance. AM in the platform-based context is already well-researched, its implications for the TWC from a managerial perspective remain unclear. To enhance our understanding, we conduct a quantitative study analyzing the utilization of AM at an international automotive supplier. Using linear mixed modeling, we examine a data set of 12743 error records and reveal that AM has performance advantages in the TWC as it reduces the error resolving time of workers. Furthermore, the impact of influencing factors such as workforce involvement, task complexity, time of work, and experience with AM are considered, evaluated, and discussed.

Keywords: Algorithmic management, traditional work context, manufacturing data.

[b]Due to space constraints in the outlet, the content of the original publication is condensed. We added Chapter 7.9 and Table 8 to the present work to provide deeper insights into the results and contribution.

7.1 Introduction

The introduction of intelligent algorithms at the workplace heavily influences various aspects of work, such as the interaction among workers and managers. If algorithms are utilized to assume workforce management practices and increasingly take on managerial roles, it is also described as algorithmic management (AM) (Lee et al., 2015). Its characteristics are mainly rooted in the gig economy, where well-known platforms such as Uber or Upwork are the key players (Cameron et al., 2023). AM can scale such platform-based businesses, enabling them to react to fluctuating demands. Since the workforce is structured and managed by AM, it can be considered a critical success factor for their business models, significantly increasing their value contribution (Benlian et al., 2022; Möhlmann et al., 2021).

Even outside the platform-based work context, AM gains more and more importance in the traditional work context (TWC) (Benlian et al., 2022). Well-established firms (e.g., in manufacturing, hospitality, or warehouses) envision how the AM approach can be integrated into their existing organizational structures and improve their processes and performance (Cameron et al., 2023). In this context, AM is perceived as a "sociotechnical process emerging from the continuous interaction of organizational members and the algorithms that mediate their work" (Jarrahi et al., 2021). Hence, managers of established organizations must consider minor adaptations before transferring AM from the platform-based work context to the TWC. For example, AM in the traditional work setting coexists with human managers. It results in a complementary character of the algorithm, as the human-to-human interaction is supported by AM (Benlian et al., 2022; Wiener et al., 2021). Moreover, the organizational logic in traditional work should still follow an organizational hierarchy and not a platform logic (Ashford et al., 2018; Cappelli & Keller, 2013; Lippert et al., 2023). Despite these adaptations, the core elements of AM remain the same as AM in the TWC still includes the analysis of the massive amounts of data in real-time to improve learning algorithms that coordinate workers and inform automated managerial decision-making (Mateescu & Nguyen, 2019; Möhlmann et al., 2021). Besides, AM in the TWC also increases managerial power by mediating the pre-existing relationship between managers and workers (Jarrahi et al., 2021). Finally, for managers in established organizations, using AM to manage their available workforce efficiently is highly relevant (Cameron et al., 2023; Veen et al., 2020).

While these performance advantages of platform companies are well noted (Benlian et al., 2022), a validation of the impact of AM in the TWC is needed (Parent-Rocheleau & Parker, 2022). From this managerial perspective, further research on relevant moderators that influence the outcome of AM in the TWC is of high interest. Hence, we raise the following research question:

What performance impact does AM have in the TWC, and what are the relevant influencing factors?

We anticipate the recent call of Cameron et al. (2023) for more quantitative approaches in this research area. Thus, we conducted a quantitative analysis within an international automotive supplier. We collected data on 15297 manufacturing errors at a German manufacturing plant between January and September 2023. Analyzing the data with linear mixed modeling, we find that AM significantly reduces error resolving time. Further moderating aspects such as workforce involvement, task complexity, time of work, and experience with AM are investigated and discussed.

7.2 Theoretical Background

AM can take over coordination and control activities traditionally performed by human managers (Möhlmann et al., 2021). As a result, an ongoing interaction occurs between workers and the algorithms that facilitate their work (Jarrahi et al., 2021). In the platform-based context, these interactions are facilitated via digital interfaces such as mobile apps managed by hidden data processes. Thus, a real co-working environment between employees and managers does not exist, and the algorithm is considered as co-worker asking to conduct a specific task (Tarafdar et al., 2022). In the platform-based work context, algorithmic matching and algorithmic control represent the two key dimensions. Algorithmic matching refers to the coordination of demand (customers) and supply (workers) and, e.g., serves as a marketplace. The platform aims to achieve the highest possible level of economic efficiency by, e.g., dynamic pricing strategies (Möhlmann et al., 2021). Algorithmic control makes use of algorithms capable of reviewing and controlling the actions of workers to ensure that their behavior aligns with the overall goals of the organization (Cram et al., 2022; Kellogg et al., 2020). This alignment can be realized, e.g., by implicit or explicit recommendations via the algorithm, restricting workers' access to complete information or targeting to reward high-performing workers with non-monetary or monetary incentives (Kellogg et al., 2020). Based on this logic, algorithms create power asymmetries and constrain the actions of workers in the platform-based context (Kinder et al., 2019; Wood, 2021).

Whereas the utilization of algorithms for supervising freelance workers is well-established within the platform economy, there is an increase in AM usage in the TWC (Benlian et al., 2022). This increase holds for companies with traditional business models, such as Amazon or Deutsche Post (Benlian et al., 2022; Lippert et al., 2023). For managers in such organizations, using AM to manage workers is relevant for enhancing processes and performance (Cameron et al., 2023). It must be noted that traditional organizations must consider some adaptations for transferring the AM approach from the platform-based work context toward the TWC (Table 6). A vital adaptation is that AM only partially substitutes managers in the TWC, and the organizational logic still follows the organizational hierarchy as compared to the platform-based work context (Lippert et al., 2023). Besides, AM complements existing organizational structures, strengthens established operations, or is attached to existent processes (Cameron et al., 2023; Wiener et al., 2021). In addition, traditional companies organize work with AM around the established team structures of separate work units, while platform-based businesses are predominately task-centric (Karanović et al., 2021). Hence, the individual output within work units of traditional companies is more complex to optimize due to organizational intersections since work unit relevant outcomes might be preferred over organizationally preferred results (Olkkonen & Lipponen, 2006). Nevertheless, the fundamental elements of AM also apply to the TWC. For example, the existing hierarchical power dynamics between managers and workers are strengthened by AM (Jarrahi et al., 2021). Besides, the collected data enhances the algorithms that manage workers and improves automated decision-making of management (Mateescu & Nguyen, 2019; Möhlmann et al., 2021).

However, studies analyzing AM in the TWC are rare or predominantly focus on the workers' perspective. For example, Kellogg et al. (2020) investigates literature-based the role of AM for reshaping established manager-worker relationships, especially when workers resist to its implementation. In the field of human resource management, Meijerink and Bondarouk (2023) show the effects of AM on workers' autonomy and value creation. In sales organizations, the salespeople are instructed to follow algorithmic recommendations made by AM, which often leads to a defensive attitude. Finally, Lee (2018) analyzes the perceived fairness and trustworthiness of algorithmic decisions in the TWC. Especially with tasks that are attributed to humans, algorithms were recognized as less fair and trustworthy.

Table 6: From platform-based towards the traditional work context

Elements to consider	Platform-based work context	Traditional work context	Sources
Role of management	Substituted by AM	Co-exists with AM	(Lippert et al., 2023)
Role of AM	Foundation of any processes	Attached to pre-existing processes	(Cameron et al., 2023; Kinder et al., 2019)
Communication	Via AM	Via AM & people	(Benlian et al., 2022; Jarrahi et al., 2021)
Form of organization	Task centric	Team and work unit centric	(Karanović et al., 2021; Olkkonen & Lipponen, 2006)
Optimization of output	Individual observation and tracking	Overall observation, tracking	(Möhlmann & Henfridsson, 2019)
Employment	Self-employed workers, no permanent contract	Direct employment with permanent contract	(Ashford et al., 2018; Lippert et al., 2023)
Work environment	Isolated, AM as co-worker	Colleagues & AM as co-workers	(Lippert et al., 2023; Tarafdar et al., 2022)

Overall, studies on AM in the TWC need to consider the managerial perspective for utilizing AM. For managers of established organizations, the validation of the performance effects of AM in the TWC, as well as possible influencing factors, are of high relevance (Parent-Rocheleau & Parker, 2022).

7.3 Model and Hypotheses

It is well known that AM has an enormous efficiency potential and performance advantage in platform-based businesses (Jarrahi et al., 2023). Uber uses AM, e.g., to monitor the productivity and performance of its workers (Möhlmann et al., 2021). Besides, AM on platforms provides employees performance metrics. These metrics allow a comparison among employees and an overall performance evaluation of each individual to increase the productivity (Healy et al., 2017; van Doorn, 2017). Within the context of platforms, workers, therefore, aim to receive above-average ratings to avoid automatically sanctioning by the platforms' AM. Hence, sanctioning AM increases platform performance (Kuhn & Maleki, 2017; Wood et al., 2019). Outside of the platform-based work context, it is generally acknowledged that algorithmic technologies benefit to employers, e.g., through improved efficiency in decision-making or coordination activities (Kellogg et al., 2020). Existing scholarship already shows in a simulation study that AM can reduce the average duration of tasks in the TWC (Kandemir & Handley, 2019). Hence, we suppose:

Hypothesis 1: AM decreases error resolving time.

In the TWC, AM is implemented in a pre-existing work environment with an established manager-worker relationship (Lippert et al., 2023). Thus, managers must actively involve workers in the implementation process to ensure successful outcomes (Jarrahi et al., 2021; Zink et al., 2008). Enhanced algorithmic transparency, understandability, or explanations, e.g., regarding the general process and outcomes, can lead to better reactions and improve usability (Kordzadeh & Ghasemaghaei, 2022; Langer & Landers, 2021). Hence, managers need to empower workers to provide feedback to the algorithmic work and raise questions when encountering confusion in the new setting (Tarafdar et al., 2022). Based on these reasons, the following hypothesis is proposed:

Hypothesis 2: Workforce involvement positively moderates the relationship between AM and the error resolving time.

For successful AM utilization, managers within the TWC need to understand the role of task characteristics which directly influence the application of the algorithm at its outcomes. Kordzadeh and Ghasemaghaei (2022) argue that for tasks with a high impact workers are more sensitive to algorithmic biases and might react unfairly to algorithmic processes. This reaction contrasts low-impact tasks, which are less prone to workers' concerns. In the field for automation, Vimalkumar et al. (2021) show that variances in task complexity lead to distinctions in their potential of automation. Whereas simple tasks with a low complexity have a higher automation potential, complex tasks are much more challenging to automate. Based on these arguments, we propose to analyze the effects regarding differing complexity levels of tasks, which describe how demanding a specific task is for the worker (Efatmaneshnik & Handley, 2021). Thus, we hypothesize the following:

Hypothesis 3: Task complexity negatively moderates the relationship between AM and the error resolving time.

Employees' well-being at the workplace is of high relevance for managers in the TWC, as workers are directly employed with a permanent contract (Ashford et al., 2018). However, working at nighttime is associated with increased health risks like sleep disturbances or disruption of the circadian rhythms (Boivin & Boudreau, 2014). Besides, the severe issues regarding workers' well-being, an excessive sleepiness during night shifts can also harm performance (Cordova et al., 2016). Existing scholarship shows that AM can positively impact the overall work environment, e.g., by avoiding overwork or enhancing decision-making (Kandemir & Handley, 2019; Kellogg et al., 2020; Parent-Rocheleau & Parker, 2022). To analyze whether managers can use AM in the TWC to enhance the working conditions during the nighttime we posit:

Hypothesis 4: Time of work (nighttime) positively moderates the relationship between AM and the error resolving time compared to daytime.

Previous studies show that more experience within a particular role or with a specific task enhances workers' knowledge or job performance (Di Pasquale et al., 2020). According to the law of practice, performance within a job increases as workers practice a task more frequently (Newell & Rosenbloom, 1982). The reasons lay in the fact that workers undergo a learning curve and enhance their performance based on task repetitions and training (Glock et al., 2019). In the gig economy, recent results show that same-day experience increases workers' productivity (Guha & Corsten, 2023). Based on these assertions, the following hypothesis is proposed:

Hypothesis 5: Experience with AM positively moderates the relationship between AM and the error resolving time.

Based on the theoretical elaboration, the general relationship between AM and error resolving time is enriched by four moderators: (i) Workforce involvement, (ii) Task complexity, (iii) Time of work, and (iv) Experience w/ AM (Figure 15).

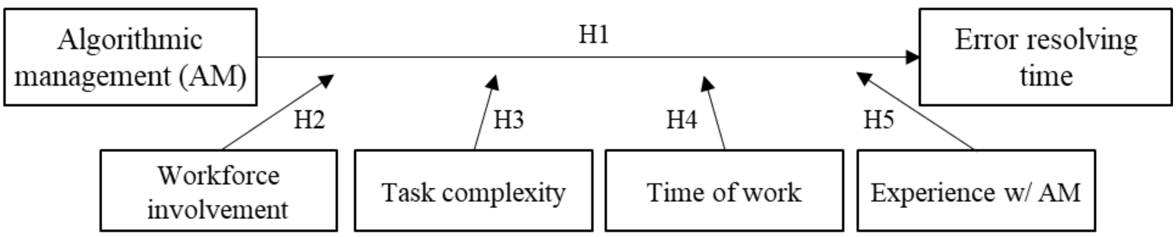


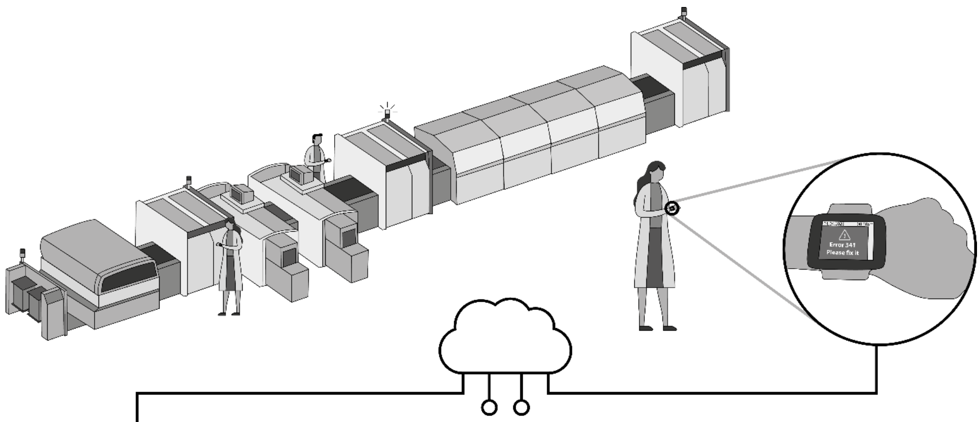
Figure 15: Research model

7.4 Methodology

7.4.1 Research Setting, Data and Sample

We analyze the production data of an international automotive supplier to answer our research question. Our research object is using smart watches as an AM approach at a German manufacturing plant. The workers in our setting are responsible for ensuring the continuous operation of nine production lines, e.g., by maintaining equipment, promptly resolving any occurring errors, proactively preventing interruptions, and reducing downtime. They are split into four teams with similar backgrounds and demographics, working in a three-shift model. On average, two workers are responsible for three manufacturing lines representing a confusing working atmosphere. Moreover, the work environment is characterized by a high task fluctuation, which requires different skills and equipment. Hence, managers have the responsibility for overseeing and coordinating their employees' work effort. Starting from April 1st 2023, AM is installed to optimize the communication on the shop floor and to deliver the right information at the right time to the right worker. AM informs the responsible worker in real time about machine alarms or events, also described as algorithmic recommending (Kellogg et al., 2020). In addition, AM provides detailed information related to the error type, position of error and how to fix it. Besides, it collects data on error resolving to predict patterns and to proactively identify upcoming errors. Finally, AM learns from workers' responses, enabling managers to adjust the work processes accordingly. An illustrative example of the error report is shown in Figure 16.

We collect production data between January 2023 and September 2023. The uncorrected dataset contains 15297 data points, and each data point represents one occurring error at a production line. The following information is linked for each error: error duration in seconds [s], date, timestamp [CET], line number, and error number. We match additional descriptive data to each record, e.g., the shift, processing team, error complexity, and whether the error is processed with or without AM (smart watch). Based on process expert review, we removed all errors with an error duration below 5 s and above 300 s to enhance data quality. In addition, we clear out all errors with missing or wrong information. This results in the final data set of 12743 errors.



#	Error duration [s]	Date	Time stamp [CET]	Shift	Team	Line number	Error number	Error complexity	Smart watch
15	5.23	2023-01-02	22:59:53	night	4	9	100	1	0
16	119.25	2023-01-03	23:04:23	night	4	5	144	3	0
17	66.84	2023-01-03	23:06:02	night	4	7	145	1	0
...	...	...	...	...	...	...	...	...	...
8255	57.05	2023-04-03	13:59:48	early	2	2	101	2	1
8256	31.14	2023-04-03	14:00:54	late	3	7	118	1	1
8257	26.23	2023-04-03	14:02:18	late	3	6	122	1	1

Figure 16: Research setting with a table illustrating sample data

7.4.2 Measures

Dependent variable. We want to quantify the error resolving time as our dependent variable. Generally, minimizing error resolving time is essential for cycle time, which is fundamental for overall production performance (Ayabakan et al., 2017; Banker et al., 2006). For that purpose, we use the specific indicator variable *error duration* in order to measure error resolving time. The definition of error duration is as follows: it refers to the time interval between the occurrence of an error and its resolution by an operator or expert. The primary goal is to reduce the error duration since therewith production downtime can be decreased and thus overall plant performance can be increased. Accordingly, we are able to collect the error duration of 22 different error types, resulting in an overall 12743 errors.

Independent variables. Starting from the 1st of April 2023, 8902 errors were processed by the operators using AM, resulting in a binary measure for AM (1=w/ AM; 0=w/o AM), which can be identified based on the error type. Besides, we included four independent variables in our model (H2-H5), namely workforce involvement, task complexity, time of work, and experience w/ AM. These independent variables will be defined in the following. The variable *workforce involvement (H2)* refers to the fact that the affected workers of a team were involved in the use case development of the AM approach at their workplace or not. In our case, the employees of team 4 were actively involved by providing feedback and brining in own ideas, whereas the employees of teams 1-3 were not involved. Thus, we measure workforce involvement by comparing team 4 with team 1-3. In order to measure *task complexity (H3)*, we use the variable error complexity. Error complexity is ordinally scaled and takes on values between 1 (low error complexity, can be easily solved by the worker) and 4 (high error complexity, workers cannot solve the error on their own). Process experts have categorized the complexity of the different error types according to a pre-defined scheme. Moreover, we considered the respective shift during which the errors were observed to measure the *time of work (H4)*. The shift model includes the early shift (6:00 am – 2:00 pm), late shift (2:00 pm – 10:00 pm), and night shift (10:00 pm – 6:00 am). As nighttime refers to the period between sunset and sunrise, we consider the night shift as nighttime and the early and late shifts as daytime. As the last dependent variable, we measure the experience effect of the workers with the AM by the variable *experience w/ AM (H5)*. To measure it, we counted the amount of days AM is in place and used by the workers, starting from 1st of April 2023 onwards.

7.5 Data Analysis

We use linear mixed modeling for our data analysis. Longitudinal data from repeated observations of 22 different error numbers at nine manufacturing lines provides evidence for the verification of this kind of modeling (Fahrmeir et al., 2013). It must be noted that linear mixed models (LMMs) are generally robust to violations of the model assumptions such as data not following a normal distribution (Schielzeth et al., 2020). The LMM is an extension of the general linear regression, allowing to model and estimate fixed and random effects. Thus, the LMM is also called the random effects model (Fahrmeir et al., 2013). In contrast to the fixed effects (unknown population parameters), random effects refer to subject-specific effects and can be described as grouping factors (McCulloch & Searle, 2000; Schielzeth et al., 2020). The overall goal of including subject-specific effects is to enhance the estimation of the fixed effects (Fahrmeir et al., 2013). We modeled two random effects: (i) manufacturing line and (ii) error number. The variable manufacturing line indicates which of the nine lines the error occurred. This is included as a random effect to avoid overlooking any bias coming from any line. Moreover, the error number was modeled as a random effect to consider modifications based on specific error types.

7.6 Results

7.6.1 Descriptive Statistics

Between January 2023 and September 2023, around 2/3 of the errors (8902) are processed with AM and around 1/3 (3841) errors without. In our sample – as a baseline – the average error duration without AM is 77.55 s. With AM, the error duration significantly decreases by 11.14

s (14.36 %) to 66.41 s. The error processing is distributed across the four teams almost equally. While team 1 processed 2856 errors (22.4 %), team 2 processed most errors (3381; 26.5 %). Team 3 & 4 processed 3249 errors (25.5 %) and 3257 errors (25.6 %). The errors occur in three different shifts in which all teams rotate. 3864 errors occurred during the early shift, representing 30.3 %, the smallest amount. 4057 errors (31.8 %) occurred in the late shift and 4822 (37.8 %) in the night shift. A total of 22 different error numbers are included in our sample, appearing on one of the nine production lines. Each error type occurs with varying frequency, between 3 and 4666 times within the nine months. Most occurring errors (11257) are attributed to complexity level 1. Besides, 1096 errors are categorized as complexity level 2, 194 as complexity level 3, and 196 as complexity level 4.

7.6.2 Linear Mixed Model

Table 7 summarizes the descriptive statistical values such as estimate, standard deviation (SD), p-value of the dependent variable *error duration w/ AM,* and all independent variables. *Manufacturing line* and *error number* are modeled as random effects. The coefficient of determination R^2 represents an essential indicator for the amount of variance explained by any linear model (Fahrmeir et al., 2013). For LMMs, reporting R^2 has become increasingly relevant. In this specific case, R^2 can be categorized into two types: *marginal* R^2 (= variance explained by the fixed factors) and *conditional* R^2 (= variance explained by both fixed and random factors) (Nakagawa & Schielzeth, 2013). Whereas the marginal R^2 can be reported with 0.015, the conditional R^2 reveals that 0.329 of variance can be explained by the entire model. It is acceptable, as most of our explanatory variables are statistically significant (Ozili, 2022). We start our analysis by examining the effect of AM on workers' performance. In particular, we consider the error resolving time (= error duration) as a relevant performance outcome. Our results show that AM has a significant negative effect on the *error duration* ($\exp(b) = 0.310$; $p < 0.001$). Thus, it can be confirmed that AM significantly reduces the error resolving time (H1) and thus enhances work performance. For *workforce involvement* (H2), we found mixed effects.

Table 7: Results of the linear mixed model

Parameter	Estimate	Standard deviation	p-value	95 % conf. interval	
				Lower	Upper
Intercept	3.787	0.105	<0.001	3.578	3.905
Algorithmic management	-0.310	0.048	<0.001	-0.404	-0.217
Team (team 4)					
Team 1	-0.102	0.046	0.025	-0.192	-0.013
Team 2	-0.082	0.050	0.102	-0.180	-0.016
Team 3	-0.168	0.044	<0.001	-0.254	-0.081
Complexity (complexity = 1)					
Complexity = 2	-0.224	0.193	0.247	-0.605	0.157
Complexity = 3	-0.107	0.212	0.613	-0.523	0.309
Complexity = 4	0.142	0.255	0.578	-0.361	0.654
Shift (night)					
Shift (early)	-0.123	0.042	0.004	-0.205	-0.040
Shift (late)	0.019	0.042	0.650	-0.063	0.102
Workforce involvement (team 4)					
Workforce involvement (team 1)	0.123	0.055	0.025	0.015	0.231
Workforce involvement (team 2)	-0.028	0.054	0.606	-0.134	0.078
Workforce involvement (team 3)	0.163	0.053	0.002	0.059	0.267
Error complexity (complexity =1)					
Error complexity (complexity = 2)	0.082	0.076	0.285	-0.068	0.232
Error complexity (complexity = 3)	0.438	0.189	0.021	0.067	0.808
Error complexity (complexity = 4)	0.224	0.195	0.250	-0.158	0.606
Nighttime (shift = night)					
Daytime (shift = early)	0.133	0.050	0.008	0.034	0.231
Daytime (shift = late)	-0.203	0.051	<0.001	-0.304	-0.103
Experience w/ AM (days)	0.002	0.000	<0.001	0.001	0.002

Dependent variable: Error duration [ln]

N = 12743; R^2 (marginal) = 0.015; R^2 (conditional) = 0.329; SD of random effects: 0.070

We can support that team 4 is significantly faster than team 1 (exp(b) = 0.013; p = 0.025) if both teams apply AM. However, we do not find this effect of team 4 compared to team 2 (exp(*b*) = -0.069; $p = 0.606$) and team 3 (exp(*b*) = -0.024; $p = 0.002$). Analyzing the level of *error complexity* (H3) reveals that AM does not work for all error levels the same way. The error duration of errors with complexity level 3 (medium level) is significantly lower with AM compared to errors with complexity level 1 (exp(*b*) = 0.263; $p = 0.021$). In contrast, we cannot identify significant effects for errors with a complexity of 4 (exp(*b*) = 0.631; p = 0,250) and complexity of 2 (exp(*b*) = -0.138; $p = 0.285$). Thus, we can only partially confirm *error complexity* as the assumed negative moderator (H3). The results concerning the *time of work* (H4) show that the early shift is significantly slower with AM compared to the night shift (exp(*b*) = 0.010; $p = 0.008$), whereas late shift is significantly faster (exp(*b*) = -0.184; $p < 0.001$) compared to the night shift. Hence, the hypothesized positive moderation effect of *nighttime* (H3) can only be confirmed for the early shift. Finally, we cannot support H5, as the error duration with AM is slightly increased with increasing *experience w/AM* (exp(*b*) = 0.002; $p < 0.001$).

We check the robustness of our results by analyzing the error duration of two error types that are not processed with AM starting April 1st, 2023. The robustness check reveals that the error duration without AM does not significantly decrease.

Table 8: Results of hypotheses tests

Hypotheses	Variable	Results
H1 (–)	Error resolving time	Supported
H2 (+)	Workforce involvement (Reference category: team 4)	Partially supported (Team 1: supported; Team 2 & 3: not supported)
H3 (–)	Task complexity (Reference category: Complexity = 1)	Partially supported (Complexity = 2: not supported; Complexity = 3: supported; Complexity = 4: not supported)
H4 (–)	Time of work (Reference category: shift = night)	Partially supported (Shift = early: supported; Shift = late: not supported)
H5 (+)	Experience w/ algorithmic management	Not supported

7.7 Discussion

As the first distinct contribution, we demonstrate with our study utilizing a quantitative analysis that the performance enhancements of workers observed in the platform business can also be recognized in the TWC. Interestingly, the performance increase is not based on individual tracking or related to penalties and sanctions in case of bad performance (Möhlmann, 2021;

Wood et al., 2019). Instead, it is based on the enhanced coordination of workers within the complex work environment and an increased decision-making efficiency related to the error resolving (Kellogg et al., 2020). It is an important finding, as it can serve as a confirmation for traditional companies to implement AM to improve performance while respecting legal obligations and further encourage platform-based businesses to use AM ethically (Möhlmann, 2021).

In addition, four relevant moderators are examined that influence the outcome of AM in the TWC. From a managerial perspective the impact of (i) workforce involvement, (ii) task complexity, (iii) time of work, and (iv) experience w/ AM is considered. Strikingly, we find out that missing workforce involvement does not negatively affect performance outcomes. This clearly contradicts to general studies on technology implementation, which promote a participatory approach as a relevant success factor (Gagné et al., 2022; Jarrahi et al., 2021; Zink et al., 2008). Most probably, the reason is that we are dealing with a highly standardized work, which generally eases automation (Goel et al., 2021). Hence, AM is not considered disruptive in the TWC and represents a rather competence-enhancing than a competence-destroying technology (Ghawe & Chan, 2022; Tushman & Anderson, 1986). This can be explained by the fact that AM is attached to the pre-existing organizational environment. Hence, it augments a few managerial activities (Jarrahi et al., 2021). In the platform context, work is broken down into small parts (gigs), which disrupt the work identity, as the purpose of the work is more challenging to recognize due to this transience of work (Ashford et al., 2018). Besides, employees can hardly control the AM in the platform context, which means that autonomy is reduced (Kinder et al., 2019). The lack of autonomy leads to a classification of AM as a disruptive system since the algorithm replaces human roles step-by-step (Jabagi et al., 2019; Jarrahi & Sutherland, 2019).

On a generic level, it is recommended to structure tasks at varying degrees of complexity on a labor platform to attract the most suitable worker (J. Taylor & Joshi, 2018). We advance the discussion by showing a U-shape relationship for the moderation effect of task complexity in the TWC. Whereas AM has limited functionality for easy and complex tasks, AM significantly impacts tasks with medium complexity. Consequently, managers need to look at the type of task before implementing AM in the TWC. Tasks with high complexity are more difficult to automate, since there are multiple possibilities to achieve a desired outcome, and further expert knowledge is needed (Efatmaneshnik & Handley, 2021; Vimalkumar et al., 2021). This finding proves that AM does not enhance workers' performance for highly complex tasks. In contrast, work performance for relatively simple tasks is also not improved by AM. One reason might be that such tasks are too simple (Parent-Rocheleau & Parker, 2022). Hence, the support of AM is not relevant for the workers. Instead, AM is highly meaningful for tasks with medium complexity. Generally, medium complex tasks indicate that not all complexity contribution elements such as the goal, input factors or process components are applying (Peng Liu & Li, 2012). Here, AM reduces perceived task complexity and enables workers to enhance their work performance (Chan et al., 2015; Kyndt et al., 2011).

Furthermore, we can show that AM eases the working environment, e.g., during night shifts. In warehouses, AM is considered to enhance working conditions by simplifying workers' jobs or by solving problems (Parent-Rocheleau & Parker, 2022). We contribute to these findings and display that AM can level out performance fluctuation during nighttime. Studies in the medical domain indicate that shifts at nighttime are linked to disturbed circadian rhythms and inadequate sleep (Boivin & Boudreau, 2014). Such conditions frequently result in psychosomatic stress, manifesting as depression, burnout, cognitive impairment, and an elevated risk of work-related errors (Cordova et al., 2016; Maltese et al., 2016). This compensating effect of AM during nighttime emphasizes that AM can be introduced by managers as a supportive IS in the TWC. Such supportive systems have already been proven to reduce perceived stress (Eisel et al., 2014).

Finally, our results do not show an influence of experience w/ AM on performance in the TWC. The reasons might be that the workers are familiar with the existing processes and can thus immediately exploit the full potential of AM (Jarrahi & Sutherland, 2019). The role of increasing knowledge and experience with the algorithm is also highly debated within the platform-based work business. On the one hand, gig workers use their increasing algorithmic competency to work around or manipulate the algorithm. This effect is also called "algoactivism" and refers to the individual or collective resistance towards AM (Jarrahi & Sutherland, 2019; Kellogg et al., 2020). On the other hand, Guha and Corsten (2023) show that same-day experience can also benefit gig workers' productivity up to a certain threshold.

Overall, our study contributes to research on AM as it validates the positive performance impact of AM in the TWC. Besides, we highlight the managerial perspective and show relevant moderating aspects that influence the success of transferring the AM approach to the TWC.

7.7.1 Practical Implications

AM has great potential for established companies. However, selecting the right application areas with distinct carefulness is essential. While AM has a considerable impact related to tasks with medium complexity.it is not reasonable to implement AM for every single task. Nonetheless, we can recommend further integrating relevant aspects from the platform-based work context within the TWC, e.g., adding competency profiles and considering task complexity. With this approach, the tasks could be deployed even more precisely to a specific worker, which leads to performance enhancement. Additional contributions, such as recommendations or instructions, could further increase the value contribution of AM in practice.

7.8 Limitations and Further Research

The present study is subject to some limitations. First, we acknowledge that work performance is a multidimensional concept that includes various additional dimensions besides error resolving time. Thus, further research could also consider soft aspects such as the leadership style (C.-K. Li & Hung, 2009). Second, the analyzed sample is limited to a time period of 9 months. It might lead to the fact that the effect of experience w/ AM (H5) could not be confirmed. However, while experience w/ AM might cause enhanced performance, it can also stimulate workarounds and a manipulation of AM (Jarrahi & Sutherland, 2019). As a future work, it would be reasonable to collect further data to analyze such consequences. Third, the data set was limited to error types that were subjected to the usage of AM. Nevertheless, most of the collected error types have not been processed using AM since 1st of April. Hence, these error types were excluded from the analysis, which might bias our results. Effort was taken to consider these errors in the robustness check. Nevertheless, further analysis might be needed as soon as AM is implemented for a more extensive range of errors.

7.9 Conclusion

Even though some scholars acknowledge the divergence between the research paths of AM in the traditional work context and platform-based work context (Meijerink & Bondarouk, 2023; Meijerink et al., 2021), others foresee significant potential in combining these two perspectives (Cameron et al., 2023). In order to integrate both views, the present study aims to analyze whether AM has a similar effect on workers' performance in the traditional work context compared to the platform businesses. Moreover, relevant moderators for the relationship between AM and error resolving time are included in the analysis. We conduct a quantitative study within an international automotive supplier and analyze 12743 manufacturing errors. Our findings contribute to this discussion of AM in the traditional work context by validating the impact of AM and by giving insights into relevant boundary criteria.

8 Algorithmic Management in Traditional Organizations – Implications for Workers' Efficiency and Work Relationships (P5)

Title	Algorithmic Management in Traditional Organizations – Implications for Workers' Efficiency and Work Relationships
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Individual contribution	The author of the present work has significantly contributed to the problem definition and study design. She has been responsible for data collection and analysis. Further, she significantly contributed to the creation of this manuscript.

Figure 17: Fact sheet publication 5

Abstract. Traditional organizations increasingly utilize algorithmic management (AM) to manage their permanent workers. While existing research has extensively explored AM within platform organizations, there is a need to understand its application in traditional work environments, given workers' close connection to the organization and the existing work relationships. Moreover, current AM research primarily focuses on possible negative effects for workers, with limited recognition of its beneficial impact within organizations. The paper addresses these aspects by investigating the effects of AM in traditional organizations, examining the role of socio-technical characteristics in enhancing workers' efficiency. Conducting mixed-methods research within an international automotive supplier, an archival dataset comprising 12743 manufacturing errors is analyzed, complemented by 15 semi-structured interviews with affected workers and managers. The results give objective evidence that AM significantly improves efficiency within traditional organizations. In addition, the interviews reveal that human managers keep a supportive role in this hybrid organizational setting, while established work relationships among co-workers are heavily influenced by AM. This research offers valuable practical contributions for the successful implementation of AM in traditional organizations, emphasizing the need for a tailored approach that considers the distinct dynamics of the traditional work context.

Keywords: Algorithmic management, traditional organizations, workers' efficiency, work relationships; hybrid organizational setting; socio-technical characteristics.

8.1 Introduction

The introduction of intelligent algorithms at the workplace significantly impacts various aspects of work, including the interaction between workers and managers. If algorithms are utilized to assume workforce management practices and take on managerial roles, it is described as algorithmic management (AM) (Lee et al., 2015). It refers to the use of algorithms to align workers' behavior with organizational expectations, constantly evolving through worker-algorithm interactions (Cram & Wiener, 2020; Jarrahi & Sutherland, 2019). AM originates from the gig economy, where platform-based organizations such as Uber or Upwork apply AM to manage and structure their large and often geographically distributed workforce. A key driver for the use of AM is its potential to enhance their efficiency and performance, e.g., by optimizing resource allocation, executing coordination tasks, controlling workers' actions, or providing personalized feedback (Benlian et al., 2022; Möhlmann et al., 2021).

In recent years, AM has been increasingly transferred to the traditional work context, where it is applied to manage permanent workers. In 2025, 74 % of respondents from over 6000 firms in six countries (France, Germany, Italy, Japan, Spain, and the United States) report using certain aspects of AM within their organizations (Milanez et al., 2025). Well-established companies (e.g., in manufacturing, hospitality, or warehouses) envision how they can integrate the AM approach into their existing organizational structures and improve their processes and performance (Cameron et al., 2023). It is also described as the "uberization" or "platformisation" of work (Fernández-Macías et al., 2023; Hirsch et al., 2024).

With the permeating integration of AM into traditional organizations, there is a growing need to adopt diverse perspectives to understand how AM is embedded within and shaping existing organizational structures (Alizadeh et al., 2025). Moreover, current assumptions need to be revisited, considering that workers do not operate independently in a short-term manner and are not detached from their organization (Gagné et al., 2022; Jabagi et al., 2019). Established social structures within traditional organizations – characterized by a permanent contract and the close collaboration of managers and workers – influence the implementation and successful utilization of AM (Lamers et al., 2024; Leavitt et al., 2024; Lippert et al., 2023). Consequently, it is crucial to understand how AM impacts workers' efficiency and work relationships in the traditional work context.

Prevalent insights on AM primarily focus on possible negative effects at the individual level, with limited recognition of its possible beneficial impact (Ping Liu et al., 2025). Several studies uncover negative consequences for workers, such as an increasing level of stress, feelings of isolation, unfair treatment, lack of transparency, or even disciplinary actions based on performance metrics (Kellogg et al., 2020; Mateescu & Nguyen, 2019; Möhlmann & Henfridsson, 2019; Möhlmann et al., 2021; Wood et al., 2019). Resistance of workers is revealed as the ultimate reaction, e.g., by ignoring or bypassing AM recommendations (Kellogg et al., 2020). However, some researchers refer to the "duality of AM", highlighting that AM also has positive effects, such as job autonomy, flexibility, and value generation (J. Jiang et al., 2025; Meijerink & Bondarouk, 2023). Moreover, automated work scheduling, resource allocation, and performance rating have the potential to enhance workers' efficiency (Becker et al., 2023; Leavitt et al., 2024). Although emerging quantitative studies investigate efficiency gains associated with AM, these often rely on subjective perception of task allocation rather than an objective measurement of actual task changes (Bai et al., 2020).

Researchers have recognized that the relationship between AM and performance needs to be investigated in the light of moderating mechanisms (Kadolkar et al., 2024; Parent-Rocheleau & Parker, 2022). Therefore, understanding the moderating mechanisms through which AM adoption benefits traditional organizations is crucial for realizing the full potential of AM, understanding its objective performance effects and its contextual impact (Cram & Wiener, 2020). Previous research has examined the moderating effects of perceived fairness (Bai et al., 2020), improvisation capability (M. Liu et al., 2024), system transparency (S. Alavi et al., 2025), or worker deviation (Sun et al., 2020) on work performance. These existing factors focus on the behavior and perceptions of workers and are primarily limited to a standardized work context. However, in the heterogeneous, knowledge-intensive environment of traditional companies with high task variety and the importance of retaining a skilled workforce (Jarrahi et al., 2023), the role of *task complexity* and *worker engagement* as potential moderating aspects needs to be considered. Hence, a comprehensive understanding of how AM impacts workers' efficiency and work relationships in the traditional work context is critical. Therefore, the following research question is addressed in this study: *How does AM impact the efficiency of workers and existing work relationships within traditional organizations?*

We adopted a mixed-methods research design within an international automotive supplier to address our research question in two steps. The combination of qualitative and quantitative seeks to understand the impact of AM in traditional organizations from different perspectives. First, we analyzed archival data of 12743 manufacturing errors, collected between January and September 2023 at a German manufacturing plant. Analyzing the data with linear mixed modeling reveals that AM significantly enhances efficiency. Second, we conducted 15 confirmatory interviews with workers and managers to gain a deeper understanding of the moderating effect of task complexity and worker engagement and find further explanations of the role of human managers and co-workers in the traditional work context. Our findings contribute to the emerging research stream on AM in traditional organizations by offering insights into the supportive role of human managers and by illustrating shifts in team dynamics in this traditional work environment. In the present work, we conclude by highlighting relevant contributions to practice, as well as key limitations and promising directions for future research.

8.2 Theoretical Background

8.2.1 Algorithmic Management in Traditional Organizations

AM is described as a socio-technical process driven by the ongoing interaction among members of an organization and algorithms that facilitate their work (Jarrahi et al., 2021; Jarrahi & Sutherland, 2019). It allows the full or partial automation of managerial activities that are traditionally performed by human managers utilizing a huge amount of data (Benlian et al., 2022; Keegan & Meijerink, 2025). Previous research describes various managerial functions carried out by AM, such as directing, evaluating, or disciplining workers (Kellogg et al., 2020). In more detail, AM supports, e.g., with allocating resources, rating performance based on predefined criteria, scheduling shifts, selecting workers, or determining payment of work automatically (Becker et al., 2023; Keegan & Meijerink, 2025). Moreover, AM can guide workers by detecting unexpected problems and supporting with fast responses (Lippert, 2024). Möhlmann (2021) describes two dimensions of AM: (i) matching and (ii) control. Algorithmic control refers to managers' use of algorithms to influence worker behavior and align it with organizational goals (Cram & Wiener, 2020). Algorithmic matching is defined as an algorithmic-mediated control of demand and supply, such as assigning workers to suitable tasks (Lippert et al., 2023; Möhlmann et al., 2021). As a result, the interpersonal interaction and human oversight are reduced, as AM is increasingly responsible for work-related decision-making (Duggan et al., 2020).

The implementation of algorithmic systems requires careful consideration of the particular organizational environment in which they are applied (Draude et al., 2020). Even though AM is expanding beyond the gig economy, current insights on AM are primarily based on research in platform-based organizations (Alizadeh et al., 2025; Keegan & Meijerink, 2025). Therefore, it is relevant to contrast the two work settings in more detail (Table 9) (Cameron et al., 2023).

In platform-based organizations, interactions between managers and workers are facilitated via digital interfaces such as mobile apps managed by hidden data processes. Thus, a real co-working environment between employees and managers is nonexistent, as the direct communication and interaction among co-workers are missing (Ashford et al., 2018). Instead, the algorithm is considered as a co-worker asking to conduct a specific task (Tarafdar et al., 2022). Consequently, workers lack social relationships and often feel dehumanized (Cui et al., 2024; Möhlmann & Zalmanson, 2017). Additionally, workers in platform organizations carry out highly standardized tasks within an isolated work environment (Baiocco et al., 2022; Wood, 2021). They are self-employed without a permanent contract, which makes them less bound to the company (Lippert et al., 2023; Petriglieri et al., 2019). Hence, the workforce is characterized as high-turnover labor, conducting low-skilled work (Wotschack et al., 2024). While technical, domain-specific competences are less relevant, one of the most significant skills of platform workers is to handle the algorithm in an intended way, e.g., to avoid sanctions (Cameron, 2024).

Within traditional organizations, a different, more standard organizational setting exists. Traditional employers maintain a close, continuous relationship with their employees, which is characterized by the direct employment of permanent workers with long-term contracts (Jarrahi et al., 2021; Schmid & Wiesche, 2024). In turn, workers within this traditional work environment experience a stable work atmosphere and are part of a predefined team with consistent relationships at a fixed workplace (Ashford et al., 2018). Managers within traditional organizations act as mentors and role models. They support their workers with skill development and open new career paths, which have positive effects on worker motivation (Ashford et al., 2018; Gagné et al., 2022). Traditional organizations introduce AM as an additional type of management that co-exists with human managers. It results in a complementary character of the algorithm, as the human-to-human interaction is supported by AM, creating a hybrid managerial setting (Benlian et al., 2022; Wiener et al., 2021). Moreover, AM complements existing organizational structures, strengthens established operations, and is attached to established processes (Cameron et al., 2023; Wiener et al., 2021). Compared to the platform-based work context, the traditional work environment is of a heterogeneous nature. Workers managed by AM in traditional organizations operate in a dynamic setting and must fulfill diverse tasks that differ in complexity (Jarrahi et al., 2023). Furthermore, the implementation of AM practices marks a remarkable change in the daily routines of workers, as AM is implemented later in the organizational history (Hirsch et al., 2024; Jarrahi et al., 2021). Hence, AM reconfigures existing knowledge forms and influences established power dynamics (Krzywdzinski, Schneiß, & Sperling, 2024).

Table 9: AM approach in traditional and platform-based organizations

Elements to consider	Approach in traditional organizations	Approach in platform-based organizations	Illustrative references
Role of management	Hybrid management, co-exists with AM	Management substituted by AM	(Lippert et al., 2023; Stelmaszak et al., 2025)
Role of AM	Attached to pre-existing processes	Foundation of any process	(Cameron et al., 2023; Kinder et al., 2019)
Employment	Workers with permanent contracts, long tenure	Self-employed workers, no permanent contract, high turnover	(Gussek & Wiesche, 2022; Petriglieri et al., 2019; Wotschack et al., 2024)
Form of organization	Team and work unit centric, hierarchical social orders	Task centric, no hierarchical social orders	(Karanović et al., 2021; Noponen et al., 2023; Olkkonen & Lipponen, 2006)
Work environment	Colleagues and algorithms as co-workers	Isolated, AM as co-worker	(Ashford et al., 2018; Tarafdar et al., 2022)
Task variety	Heterogeneous, high task diversification	Homogenous, standardized tasks	(Jarrahi et al., 2023; Jarrahi et al., 2021; Parent-Rocheleau & Parker, 2022)
AM implementation	Later in the organizational history	Organization based on AM, no implementation	(Ashford et al., 2018; Jarrahi et al., 2021; Timko & van Melik, 2021)
AM development	In negotiation with organizational actors	Non-transparent to affected workers	(Krzywdzinski, Schneiß, & Sperling, 2024; Möhlmann et al., 2021)

Current research on AM in traditional organizations is dominated by the logistics sector and the prime example of Amazon warehouses (Hirsch et al., 2024; Vallas et al., 2022). Considering the work environment of Amazon warehouses, it becomes evident that this specific context is characterized by recruiting low-wage employees who work like robots as pickers or sorters, with a limited need for particular skills or expert knowledge (Vallas & Kronberg, 2023). Similar to Amazon, UPS equips seasonal workers with computing devices to ensure correct deliveries even though workers have limited knowledge of corresponding zip codes (Woyke, 2018). Meanwhile, Alibaba uses AM in its warehouses to allocate picking tasks to its temporary workers (Bai et al., 2020). However, further research outside the logistics field is needed as the diverse applications of AM within traditional organizations, given the heterogeneous context, remain largely unexplored in current research (Lippert et al., 2023). Moreover, few studies have examined the specific ways in which existing social structures within traditional organizations might influence the implementation and utilization of AM (Lamers et al., 2024). Emerging research indicates, e.g., the importance of maintaining trust with workers during AM implementation (Leavitt et al., 2024). Nevertheless, the specific ways how human managers complement AM in traditional organizations need to be further investigated (Cui et al., 2024).

Preliminary quantitative research on workers' productivity suggests that AM increases work performance (Bai et al., 2020). However, this conclusion requires further validation, as the observed effect is based on workers' subjective belief that their task assignments had changed, rather than on an actual alteration of task allocation among the observed groups. Further researchers studied human deviation from AM and revealed that deviation increases packing time, which in turn has adverse effects on operational efficiency in Alibaba warehouses (Sun et al., 2020). Besides such performance-related research, Stelmaszak et al. (2025) combine the human perspective with analyzing patent data of a ride-hailing platform to collect information on the technical details and intended interactions of the algorithms and workers. The results reveal that algorithms use human input to align workers' behavior with organizational goals. Overall, a comprehensive understanding of how AM impacts workers' efficiency and work relationships in the traditional work context is critical.

8.2.2 Socio-technical Moderators to explain how AM impacts Workers' Efficiency

We apply the socio-technical perspective to analyze the impact of AM on efficiency within traditional organizations. It builds on the idea that the interconnection between the technical system (e.g., the processes) and the social system (e.g., humans within the organization) is highly relevant for the joint optimization of organizational outcomes within a specific context (Cherns, 1976; Makarius et al., 2020; Sarker et al., 2019). The duration of a process is an important success factor for performance and efficiency within organizations (Kandemir & Handley, 2019). Hence, efficiency is measured by the processing time of an error occurring at the manufacturing line, which is critical in reducing cycle time (Banker et al., 2006). Moreover, socio-technical moderators are identified to understand and explain how efficiency can be achieved in the traditional work context. It includes social factors (e.g., worker engagement) and technical aspects (e.g., task complexity) that organizations need to consider to achieve desired outcomes, such as increasing efficiency (Parent-Rocheleau & Parker, 2022). More specifically, *task complexity* and *worker engagement* are relevant moderators in traditional organizations based on the following reasons.

First, the aspect of *worker engagement* represents an essential socio-technical moderator, given that workers are closely bound to the company. Especially within traditional organizations, a different approach needs to be taken to achieve desired outcomes, given that the workforce typically possesses a long tenure and tends to stay within the organization for a significant period (e.g., due to permanent contracts) (Jarrahi et al., 2023; Lippert et al., 2023). In addition, existing labor unions can leverage their power resources to influence the adoption and utilization of AM (Dupuis, 2025). Therefore, fostering worker engagement, involving workers in AM implementation, and learning from their experiences with AM is crucial to ensure effective AM usage over the years (Cui et al., 2024). Moreover, a participatory approach for algorithmic work can also help to increase workers' well-being and initial acceptance of the new system at their existing workplace (Evers et al., 2019; Lee et al., 2021; Wotschack et al., 2024).

Second, when focusing on the technical aspects, we conceptualize *task complexity* as the second socio-technical moderator to consider (Sarker et al., 2019). In traditional organizations, the effectiveness of AM is fundamentally tied to its ability to manage and support tasks that vary in complexity, as workers need to fulfill a variety of tasks that are less standardized compared to the gig economy (Wood, 2021). Moreover, task complexity represents a highly relevant task characteristic that directly impacts workers' performance (Peng Liu & Li, 2012). Hence, it is relevant to investigate whether AM can be applied for tasks with varying complexity, as it has already been noted that objective task complexity needs to be considered when analyzing, e.g., the effects of decision-support systems on performance (Chan et al., 2015).

Based on the socio-technical perspective and the special characteristics of the traditional context, we develop a research model that indicates how AM impacts efficiency, considering specific socio-technical moderators (Figure 18).

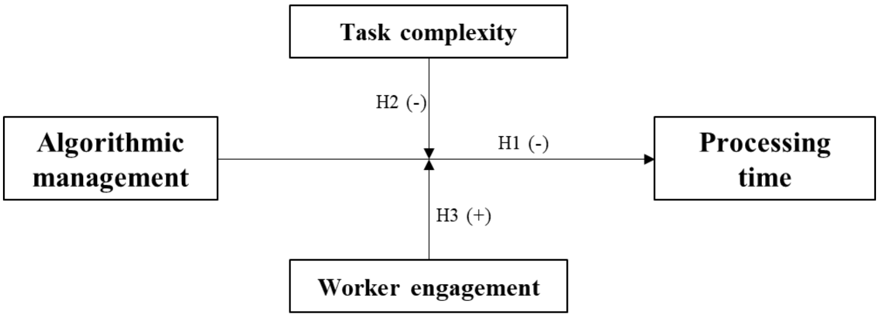


Figure 18: Research model

8.2.3 Research Model

We hypothesize that AM has a positive impact on organizational outcomes. It is well known that AM has an enormous efficiency potential and performance advantage in platform-based businesses (Jarrahi et al., 2023). Uber uses AM, e.g., to monitor the productivity and performance of its workers (Möhlmann et al., 2021). Outside of the platform-based work context, it is generally acknowledged that algorithmic technologies benefit employers, e.g., through improved efficiency in decision-making or coordination activities (Kellogg et al., 2020). As an example, warehouse workers at Amazon are guided by wristbands to fulfill orders faster and reach daily delivery targets (Yeginsu, 2018). Moreover, Amazon uses scanners and computers to track productivity in a highly visible way, conditions workers to associate these technologies with disciplinary consequences (Wiggin, 2025). A study at Alibaba Group reveals that the algorithmic assignment in picking bills increased workers' picking efficiency (Bai et al., 2020). All in all, digital devices help to monitor and discipline workers by providing feedback or improving role clarity. A primary consequence of AM implementation, therefore, is to improve workers' performance systematically (Jee, 2019; Parent-Rocheleau & Parker, 2022). Hence, we suppose:

Hypothesis 1: Algorithmic management decreases processing time.

For successful AM utilization, it is essential to reflect on the scope of application that directly influences the impact of the algorithm. Specifically, considering the level of task complexity is highly relevant for achieving desired outcomes, as it describes how challenging a specific task is for the worker (Efatmaneshnik & Handley, 2021). Generally, high task complexity indicates that several complexity contribution elements, such as the goal, input factors, or process components, are applied (Peng Liu & Li, 2012). In the field of automation, Vimalkumar et al. (2021) demonstrate that variations in task complexity result in distinctions in their potential for automation. While simple tasks with low complexity have higher automation potential, complex tasks are much more challenging to automate. This finding is in line with earlier research on computer-based monitoring, highlighting that it can decrease work performance for complex tasks (Aiello & Svec, 1993). Further researchers argue that for tasks with a high impact, workers are more sensitive to algorithmic biases and might react unfairly to algorithmic processes. This reaction contrasts with low-impact tasks, which are less prone to workers' concerns (Kordzadeh & Ghasemaghaei, 2022). Consequently, we predict that AM is more beneficial for easy tasks within traditional organizations, as it includes less human input to the specific task. Thus, we hypothesize the following:

Hypothesis 2: Task complexity negatively moderates the relationship between AM and the processing time.

We anticipate that worker engagement will positively influence processing time, as it emphasizes workers' active involvement in the implementation process of AM. Earlier research supports the statement that user involvement is relevant for IT system success (Harris & Weistroffer, 2009). In algorithmic work, enhanced algorithmic transparency, understandability, or explanations, e.g., regarding the general process and outcomes, can lead to better reactions and improve usability (Kordzadeh & Ghasemaghaei, 2022; Langer & Landers, 2021). Recent research states that managers need to empower workers to provide feedback on the algorithmic work and raise questions when encountering confusion in the new setting, as it can help to mitigate concerns or resistance of workers (Cui et al., 2024; Tarafdar et al., 2022). Moreover, worker engagement can optimize working conditions, which has additional positive effects on the well-being of workers and the overall setting at the workplace (Lee et al., 2021). Based on these assertions, the following hypothesis is proposed:

Hypothesis 3: Worker engagement positively moderates the relationship between AM and the processing time.

8.3 Methodology

To provide a robust empirical assessment of the research model and the related hypotheses, we implemented a sequential, mixed-method design. The combination of qualitative and quantitative approaches supports the development of a complementary understanding from different perspectives and overcoming the methodological weaknesses of a single method (Reis et al., 2022; Venkatesh et al., 2013). Therefore, we adopt a mixed-methods research design and integrate qualitative and quantitative techniques within a single research project (Venkatesh et al., 2023). First, the quantitative assessment includes the analysis of an archival data set of production data provided by an international automotive supplier. Second, the qualitative analysis contains 15 semi-structured interviews with workers and managers of the organization.

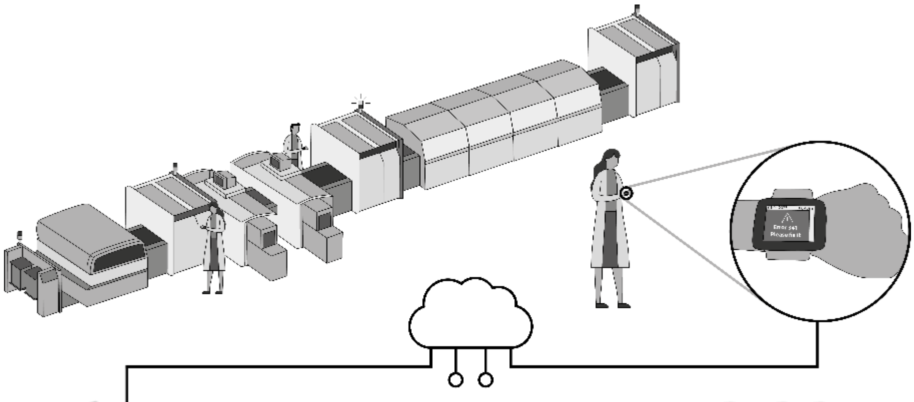
8.3.1 Research Setting

The workers in our setting are responsible for ensuring the continuous operation of nine manufacturing lines, e.g., by maintaining equipment, promptly resolving any errors that occur, proactively preventing interruptions, and reducing machine downtime. They are split into four teams with similar backgrounds and demographics, working in a three-shift model. On average, two workers are responsible for one or two manufacturing lines, representing a confusing and complex working atmosphere. Moreover, the work environment is characterized by a high task fluctuation, which requires different skills and equipment, as well as profound technical knowledge. Hence, managers have the responsibility of overseeing and coordinating their employees' work efforts on the shop floor. Starting from 1 April 2023, smart watches as an AM approach are installed to optimize the communication on the shop floor and to deliver the correct information at the right time to the right worker. The investigated system can be considered as AM, as the two functionalities of matching and control (Möhlmann et al., 2021) are fulfilled. AM controls workers of all four teams by providing real-time alerts on critical machine events via a wearable device. Additionally, AM coordinates open tasks by matching them to the relevant workers according to their position on the shopfloor. In this way, AM aligns workers' behavior with the organizational goals and empowers workers to meet daily performance targets. Workers receive real-time feedback on their performance and daily targets via the wearable device, e.g., by displaying the progress on the current production orders. Moreover, AM structures work more comprehensively by anticipating upcoming issues and proactively scheduling tasks to foster a more stable production environment. An enhanced coordination of work is achieved as AM delivers detailed information on relevant error types and their exact position. Furthermore, AM leverages collected data on error resolution and production schedules to predict and mitigate future errors, optimizing workflow and minimizing downtime.

8.3.2 Study 1: Archival Data

Data Set

The archival data set contains production data from one German manufacturing plant of the international automotive supplier. Data is extracted from the internal manufacturing execution system, which holds detailed information on the error history between January 2023 and September 2023. We use the start and end points of an occurring error to calculate the error duration for each incident. The uncorrected dataset contains 15297 data points, and each data point represents one error that occurred at a manufacturing line.



#	Error duration [s]	Date	Timestamp [CET]	Shift	Team	Line number	Error number	Error complexity	AM
15	5.23	2023-01-02	22:59:53	night	4	9	100	1	0
16	119.25	2023-01-03	23:04:23	night	4	5	144	3	0
17	66.84	2023-01-03	23:06:02	night	4	7	145	1	0
...	...	...	...	...	...	...	...	...	...
8255	57.05	2023-04-03	13:59:48	early	2	2	101	2	1
8256	31.14	2023-04-03	14:00:54	late	3	7	118	1	1
8257	26.23	2023-04-03	14:02:18	late	3	6	122	1	1

Figure 19: Research setting with illustrative error report

The following information is linked for each error: error duration in seconds [s], date, timestamp [CET], line number, and error number. We match additional descriptive data to each record, e.g., the processing team, shift, error complexity, and whether the error is processed with or without AM. The variables processing team and shift are retained from the yearly shift schedule and reflect the real circumstances of our natural experiment. Moreover, the level of error complexity is assigned to each error type by process experts. Based on discussions with process experts, we remove all errors with durations below 5 s and above 300 s to enhance data quality. In addition, we clear out all errors with missing or wrong information. This results in the final archival data set of 12743 errors. An illustrative example of the error report is shown in Figure 19.

Data Analysis

We used linear mixed modeling for our data analysis. Longitudinal data from repeated observations of 22 different error numbers at nine manufacturing lines provides evidence for the verification of this kind of modeling (Fahrmeir et al., 2013). As a graphical examination of the residuals for normality revealed a deviation from normal distribution and skewed data, we transformed it. This has been done by calculating the natural logarithm of our dependent variable to generate an enhanced symmetric distribution and hence fit the data within the scope of the linear model (West, 2022). After the transformation, the residual plot showed no evidence of a non-linear relationship. It must be noted that linear mixed models (LMMs) are generally robust to violations of the model assumptions, such as data not following a normal distribution (Schielzeth et al., 2020). The LMM is an extension of the general linear regression, allowing for the modeling and estimation of fixed and random effects. Thus, the LMM is also called the random effects model (Fahrmeir et al., 2013). In contrast to the fixed effects (unknown population parameters), random effects refer to subject-specific effects and can be described as grouping factors (McCulloch & Searle, 2000; Schielzeth et al., 2020). The overall goal of including subject-specific effects is to enhance the estimation of the fixed effects (Fahrmeir et al., 2013). We modeled two random effects: (i) manufacturing line and (ii) error number. The variable 'manufacturing line' specifies on which line the respective error occurred. This is included as a random effect to account for any potential bias arising from individual lines. Moreover, the variable 'error number' is modeled as a random effect to consider modifications based on specific error types. Table 10 presents an overview of the definition and operationalization of the variables.

Table 10: Measures

Construct	Definition	Operationalization
Dependent variable:		
Processing time	Important component to reduce cycle time to increase performance and efficiency, as more products can be produced in the same period of time (Ayabakan et al., 2017; Banker et al., 2006; Maedche, 2019).	Measuring error duration, which is the time interval between the occurrence of an error and its resolution by a worker.
Independent variable:		
Algorithmic management	The support of algorithms for workforce management (Lee et al., 2015).	Usage of smart watches as an AM approach on the shop floor, with the goal of bringing the right information to the right worker at the right time.
Fixed effects:		
Team	Indicates which team processed the error.	The timestamp of each error is used to determine the appropriate team based on the predefined working schedule.
Complexity	Indicates the complexity level of each error.	The error number of each error is used to categorize the errors in values between 1 (very low error complexity) and 4 (high error complexity, hard to solve by the workers).

Worker engagement	An active involvement of workers in the implementation process to enhance outcomes. Managers can e.g., empower workers to provide feedback on the algorithmic work and raise questions when encountering confusion in the new setting (Cortellazzo et al., 2019; Jarrahi et al., 2021; Tarafdar et al., 2022).	Worker involvement: Workers of team 4 were involved in the use case development of the AM approach at their workplace, e.g., by providing feedback and contributing their own ideas. Workers of team 1-3 were not involved. It is the interaction term of the two independent variables, *team* and *smart watch*.
Task complexity	Task complexity depends on various complexity sources such as the goal of a task, the path to achieve the goal as well as the available information and input factors (Peng Liu & Li, 2012; Vimalkumar et al., 2021).	Error complexity: Categorization by process experts in values between 1 (very low error complexity) and 4 (high error complexity). It is the interaction term of the two independent variables, *error complexity* and *smart watch*.
Random effects:		
Manufacturing line	A sequence of machines with workers in a factory through which a product progresses as it is assembled or produced.	Specified by the line on which the respective error occurred.
Error number	Numeric code that indicates the type of error.	Specified by the respective error number.

Descriptive statistics

Between January 2023 and September 2023, around 2/3 of the errors (8902) are processed with AM, and around 1/3 (3841) errors without (Table 11). In our sample – as a baseline – the average error duration without AM is 77.55 s. With AM, the error duration significantly decreases by 11.14 s (14.36 %) to 66.41 s. The error processing is distributed almost equally across the four teams, and the errors appear at any of the nine manufacturing lines.

Table 11: Descriptive statistics

Variable	# errors	Duration [s]
Errors with AM	8902	66,4
Errors w/o AM	3841	77,6
Team 1	2856	
Team 2	3381	
Team 3	3249	
Team 4	2357	
Line 1	1064	
Line 2	654	
Line 3	1885	
Line 4	1272	
Line 5	1607	
Line 6	2115	
Line 7	910	
Line 8	1194	
Line 9	2042	

8.3.3 Study 2: Confirmatory Semi-structured Interviews

While the quantitative design includes the analysis of an archival data set provided by an international automotive supplier, the subsequent qualitative analysis comprises semi-structured interviews with workers of the company. We conduct the second study to refine and understand the results found in study 1 (Ivankova et al., 2006; Venkatesh et al., 2023). The qualitative nature of study 2 is suitable to gather in-depth explanations regarding the background of efficiency gains, the role of different tasks and workers' engagement, and the influence of our unique work environment on organizational outcomes.

Data collection and analysis

Between January and February 2025, we collected interview data from 15 interviews with (i) workers who experience AM during their daily work and (ii) respective managers and project leaders. We conducted seven semi-structured interviews with shop floor workers and eight interviews with direct managers of the workers or project leaders (Table 12).

Purposeful sampling was applied to generate rich information (Patton, 2009). During the interviews, we asked about their perception of the performance increase with AM and the underlying reasons. We specifically asked the shop floor workers about their individual experiences with AM, their different tasks with varying complexity, their involvement in the implementation process, and the role of their co-workers and managers. In the interviews with managers and project leaders, we focused on the overall perception of AM in their area of responsibility, the efficiency effects, the implementation process, and the collaboration with their workers. The data was analyzed based on overarching themes that reflect our area of interest. Interview data were transcribed and coded according to the predefined general themes and constructs (Miles et al., 2020; Venkatesh et al., 2023).

Table 12: Overview of semi-structured interviews with workers, managers, and project leaders

Interview	Role	Years in position	Interview duration
#1	Worker on the shop floor	5 years	25 min
#2	Worker on the shop floor	4 years	20 min
#3	Worker on the shop floor	2 years	21 min
#4	Worker on the shop floor	3 years	16 min
#5	Worker on the shop floor	2 years	24 min
#6	Worker on the shop floor	29 years	21 min
#7	Worker on the shop floor	4 years	15 min
#8	Project leader AM project	5 years	52 min
#9	Co-project leader AM project	1 year	28 min
#10	Central project coordinator	4 years	40 min
#11	Project leader at respective plant	5 years	58 min
#12	Production supervisor	3 years	14 min
#13	Deputy team coordinator	3 years	35 min
#14	IT coordinator in manufacturing	8 years	37 min
#15	Team coordinator	2 years	11 min

8.4 Results

8.4.1 Results of Study 1

We present the results of the LMM, used to analyze our hypotheses (Following logarithmic transformation of the data, it is crucial to interpret the effects as multiplicative on the original scale. Consequently, the results represent proportional changes, reflecting ratios rather than absolute differences. In this context, exponentiated coefficients indicate the multiplicative change in the original outcome associated with a one-unit increase in the predictor variable. The results of the LMM show that AM has a significant negative effect on the *error duration* ($\exp(b) = 0.733$; $p < 0.001$). Thus, it can be confirmed that AM significantly reduces the processing time (H1). Analyzing the level of *error complexity* (H2) reveals that AM does not work for all error levels the same way. The processing time of errors with complexity level 3 (medium level) is significantly higher with AM compared to errors with complexity level 1 ($\exp(b) = 1.550$; $p = 0.021$). In contrast, we cannot identify significant effects for errors with high error complexity ($\exp(b) = 1.251$; $p = 0.250$) and low error complexity ($\exp(b) = 1.085$;

$p = 0.285$). Therefore, we can only partially confirm *error complexity* as the assumed negative moderator (H2). Finally, for *worker involvement* (H3), we also find mixed effects. We can support that team 1 is significantly slower than team 4 (exp(*b*) = 1.131; $p = 0.025$) if both teams apply AM. However, we do not find this effect of team 2 (exp(*b*) = 0.972; $p = 0.606$) and team 3 (exp(*b*) = 1.178; $p = 0.002$) compared to team 4. We check the robustness of our results by analyzing the error duration of two error types that are not processed with AM starting 1 April 2023. The robustness check reveals that the error duration without AM does not significantly decrease.

The coefficient of determination R2 represents an essential indicator for the amount of variance explained by any linear model (Fahrmeir et al., 2013). For LMMs, reporting R2 has become increasingly relevant. *In* this specific case, R2 can be categorized into *two types*: marginal R2 (= variance explained by the fixed factors) and conditional R2 (= variance explained by both fixed and random factors) (Nakagawa & Schielzeth, 2013). Whereas the marginal R2 can be reported as 0.015, the conditional R2 reveals that 0.329 of the variance can be explained by the entire model. It is acceptable, as most of our explanatory variables are statistically significant (Ozili, 2022). The standard deviation (SD) for random effects can be reported as 0.070, which reveals a low variability among different manufacturing lines and error numbers.

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compared to team 4. We check the robustness of our results by analyzing the error duration of two error types that are not processed with AM starting 1 April 2023. The robustness check reveals that the error duration without AM does not significantly decrease.

The coefficient of determination R^2 represents an essential indicator for the amount of variance explained by any linear model (Fahrmeir et al., 2013). For LMMs, reporting R^2 has become increasingly relevant. In this specific case, R^2 can be categorized into two types: *marginal R^2* (= variance explained by the fixed factors) and *conditional R^2* (= variance explained by both fixed and random factors) (Nakagawa & Schielzeth, 2013). Whereas the marginal R^2 can be reported as 0.015, the conditional R^2 reveals that 0.329 of the variance can be explained by the entire model. It is acceptable, as most of our explanatory variables are statistically significant (Ozili, 2022). The standard deviation (SD) for random effects can be reported as 0.070, which reveals a low variability among different manufacturing lines and error numbers.

Table 13: Results of the linear mixed model

Parameter	**Estimate**	**Standard deviation**	**p-value**	**95 % conf. interval**	
				Lower	**Upper**
Intercept	3.787	0.105	<0.001	3.578	3.905
Algorithmic management	-0.310	0.048	<0.001	-0.404	-0.217
Team (team 4)					
Team 1	-0.102	0.046	0.025	-0.192	-0.013
Team 2	-0.082	0.050	0.102	-0.180	-0.016
Team 3	-0.168	0.044	<0.001	-0.254	-0.081
Complexity = 1					
Complexity = 2	-0.224	0.193	0.247	-0.605	0.157
Complexity = 3	-0.107	0.212	0.613	-0.523	0.309
Complexity = 4	0.142	0.255	0.578	-0.361	0.654
Workforce involvement					
Workforce involvement (team 1)	0.123	0.055	0.025	0.015	0.231
Workforce involvement (team 2)	-0.028	0.054	0.606	-0.134	0.078
Workforce involvement (team 3)	0.163	0.053	0.002	0.059	0.267
Error complexity					
Low error complexity	0.082	0.076	0.285	-0.068	0.232
Medium error complexity	0.438	0.189	0.021	0.067	0.808
High error complexity	0.224	0.195	0.250	-0.158	0.606

Dependent variable: Error duration [ln]

N = 12743; R^2 (marginal) = 0.015; R^2 (conditional) = 0.329; SD of random effects: 0.070

8.4.2 Results of Study 2

The interviews with workers and managers reveal more profound insights into the AM application within a traditional organization. Study 2 offers detailed background information for our quantitative results, while providing additional qualitative explanations to enhance our understanding of this particular context.

8.4.2.1 Confirmatory Semi-structured Interviews

The interviews strengthen our results on the positive impact of AM on efficiency found in study 1. Workers on the shop floor reported positive experiences with the processing time, particularly under the coordination of AM. One worker describes how AM improves the structure of their work, by making it more organized: *"Work is faster and more structured. Just because we now have the sequence, you can say: Ok, I am working on this task, I am ticking it off and then move on to the next task."* In addition, AM proactively provides the information, particularly for recurring tasks during the workday. One interviewee highlights that AM provides helpful messages that remind them of relevant next steps: *"You get the notifications for the regular tasks a little bit in advance. There is always a certain amount of time to finish your current work so that you can plan for it and not only notice when it is too late."* Furthermore, AM offers high transparency on the current workload and upcoming tasks, as it provides *"good overview of the order status"*. A worker describes how she structures her working day accordingly, e.g., by deciding when to take a break: *"This allows you to plan things. I would rather take a break now since I have to set up the machine in 30 minutes. In this way, it doesn't get too tight."*

From a management perspective, AM reduces processing time by enabling workers to maintain a comprehensive view of the current shop floor situation. It allows workers to concentrate on relevant tasks without losing track of important issues. One manager describes within the interview: *"The employee must have an overview of the line. If an employee loses the overview for a moment, the device will bring him back. At least the employee knows the machine is down, or the station needs my help right now."*

Elaboration on task complexity

Our first study revealed that AM has the most significant benefit for tasks with medium complexity and less benefit for easy and complex tasks. It is surprising, as we expected it to work well for easy tasks. However, our interviewees note that the easy tasks involve simple information that is not particularly essential for production at a specific time. Workers can postpone the task for now and deprioritize it for more urgent activities. One worker explains the situation: *"Sometimes it is just a hint; for example, the paste is at the limit. Then the printer continues to run, but AM says: 'Wait a minute, you need to pay attention.' I can ignore it for the moment, but I know what's going on."*

In contrast, medium complex tasks refer to machine disruptions that require immediate attention from workers. Several workers emphasize that AM is necessary for medium-complex tasks to ensure the manufacturing line operates as efficiently as possible. Machine disruptions have a direct impact on the overall performance of the manufacturing plant. Here, AM improves workers' attention, enabling them to solve the issue faster. One interviewee summarizes the high relevance of AM for medium complex tasks: *"I think it's good that all the tasks show up, because you simply get all the information directly. But if I had to choose one type of task, it would be the line disruptions. Whether there is a box or not is not as relevant as if the line stops and you don't reach your percentages during the day or don't reach the production volume."*

Interestingly, the interviews reveal that workers perceive AM as less beneficial for complex tasks, as the direct exchange and interaction with the manager is missing. For very complex tasks, workers cannot solve the issues independently, and consulting with managers to leverage their experience and specialist know-how is essential. The workers describe complex issues as those characterized by unknown error patterns that rarely occur. Hence, managers would rather provide verbal instructions via phone or even physically assess the issue on the shop floor. One worker describes the situation with AM for complex tasks: *"We have a team coordinator outside who is there when we have complex problems. We can't solve everything. It would be nice. […] But I think it's always better to talk about complex tasks. Because then you can immediately say what the problem is. Then the team coordinators can say, 'Hey, try this and this.' You don't have that with AM. Then you just pass the problem on to them, but they don't know the real problem is at the station; they would still have to come anyway."*

Insights on worker engagement

When asked about how the involvement of workers in the implementation process might influence the efficiency, workers described that a continuous information flow is more important than a deep involvement in the use case development. A production supervisor emphasized the importance of sharing only essential information, ensuring that workers avoid the overload of excessive details: *"It is important to inform employees if a general change is* *made, but it doesn't have to be about every little detail."* If workers are involved, the focus would be mainly on the general usage of the devices in the workplace. Less attention has been devoted to developing specific use cases since the tasks remained the same, but the management approach shifted. One worker explains the involvement as follows: *"In the beginning, we had different models of the devices. So, we were involved a little bit, in terms of the straps, for example, and which model we liked the most from those presented."*

In this context, a project leader describes that many discussions and exchanges with the workers focused on improving the devices' wearing comfort: *"Workers told us that the device feels uncomfortable on the skin. We have therefore purchased interchangeable wristbands and sweatbands to increase comfort."*

All interviewees agreed they do not need extensive experience using AM for their work, as it works *"just like a smartphone."* The general set-up at the beginning of a shift is intuitive and easy to handle: *"That's self-explanatory. I know exactly where I have to go. When I get the watch, I switch it on and enter a PIN. Then, depending on which station I'm assigned to, I assign the station to my watch. It is relatively simple."* Even workers absent during the introduction faced no obstacles related to the handling, with one noting: *"I was on holiday at the time of the introduction. I then had an individual briefing. But it is all self-explanatory."*

Interestingly, the workers told us about new colleagues who need less human guidance due to the close coordination by AM. Being managed by AM helps to structure the overwhelming atmosphere, as explained by a worker: "*At the beginning, I was always a bit stressed at work, but when AM tells me: 'You have to prepare the machine now!', then I would say it's a bit more pleasant."* Interviewees further explained that AM supports newcomers in developing an overview of the different activities and quickly establishing an efficient routine. One team member describes: *"We currently have girls we are training. They just finished their apprenticeship. AM is absolutely helpful. […] They are now starting to work independently, and AM is great because it often reminds them of things they would have forgotten."*

8.4.2.2 The Effect of AM on Team Collaboration

As part of the interviews, we could further observe a shift in team dynamics with AM. While AM provides structure and coordination, it does not entirely replace traditional collaborative behaviors among co-workers. Our interviewees explain how they directly interact and align with co-workers on the shop floor, independently of the AM instructions. In stressful situations, co-workers assume each other's responsibilities, even when it deviates from the algorithmic assignment to support each other: *"There are usually two or three of us on a production line. Everyone has their area of responsibility. You have eye contact, which allows you to see if the other person is busy. [...] And I can see what kind of issue we have. And then I just check what my colleague is doing now, whether he has noticed that there is a problem. And if he is busy at the moment, then I will go over there too."*

Moreover, managers emphasize that direct communication between workers is crucial for maintaining motivation, as it allows them to organize the workday according to the specific needs of each employee. If someone needs a break or wants to rotate tasks, this is quickly aligned among the co-workers: *"It is agreed in advance between the co-workers who will take over which tasks. And they then coordinate with each other. If one person says he or she is going to take a break, the other knows: ok, I have to take care of everything in the meantime. [...] The line and the sides are also switched regularly. If one co-worker says: I have been doing a certain task for the last two days. Then another says: Yes, let's swap, I'll do [this task] and you do another one."*

During the interviews, we experienced several times how workers were notified about the current activities of their colleagues, even when those colleagues were out of sight and located in another room outside the shop floor. The algorithm disrupted our conversation, and one worker told us: *"Look! Now you can see, in this moment, my colleague is setting up the machine."* At any point in time, the workers have high transparency regarding the work of their co-workers. Another interviewee explained to us that she knows exactly which tasks her colleague should take care of now: *"Now with the magazines, for example, you can see that I get the notification there's only one of five left, which means that my colleague needs to start filling them up again. And I know which colleague that is, I hope he does too. [...] Otherwise, I'll walk over to him, and I'll tell him straight away: Mike[c], you need to go back down and take care of it."*

8.4.2.3 The Role of Human Management

The interviews revealed that human managers still fulfill an important role within the hybrid organizational setting. The workers emphasized that it is essential for them to have their supervisors available to discuss any issues they may have. One worker explains that their team coordinator is always approachable during the workday, as he is *"working with us in the same shift"*. Hence, workers perceive that their team coordinators are reachable at *"any time if*

[c] Name adjusted for privacy reasons.

something is bothering us". The team coordinators are responsible for organizational activities, including the working schedule. Furthermore, workers describe the relevance of face-to-face meetings in the morning. Within the meeting, team coordinators share general updates, and the work is allocated among the workers: *"We always have a meeting with the team coordinator in the morning to decide who takes over which production line. [...] He also gives us information from the office at the start of the shift. Or when we start the night shift on Sunday, if there are any updates. He also tells the whole team what's new, for example, if there have been any problems."*

All managers in our interviews shared the common view that AM should be designed to make the work more convenient for their workers. Managers in our sample feel responsible for supporting and protecting their workers: *"I always see it that way; it should make things easier for workers. [...] It should reduce the workload."* A production supervisor told us how he took care that AM is not applied for every task to reduce the level of stress within his team: *"The central part of the work is the assembly. We don't use AM for the main work because I believe it would put too much stress and strain on the workers."* The interviews with managers further revealed that they understand the workers' perspective well and empathize with any issues caused by AM: *"My workers are increasingly forced to fulfill tasks supported by AM, due to a lack of alternatives. That is a slap in the face."* Consequently, the managers actively addressed concerns, streamlined the application on the shop floor, and supported the teams during implementation.

8.5 Discussion

As AM is spreading across traditional organizations, there is a need to investigate its impact on established structures from additional perspectives. We demonstrate through our sequential, mixed-methods study that the efficiency enhancements of workers observed in the platform business can be validated in traditional settings, particularly within a challenging work environment that demands technical expertise. Furthermore, we contribute to the emerging research stream on AM in traditional organizations by (i) offering insights into the role of human managers, (ii) illustrating shifts in team dynamics in this traditional work environment, and (iii) highlighting the joint optimization of all organizational actors in this traditional work environment.

8.5.1 Contextual Impact of AM: The Supportive Role of Human Managers

Prior research acknowledges that the application of algorithmic systems must be contextualized within their specific organizational setting (Draude et al., 2020). Particularly in environments where workers are closely tied to the organization through permanent contracts, a tailored AM approach is necessary (Jarrahi et al., 2021). Our findings enhance the current understanding of the successful utilization of AM in traditional organizations by revealing that efficiency increases in this context is achieved based on enhanced coordination that is adapted to the specific needs of workers within this work environment. While workers managed by AM in platform organizations are dealing with low task variety and carry out highly standardized work (Möhlmann et al., 2021; Wood, 2021), workers in traditional organizations must consider a variety of tasks conducted with and without AM, depending on the area of application. This finding highlights that the human ability for a contextual judgement of the situation and prioritization remains relevant, especially within traditional organizations that operate in an environment demanding specialized technological expertise (Dupuis, 2025).

The effectiveness of AM within traditional organizations is supported by human managerial actions. While it is acknowledged that algorithms do not replace human managers but instead form a "symbiotic division" of labor (Jarrahi et al., 2023), few studies have examined the specific ways how human managers complement AM in traditional organizations (e.g., Leavitt et al. (2024), Cui et al. (2024)). We contribute to this emerging discourse by highlighting two relevant roles of human managers within this partnership: (i) shapers during AM implementation and (ii) collaborators while working with AM. First, our findings demonstrate that human managers in traditional organizations actively influence the design of the AM system and make strategic decisions that benefit their workers. In contrast to the gig economy, where workers are disconnected from their organization, need high self-responsibility, and are exposed to greater individual pressure (Ashford et al., 2018; Gagné et al., 2022; Timko & van Melik, 2021), the managerial support based on long-term employment and close relations with human managers appear to positively impact the successful implementation of AM without harming workers. This finding complements prior research revealing on a theoretical level that the ability of human managers to augment algorithms (e.g., by correcting data collection) and explain algorithmic logics is highly relevant for maintaining workers' trust within organizations during AM implementation (Leavitt et al., 2024). In this context, Krzywdzinski, Evers, and Gerber (2024) note that there is a risk of work intensification, especially for capital-intensive, skilled work such as tasks of machine operators. Strong bargaining power of workers and labor unions is identified as a way to prevent such effects (Dupuis, 2025; Wood, 2024). Within the present work, we show that human managers and project leaders perceived it as their responsibility to create a favorable environment, e.g., through a proactive exclusion of certain application areas. Hence, human managers also represent relevant voices for their workers to align organizational goals with algorithmic outcomes (Leavitt et al., 2024).

Second, following the successful implementation, we demonstrate that workers in traditional organizations receive support from human managers when carrying out work with AM. Therefore, we contribute to research on combining humans and algorithms by providing an in-depth description related to the configuration of the hybrid managerial setting in which algorithms and humans jointly manage workers (Hirsch et al., 2024; Stelmaszak et al., 2025). While first studies in the gig economy highlight that the combination of human and algorithmic management has positive effects on worker well-being and performance (Cui et al., 2024), detailed explanations on the hybrid managerial setting in traditional organizations are currently missing. Our study reveals that human managers keep the role as mentors and advisors during the workday, e.g., by engaging in collaborative problem solving, a capability that current AM systems do not provide. Hence, human managers can cultivate continuous learning and personal growth (P. Zhang et al., 2025). Furthermore, studies in the gig economy highlight that a complementary collaboration between algorithmic and human management includes co-determined work arrangements that improve work flexibility and worker engagement while benefiting the organization and workers (Cui et al., 2024). We extend this finding by revealing that human managers in traditional organizations apply this approach and set relevant space for fostering direct communication among workers, e.g., through a daily meeting at the beginning of each shift to configure and adapt AM for the workday. In this way, we illustrate how human managers realize synergies of algorithmic and human management in traditional organizations.

8.5.2 Shifting Team Dynamics

Our analysis reveals that implementing AM in traditional organizations further impacts existing team dynamics. As current knowledge on how AM affects team dynamics is still in an early stage (Granulo et al., 2024; Ping Liu et al., 2025), our study contributes to the emerging discourse in several ways. First, we can demonstrate that the successful application of AM involves situational optimization across team members, even when bypassing AM. Adapted to the current situation and scope, team members engage in informal coordination to ensure operational continuity. Bypassing AM is also a common phenomenon in the gig economy, e.g., through personal negotiations with clients (Kellogg et al., 2020) or by gaming the system

(Möhlmann & Zalmanson, 2017). However, workarounds in the gig economy are viewed negatively by platform organizations because they violate platform rules and need to be reduced (Wiener et al., 2021). In addition, the isolation of workers on platforms does not even allow social interactions among co-workers (Wood et al., 2019). Contrary to these mechanisms in platform-based organizations, we reveal that in traditional organizations, workers join forces to engage in workarounds and collective bypassing of AM. Dupuis (2025) noted that, with the presence of co-workers and established collaboration, workers are encouraged to express concerns, adjust responsibilities, and shape AM. Hence, team resilience can be strengthened by fostering self-regulating teams and promoting workers' self-management (Ping Liu et al., 2025). Our findings represent an essential extension of this discourse, as we illustrate that a direct exchange between workers that deviates from AM is crucial in stressful situations to optimize team dynamics. Moreover, the spontaneous support among co-workers in traditional organizations is relevant to achieving enhanced outcomes, as it is driven by human intuition, informal collaboration, and situational awareness.

Second, we demonstrate that the collaboration with co-workers mitigates the dehumanizing effects of AM. In the gig economy, AM can foster dehumanization and create a social burden, leading to reduced cooperation and teamwork (Lee, 2018; H. Park et al., 2021). Moreover, it has been found that AM can lead to an objectification of co-workers and a decrease in prosocial motivation (Granulo et al., 2024). Earlier research already mentioned that human managers can tackle dehumanization, e.g., by adjusting the work environment or providing algorithmic explanations (Cui et al., 2024). We contribute to this conversation by highlighting that co-workers in traditional organizations also remain relevant for the successful utilization of AM. Workers achieve team spirit and well-being by jumping in and supporting each other, e.g., by deciding when to take a break. Hence, workers leverage their social relationships to optimize their comfort at the workplace and mitigate the dehumanizing effects of AM.

Finally, our findings provide evidence for an emerging hybrid interaction among workers within traditional organizations, as AM introduces a new dimension of virtual interaction that complements the existing, physical interaction. So far, most research focuses on the effects of AM on the physical relationship between managers and workers (Jarrahi et al., 2021; Kellogg et al., 2020) or the physical interaction among gig workers and conventional workers (Maffie, 2024). We extend this discourse by offering insights into how AM, in turn, adds virtual interactions among co-workers within a physical environment. In the gig economy, this virtual interaction takes place in informal online communities, where workers actively share information or complaints (Jabagi et al., 2019; Möhlmann et al., 2021). Our study reveals that AM in traditional organizations provides workers with new real-time transparency, offering insights into co-workers' activities and performance (e.g., open tasks). In addition, this virtual interaction even turns into a physical intervention and direct exchange among colleagues within traditional organizations, as workers are able to approach the responsible colleague directly. This finding provides first evidence on the multi-dimensional impact of AM on workplace dynamics (Granulo et al., 2024).

8.5.3 Embedding AM for Joint Optimization in a Hybrid Socio-technical Setting

Overall, the role of humans as key actors in shaping AM remains underexplored in current research (Lamers et al., 2024). Our study illustrates the importance of human actors within traditional organizations in two ways. First, research at the managerial level already describes the complementary actions of human and algorithmic management to achieve both performance and humanistic outcomes as humanistic AM (Cui et al., 2024; Lamers et al., 2024). We extend this approach by incorporating the worker level, which reveals the importance of informal coordination and collaboration among co-workers. Hence, our results indicate that the combination of human managers and workers with algorithmic capabilities helps to ensure both technical efficiency and desired social outcomes. These insights complement recent findings from the gig economy, revealing that a moderate level of AM unlocks positive effects on worker performance (Lin et al., 2025). Our study demonstrates that established relationships among human managers and co-workers, along with the existing organizational setting, create a moderate AM level that supports a humanistic AM approach.

Second, our investigation uncovers that the successful utilization of AM in traditional organizations requires an optimized interplay among different organizational layers, such as human managers, project leaders, and co-workers. These hierarchical layers represent a distinct characteristic of traditional organizations and need to be considered when implementing AM. Krzywdzinski et al. (2024) already showed that close collaboration between central and local management can strengthen successful AM implementation. Moreover, additional organizational actors, such as process engineers and data scientists, are facilitating its integration (Krzywdzinski, Schneiß, & Sperling, 2024). We build on these arguments by illustrating that joint optimization across all actors in a hybrid socio-technical setting is relevant for achieving desired outcomes in the context of AM (Sarker et al., 2019). Consequently, organizational actors, rather than technological logics, determine how AM is utilized within traditional organizations (Noponen et al., 2023).

8.5.4 Implication for Practice

The implications of our research extend beyond theoretical contributions and offer several implications for practice. From a practical perspective, our study highlights the valuable and strategic role of human managers in a hybrid managerial setting. Human managers play an active role by stepping in, guiding the AM implementation process, taking responsibility for their workers, and supporting with strategic decisions (Wiggin, 2025). Hence, organizations should train managers to establish expertise in human-algorithm collaboration. Such new roles are also described as "algorithmists" (Gal et al., 2020) or "algorithmic auditors" (Brown et al., 2021; Parent-Rocheleau & Parker, 2022). In this way, human managers act as mediators in the new work setting, being able to mitigate the potential negative effects of AM on their workers, e.g., by providing emotional support and ensuring worker acceptance (Bittner et al., 2024; Krzywdzinski, Schneiß, & Sperling, 2024; Ping Liu et al., 2025). Second, we emphasize the importance of traditional organizations utilizing their established social relationships to implement AM, thereby achieving a joint optimization of organizational outcomes. Among others, this includes cultivating a work environment that encourages teamwork and communication, allowing employees to support each other in utilizing AM effectively. For instance, AM should be designed to empower existing, informal collaboration mechanisms among co-workers rather than trying to control them strictly. In this way, possible negative effects of missing social interactions and a lack of human intuition can be mitigated (Lee, 2018). Third, the development of a tailored AM approach is necessary to consider the respective task characteristics when utilizing AM, ensuring that it is applied in contexts where it can provide the most benefit. In our case, it refers, e.g., to the filtering of non-critical tasks or the escalation of highly complex tasks that require managerial support. Moreover, tasks with a high frequency were excluded from AM to prevent an overwhelming atmosphere. This shows how the experience and judgement of workers and managers should be utilized to align the AM approach with organizational needs. Workers should not be treated as passive users of AM, but rather be involved in the organization's decisions related to AM practices (Granulo et al., 2024). Involving humans in the decision-making on AM design helps to exploit real benefit (Gagné et al., 2022). Overall, our results offer practical insights for traditional organizations seeking to implement AM within their existing organizational structures. By focusing on socio-technical characteristics, organizations can leverage existing social relationships to utilize AM, improve efficiency, and drive success within traditional organizations.

8.5.5 Limitations and Future Research

The present study is subject to some limitations that offer pathways for future research. We acknowledge that, in addition to efficiency, further organizational outcomes remain relevant for traditional organizations, such as customer satisfaction and cost effectiveness. Even though efficiency represents an important organizational outcome in the manufacturing industry (Cameron, 2024), further research could focus on alternative organizational performance goals. In addition, we used a large archival data set of production data from a single automotive supplier. It might weaken the generalizability of our results, as efficiency is a multi-dimensional concept that encompasses not only error processing time but also other dimensions. Discussions with manufacturing experts of the company confirmed that error processing time is a relevant metric for the organization. Further research could consider alternative metrics such as cycle time or lead time (Banker et al., 2006). Finally, we did not study soft organizational outcomes in detail, such as the effects of AM on workers' satisfaction and their well-being. We further did not consider possible negative consequences for human managers. Our interviews provide valuable insights into how workers maintain a strong sense of teamwork and achieve situational optimization within the team, even when bypassing the algorithm in stressful situations. Future research could focus on this aspect in more detail by investigating how the collaboration among co-workers is changing with AM. Moreover, it could also be valuable to focus on the challenging consequences for human managers, such as the reduction of middle management (Baiocco et al., 2022) or the effects of union power (Dupuis, 2025). Overall, we encourage further research on AM in traditional organizations to explore this relevant phenomenon across different industry sectors and from additional perspectives.

8.6 Conclusion

Traditional organizations are increasingly integrating AM into their established work environment. Given workers' strong connection to the organization and the existing work relationships, a distinct AM approach is crucial for its successful implementation and utilization. Hence, more perspectives are needed that analyze how AM is integrated into established organizational structures. In the present work, we provide a comprehensive examination of AM within traditional organizations, highlighting socio-technical factors that influence workers' efficiency. By combining manufacturing data of an international automotive supplier with semi-structured interviews, we derive several findings. Our results give objective evidence that AM significantly improves efficiency, also in complex work environments that require specialized technical knowledge. Human managers are important shapers of AM during its implementation and remain key collaborators in achieving positive outcomes. In addition, established work relationships among co-workers are influenced by AM in several ways. These insights contribute to emerging AM research in traditional organizations by highlighting the importance of socio-technical characteristics that enable organizations to enhance AM utilization while maintaining human oversight. As traditional organizations face the challenges of integrating AM, our study highlights the need for a tailored approach that considers the unique dynamics and social structures of the traditional work environment.

Part C

9 Summary of the Results

Data-driven technologies are increasingly important for workers and work within incumbent firms. The present work aims to provide a deep understanding of this transformative process concerning various aspects, dimensions, and contexts. Through the five publications embedded in the present work, we address three main research questions that guide our research path. In the following, we summarize the key results for each research question in detail.

RQ1: *How do engineers perform data science work?*

The characteristics of hybrid data science work. In the first study (P1), we offer a distinct analysis of engineers as an essential group of domain experts in established manufacturing companies and their role in emerging data science work. We identify that engineers reconfigure their existing engineering role by incorporating the data science perspective. Hence, we highlight the hybrid practice of data science work, which consists of four work elements: (i) approach, (ii) analytical diagnosis, (iii) problem categorization, and (iv) decision-making. For each work element, the engineering work practices (reactive, knowledge-based, event-driven, and based on physical model) and the data science work practices (predictive, data-based, systematic, and based on data model) are derived and mapped.

RQ2: *How do organizations build trust in AI-based systems?*

The role of reliability for building trust in AI. Studying the implementation and operation of an AI-based system within an international production network, we illustrate the dynamic interplay between building trust and the workers' accepted level of AI reliability (P2). Our results demonstrate that workers are willing to accept a lower level of AI reliability without a negative impact on building trust in AI. To explain this unexpected finding, we derive specific organizational measures along the five phases of the AI lifecycle: (i) organizational setting, (ii) input data, (iii) promotion, (iv) performance, and (v) robustness. Furthermore, we highlight that verifying and validating the performance of the AI-based system (phase 4) represents the most crucial measure.

The use of an ethical framework for trust calibration. By further focusing on the verification and validation phase of the AI lifecycle, we clarify the importance of an ethical framework for trust calibration in AI (P3). Using the interview data and project management documents, we can excerpt and illustrate the ethical framework based on the FMEA approach. Additionally, we evaluate the effectiveness of the ethical framework and show that targeting AI reliability and AI safety represents a critical success factor. It provides simple comparison patterns, which are crucial for developing a deeper understanding of the AI-based system and its related pitfalls.

RQ3*: What impact does AM have within traditional organizations?*

Performance impact of AM in incumbent firms and underlying success criteria. In the quantitative analysis (P4), we explore whether AM has similar effects on workers' performance in the traditional work context compared to the gig economy. Our results show that AM increases work performance in the traditional work context, as it reduces the error resolving time of manufacturing errors. Moreover, we analyze four influencing factors for this positive cause-and-effect relationship. First, workforce involvement does not imply a positive moderation effect. Second, we observe a U-shaped relationship for task complexity, as AM enhances work performance for tasks with medium complexity but lacks functionality for easy and complex tasks. Third, we identify a positive effect of AM during the night shift as compared to the early shift. Finally, our results do not show that experience with AM is relevant for work performance, as it is a highly standardized process.

Implications for Workers' Efficiency and Work Relationships. Extending the quantitative analysis with confirmatory semi-structured interviews (P5), we provide a detailed examination of AM within traditional organizations. Our findings reveal that AM significantly improves efficiency, also in a heterogeneous work environment that demands specialized technical knowledge. In addition, socio-technical factors such as task complexity and worker engagement need to be considered, given the close connection among permanent workers within the traditional work context. The interviews further reveal that human managers are important shapers of AM during its implementation and remain key supporters in achieving positive outcomes. Moreover, established work relationships among co-workers and existing team dynamics are influenced by AM in several ways, e.g., as AM introduces a new dimension of virtual interaction. Overall, the joint optimization across all organizational actors in a hybrid socio-technical setting is crucial for achieving positive outcomes of AM within traditional organizations.

Table 14: Summary of the results

P	RQ	Key findings
P1	RQ 1	▪ Reconfiguration of existing engineering role by engineers due to increasing data science work, combining the engineering and data science perspective ▪ Identification of hybrid practice of data science work, consisting of - four work elements: approach, analytical diagnosis, problem categorization, and decision-making - engineering work practices: reactive, knowledge-based, event-driven, and based on physical model - data science work practices: predictive, data-based, systematic, and based on data model
P2	RQ 2	▪ Development of a process for AI implementation and operation along the five phases of the AI lifecycle ▪ Illustration of the dynamic interplay between building trust and the accepted level of AI reliability ▪ Workers accept a lower level of AI reliability without a negative impact on the building of trust in AI ▪ First identification of the supportive organizational measures with corresponding targets within each phase: - Phase 1: Organizational setting - Phase 2: Input data - Phase 3: Promotion - Phase 4: Performance - Phase 5: Robustness
P3	RQ 2	▪ Extension of the trust calibration process by the impact of the ethical framework during the fourth phase (validation & verification) ▪ Illustration of the ethical framework based on FMEA ▪ Evaluation of the effectiveness of the ethical framework that targets AI reliability and AI safety
P4	RQ 3	▪ Analysis of the quantitative impact of AM in the traditional work context ▪ AM increases work performance by reducing the error resolving time of manufacturing errors ▪ Analysis of influencing factors for this positive relationship - Workforce involvement: no moderation effect is recognizable, showing that AM is not disruptive in the traditional work context - Task complexity: U-shaped relationship, as AM enhances work performance for tasks with medium complexity - Time of work: positive effect of AM during the night shift as compared to the early shift - Experience with AM: not relevant for work performance, as it is a highly standardized process

P5	RQ 3	▪ Combining the quantitative analysis with semi-structured interviews of affected workers and managers ▪ Offering objective evidence that AM significantly improves efficiency, also in complex work environments that require specialized technical knowledge ▪ Analysis of the collaborative dynamics among workers and human managers with AM - The supportive role of human managers: human managers are (i) shapers during AM implementation and (ii) collaborators while working with AM - Shifting team dynamics: AM does not replace traditional collaborative behaviors among co-workers, but adds new dimensions of collective bypassing, situational optimization, and hybrid interaction - Joint optimization: cooperation among existing organizational actors remains crucial for achieving desired outcomes when utilizing AM

10 Discussion

The five publications in the present work provide a deeper understanding of the effects of data-driven technologies on work and workers within incumbent firms. Based on the summary of our results, we discuss the contributions regarding the characteristics of hybrid professional roles, the dynamic trust-building in AI, the performance impact of AM, as well as the implications of AM for established organizational structures and work relationships. If suitable, we enrich our statements with illustrative quotes from our studies. Finally, we discuss the overall implications related to the digital transformation process.

10.1 Detailed Characteristics of Hybrid Professional Roles

Our first publication reveals the transformative impact of data-driven technologies on workers within incumbent firms. In particular, we observe that data science alters work practices in the sense that the established engineering perspective and the new data science perspective are combined. While the evolvement of such hybrid work practices are generally acknowledged (van den Broek et al., 2021), we contribute to the research stream on hybrid work by providing a detailed example of the characteristics of the hybrid professional role of engineers. Depending on the situation, workers integrate the exploration of new data science work practices and the exploitation of existing capabilities (Birkinshaw & Gibson, 2004; Gregory et al., 2015; Schnellbächer et al., 2019), resulting in a continuous interconnection between the two perspectives:

> *"So, practically, we are trying to find correlations between the failed parts and the OK parts. And usually, these correlations, these problems are coming from some parameter setups or even supplier data. With a short data analysis, we can just point back to the fact that most of the failures are caused by a specific supplier batch, and then, of course, the physical analysis would also be needed. So, practically, the data is being used to speed up the problem-solving process. [...] Maybe right away, in 10 or 20 minutes, we can already see that 80 % of the failures are caused by the loose screw on the workpiece carrier. Of course, based on the data, we would only see that the workpiece carrier is causing the issue, and when we check it physically, we know this is being caused by the loose screw." (#26; Table 15)*

We further extend data science research by examining the perspective of engineering workers. It is relevant as engineers have developed a solid, distinct professional role identity over the last decades (Morelock, 2017; Rodriguez et al., 2018). Research on IT workers, such as data scientists, indicates that data science simultaneously builds and threatens their professional identity. That means IT is already an integral aspect of their work (Vaast & Pinsonneault, 2021). In contrast, we reveal that engineers neither feel threatened by data science nor discard the engineering work practices:

> *"I don't think the content of my work will change at all. [...] Engineering work today – especially R&D – is already characterized by the fact that we generate some kind of input, e.g., through experiments, tests, and data that we receive from external sources, including suppliers. This data is then evaluated to derive findings and then – to put it simply – do something right or wrong. In other words, the bottom line of my work is to build up knowledge. And I believe that this will remain the same and that you will continue to need the expertise, the experience, of the individual engineer." (#22; Table 15)*

In a broader context, a reason might be that engineers do have an IT identity by nature, as their work is not built on IT. Instead, it is relevant to have deep knowledge in domains related to science and math (Morelock, 2017). Consequently, engineers need to develop their IT identity alongside their professional role identity. Our results show that they enhance their existing work practices through data science leading to a calibration and verification of their established work results. Hence, we identify how engineers rely on their know-how to address limitations of their know-what (Lebovitz et al., 2021). Moreover, we indicate that engineers can take on a data science role in addition to their current role. While maintaining their organizational position within their home department, engineers officially assume an additional data science role:

> *"Many engineers have taken on these data roles. They have already worked in their area, and now we enable them to take on these additional roles. They become data scientists, which was not previously included in their job description, particularly at the time of their hiring. [...] I think that is why it is so important to have clear and transparent communication about the new additional role, not only with the workers and their management but also with the whole community. In this way, the workers can benefit from the external effects associated with this additional role description." (#05; Table 15)*

10.2 Enhanced Understanding of Dynamic Trust-Building in AI

Within P2 and P3, we contribute to a more profound comprehension of the field of trust theory in terms of understanding trust calibration and trust-building in AI (e.g., Glikson & Woolley, 2020; McKnight et al., 2011; Thiebes et al., 2021). The unique characteristics of AI-based systems compared to basic technology provide evidence to enhance the current body of knowledge related to AI's trust-building process and the existing system-like trusting beliefs (McKnight et al., 2011). In particular, we argue that our understanding of the trusting belief "reliability" is limited, as offering consistent measurements does not guarantee that they perceive or understand the information in the context of AI (Faltaous et al., 2018; Hoff & Bashir, 2015). Consequently, the purpose of the present work is to depart from the linear effects of reliability on trust-building in AI.

Studying the implementation of an AI-based system within an international production network, we find that our first distinct contribution is that workers are using the AI-based system despite its lower reliability. Hence, we offer a new perspective on the established trusting belief, contradicting research that suggests workers refuse the application of technology when they doubt its reliability (Forster et al., 2018; Lankton et al., 2015). In the broader context, this finding gives evidence for an existing threshold where workers perceive the AI-based system as "reliable enough". The so-called "trust tipping point" has already been observed in e-commerce related to the trustworthiness of websites (Adam et al., 2024; B. Q. Liu & Goodhue, 2012).

To find detailed explanations on how to cross the trust threshold, we provide in-depth information on the dynamic trust-building in AI and its interplay with workers' accepted level of reliability. While existing scholarship posits a static trust-building process (Glikson & Woolley, 2020), we can highlight that the static relationship, as reported in the literature, needs to be revised. We identify relevant organizational measures for trust-building within each phase as we consider the five phases of the AI lifecycle (Q. Lu et al., 2022). From a broader perspective, these measures describe how workers reach the trust tipping point and perceive the AI-based system as "reliable enough". In our example, a detailed investigation of the fourth phase (P3) reveals that using an ethical framework enhances the trust calibration of workers in an advanced stage of the AI implementation process. It is in line with earlier research on online vendors, which reveals that reaching the trust threshold takes more time in high-risk contexts than in low-risk contexts (Chang et al., 2006). We can transfer this finding to the context of AI and show that during the AI validation and verification phase, workers calibrate their level of trust in AI through a systematic risk assessment that enhances explainability and addresses ethical concerns in a structured way (Chen, 2020; Thiebes et al., 2021). Moreover, it is an example of an AI tool operating in parallel with human experts. Although this practice is expensive, it ensures high-quality AI performance (Lebovitz et al., 2021).

10.3 Performance Effects of Algorithmic Management in Incumbent Firms

Publication 4 provides novel insights into an under-researched area of AM application, namely the traditional organizational setting of incumbent firms. While the platform perspective is primarily addressed, research in a non-platform context is emerging (Cameron et al., 2023). The differing circumstances of AM in the traditional work context (e.g., the pre-existing organizational structures and human managers) give evidence to investigate the implications of AM in incumbent firms (Benlian et al., 2022; Jarrahi et al., 2021). We contribute to the field of AM by validating the economic value of AM within the traditional work context using real-world data, which aligns with previous studies on the organizational benefits of AM (Kellogg et al., 2020). Even more interesting, we extend the current body of knowledge by showing that performance enhancement can be achieved without worsening working conditions or increasing technostress (Cram et al., 2022). Instead, we show that production workers can benefit from stress reduction (Kandemir & Handley, 2019). For example, our study unveils performance enhancements during challenging working times, such as the night shift. This finding suggests that implementing AM can be particularly beneficial by improving work performance during periods traditionally associated with a lower performance level (Cordova et al., 2016). A member of the project team describes the positive effects of AM on the work environment as follows:

> *For example, workers are stressed by having five lights blinking [on the machines]. They think: "Where do I have to go first?" We can tell them because we know what is happening at the machines. (#01; Table 16)*

This finding underscores the potential of AM to significantly enhance performance in incumbent firms while upholding the high value of privacy and minimizing monitoring practices to a reasonable extent (Benlian et al., 2022; Morse, 2022). In doing so, we make a relevant contribution to the AM literature, presenting a unique case that showcases the positive impact of AM on the overall work environment (Kandemir & Handley, 2019; Kellogg et al., 2020; Parent-Rocheleau & Parker, 2022).

Considering the managerial perspective, we cannot confirm that workforce involvement positively affects performance outcomes. This finding contradicts various studies on the participatory approach to technology implementation (Gagné et al., 2022; Ghawe & Chan, 2022). The results indicate that AM in the traditional work context is not disruptive, as it only supports managerial activities (Jarrahi & Sutherland, 2019). Furthermore, the work type we examine can explain the findings. As described in Chapter 2.3, production work is characterized by manual activities carried out by physical workers who are driven by structure and concrete instructions (Bechky, 2003). It differs from IT work and AM in the gig economy, where IT workers struggle with decreasing work flexibility based on the limited bargaining power over their working time (Wood et al., 2019). Consequently, it is highly relevant to consider the work characteristics before implementing AM.

Expanding the scope, we can transfer some of our findings from incumbent firms to platform-based businesses. Our contribution to the AM literature reveals a U-shaped relationship for the moderating effect of task complexity. We find that the impact of AM is limited for both easy and complex tasks, while it exerts a significant influence on tasks with medium complexity. Based on our knowledge, these insights are novel as the specific characteristics of tasks in the context of AM have so far only been considered in relation to algorithmic biases and perceived fairness (Kordzadeh & Ghasemaghaei, 2022) or in the context of attracting the suitable worker (J. Taylor & Joshi, 2018). By establishing a connection between task complexity, work performance, and the selection of appropriate AM tasks, we enrich the discussion and provide valuable insights for successful AM utilization, even in platform businesses.

10.4 The Impact of Algorithmic Management on Team Dynamics and the Supportive Role of Human Management

Publication 5 provides underlying explanations of the effects of AM in incumbent firms. While it is already acknowledged that algorithms create a partnership of "symbiotic division" of labor (Jarrahi et al., 2023), we contribute to this by highlighting supportive managerial actions that increase the effectiveness of AM in incumbent firms. For example, we illustrate that workers experience an enhanced implementation of AM due to managerial support and existing social structures within incumbent firms. Moreover, managers retain a close relationship with their workers and provide support with complex tasks. In contrast, workers in the gig economy experience less organizational embeddedness, missing managerial support, a lack of mentors, and are exposed to a greater degree of individual accountability and pressure (Ashford et al., 2018; Gagné et al., 2022; Timko & van Melik, 2021). Hence, we enrich the current understanding by offering a detailed explanation of how algorithms and humans collaboratively manage workers and jointly form a hybrid managerial setting (Hirsch et al., 2024; Stelmaszak et al., 2025).

Existing research describes the complementary actions of human managers and algorithmic management to achieve both performance and humanistic outcomes as *humanistic AM* (Cui et al., 2024). We extend this phenomenon to the worker level and reveal that the successful utilization of AM in incumbent forms involves informal collaboration among co-workers. To ensure operational optimization, workers may even disregard AM if it is necessary to ensure operational continuity in the current situation. While bypassing AM is also a common phenomenon in platform-based companies, e.g., by engaging in personal negotiations with clients (Kellogg et al. 2020), we show that in incumbent firms, bypassing AM is driven by the spontaneous support among co-workers, human intuition, and situational awareness.

Besides, our findings provide evidence for a hybrid interaction among workers, as AM introduces a new dimension of virtual interaction that complements the existing, physical interaction. Hence, we contribute to emerging research on the effects of AM on workplace dynamics (Granulo et al., 2024) by highlighting how AM impacts the interaction among co-workers. In the context of gig work, co-worker interaction occurs within informal online communities established, e.g., to exchange hints or complaints (Jabagi et al., 2019; Möhlmann et al., 2021). We illustrate that within incumbent firms, virtual interaction via AM can transform into direct interpersonal exchange among co-workers. All in all, for the successful utilization of AM in traditional organizations, we detect that it is highly relevant to maintain human oversight. In this way, the joint optimization across existing organizational actors, rather than technological logics, determines how AM is used within traditional organizations (Noponen et al., 2023).

10.5 Bridging the Gap: From Data-driven Technologies to Desired Outcomes

Incumbent firms are investing significant efforts to integrate and embed data-driven technologies to improve internal processes, drive product innovation, and retain their competitive advantage. Several aspects need to be considered to bridge the related gap between the technology and the desired outcomes. Our five publications offer various insights into this underlying digital transformation process and its implications for work and workers by focusing on (i) the appropriate *usage* of the technology (P2 & P3), (ii) the development of new *management* forms (P4 & P5), and (iii) the reconfiguration of *work* practices (P1 & P5). Consequently, we show how data-driven technologies unfold a transformative impact on various levels.

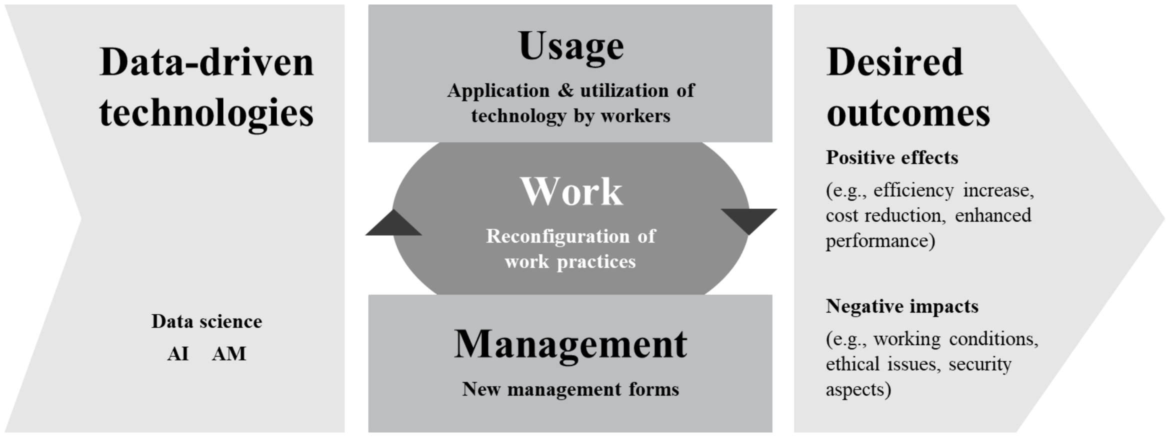

Figure 20: From data-driven technologies to desired outcomes

In the broader context, we contribute to digital transformation research in two ways. On the one hand, we enhance the current understanding by analyzing the implications for work and workers within incumbent firms (Trenerry et al., 2021). While strategic aspects and technological issues are already well-known (Fernandez-Vidal et al., 2022; Vial, 2019), we emphasize the importance of workers for driving the transformation, e.g., by reconfiguring established work practices (P1). On the other hand, we extend digital transformation research by highlighting the interconnection among three building blocks: (i) usage, (ii) work, and (iii) management (Figure 20). As scholarship calls for a long-term normalization of the transformation process (Carroll, Conboy, et al., 2023; Carroll, Hassan, et al., 2023), we show that only the continuous reconfiguration of work practices (P1) in combination with technology usage (P2 & P3) and new management forms (P4 & P5) can reduce digital transformation failure rates and lead to desired outcomes for incumbent firms.

11 Implications

The findings of the present work have implications for both theory and practice. The following paragraph describes the theoretical contributions towards relevant research streams in more detail. Based on the theoretical insights, we derive and discuss the practical contributions.

11.1 Implications for Theory

Data science work research: Our results contribute to the research stream of domain-specific data science work (Lebovitz et al., 2021; Parmiggiani et al., 2022), especially to the ongoing discussion concerning the changes of employees' roles and skills (Vial, 2019). While prior studies focus on the role of IT departments and data scientists (Dremel et al., 2017; Nelson & Irwin, 2014), we illustrate a new work setting that engineers create. Hence, we give evidence of the **relevance of domain experts** in shaping hybrid data science work. In this context, we demonstrate that engineers do not discard the existing work practices (Strich et al., 2021). Instead, **data science complements the established work** and becomes part of the established job. Moreover, we extend current research on hybrid work practices (van den Broek et al., 2021) by identifying the specific **characteristics of hybrid data science work**, combining data science and engineering work practices.

Trust theory: The present work makes several noteworthy contributions to trust theory, particularly to the literature on trust in AI (McKnight et al., 2011; Thiebes et al., 2021). As a new perspective, we focus on the **dynamic process of building trust in AI**, including the unique role of workers' expectations regarding the trusting belief of "AI reliability". The present work contributes to prior discussions in the context of IT systems, emphasizing that lower reliability will prevent workers from applying the technology (Lankton et al., 2015). We can give evidence that workers are willing to **reconfigure their expected level of reliability** in combination with their increasing experience with the AI system. This supports the idea of a specific **threshold** at which workers perceive the AI-based system as "reliable enough". These findings extend current studies highlighting the importance of a continuous and **dynamic AI implementation** process (Hengstler et al., 2016). Besides, we illustrate five **supportive organizational measures** within the phases of the AI lifecycle.

Ethical frameworks in practice: As an additional digression, we contribute to the literature of AI ethics in computer science (Allen et al., 2006; Holzinger & Muller, 2021). In this context, we provide insights into the **utilization of an ethical framework** in practice for trust calibration in AI. The ethical framework enhances both the explainability and robustness of

AI-based systems, as it provides **analogous patterns of AI reliability** and safety, making the AI models more understandable and interpretable (Holzinger, 2021). Consequently, we present a practical example of continuous trust calibration. Furthermore, the ethical framework serves as a systematic approach to risk management by effectively addressing ethical concerns in a structured manner (Chen, 2020; Thiebes et al., 2021).

Algorithmic management in traditional organizations: We contribute to the literature on AM by enhancing our understanding of AM in incumbent firms and combining the two AM research streams related to the platform-based work context and the traditional work context (Cameron et al., 2023). First, our primary focus is to analyze the performance impact of AM to clarify an essential aspect of platform businesses – the immense productivity potential (Jarrahi & Sutherland, 2019). We can show that the **performance increase in the traditional work context** is not based on individual tracking or gained by penalties and sanctions in case of bad performance, as it is recognizable in the platform-based context (Möhlmann et al., 2021; Wood et al., 2019). Instead, it is based on the enhanced coordination of workers within the complex work environment and an increased decision-making efficiency related to error resolving (Kellogg et al., 2020). It serves as a confirmation for incumbent firms to implement AM while still respecting legal obligations and encourages platform-based businesses to use AM ethically (Möhlmann, 2021). Second, we extend the current literature in AM related to the **role of task complexity and worker engagement** as we investigate from a managerial perspective the moderating influence of human- or task-related factors towards the respective performance outcomes (Parent-Rocheleau & Parker, 2022). Third, we offer novel insight into the **supportive role of human managers,** as we highlight two relevant roles of human managers for implementing AM in incumbent firms and show how they counterbalance possible negative outcomes of AM (Cameron et al., 2023). On the one hand, they act as shapers during AM implementation. On the other hand, they are collaborators while working with AM. By implementing AM, a **hybrid managerial setting** is created in which human managers and algorithms jointly optimize organizational outcomes (Hirsch et al., 2024; Stelmaszak et al., 2025). Fourth, we contribute to the emerging research on the impact of AM on workplace dynamics (Granulo et al., 2024). We illustrate that AM is **shifting team dynamics** and creating a **hybrid interaction among co-workers**, e.g., by adding a novel dimension of virtual insights that complements the existing physical interaction. Moreover, workers utilize informal coordination to maintain operational continuity, even by bypassing AM. Finally, we reveal that the **joint optimization of existing organizational actors** remains relevant for the successful implementation of AM. In this way, humans rather than technological logics determine how AM is used within traditional organizations (Krzywdzinski, Schneiß, & Sperling, 2024; Noponen et al., 2023).

Digital transformation research: All in all, the present work contributes to digital transformation research (e.g., Carroll, Conboy, et al., 2023; Ghawe & Chan, 2022; Hanelt et al., 2021; Vial, 2019) by highlighting different aspects of the digital transformation process. In particular, we enhance the current understanding by showing several **implications for work and workers** within incumbent firms (Trenerry et al., 2021). Overall, we systematize the interplay among technology utilization, the reconfiguration of work, the role of new management forms, and the respective performance outcomes to normalize digital transformation in incumbent firms.

11.2 Implications for Practice

Our results provide several implications for different target groups in practice. Mainly, we can derive valuable contributions for (i) the workers within incumbent firms, (ii) the leaders within this environment, as well as (iii) corresponding project teams, and (iv) IT departments responsible for technology implementations.

The main focus of the present work is to understand the perspective of *workers* in incumbent firms regarding the implementation of data-driven technologies and their impact on their work. The workers are primarily the ones who experience the challenging effects of the digital transformation process. In this regard, our findings guide workers within incumbent firms on multiple levels. First, they demonstrate various approaches for managing the growing application of data-driven technologies, such as data science, to workers. As many workers still have concerns regarding the impact of digitalization on their jobs, we offer a more reassuring perspective. Domain experts with a solid technological background can significantly benefit from this technological shift. In this context, workers must recognize their individual responsibility in taking action and actively participating in the transformation of their own roles. Workers who continuously develop their expertise and skills can leverage data science in numerous ways. It is related to the second aspect, which involves illustrating the hybrid data science practice. The characteristics of hybrid data science work offer workers profound insights into the design of their future work and potential benefits. For example, we show that data science can greatly enhance the diagnosis of technical problems and the decision-making process. It is the first direction and initial milestone for workers to get involved in data science projects within incumbent firms.

We contribute with further implications for *leaders and organizational decision-makers*. First, it is crucial to acknowledge and address any skepticism or anxiety that may exist within the leadership group. For example, the implementation of AI-based systems might raise doubts, mistrust, and uncertainty about the fulfillment of expectations. This is especially true due to the inherent challenge in evaluating the reliability of AI models. Our work reveals that comparable benchmarking related to the AI outcome supports an enhanced understanding of the AI-based system. It can be achieved through methods such as FMEA, if used to calculate the ethical impact of AI failures. Second, we offer recommendations to leaders on effective strategies for moderating digital transformation within their area of responsibility. For example, leaders are extremely relevant for encouraging employees to apply data science methods or AM in their daily work. In this context, they should create an environment that enables workers to pioneer new work practices and find unconventional ways to solve problems. In addition, maintaining continuous communication at the top management level regarding digital transformation enhances workers' openness and facilitates the successful implementation of data-driven technologies within the organization. Besides, it is crucial to be transparent regarding the functionality of new AM tools and their implications on established processes. By promoting the positive effects on workers (e.g., reduced stress), the acceptance of the new technology can be increased.

Our findings might also be helpful for the *project teams and IT departments* that develop and implement a new data-driven technology within incumbent firms. Project teams should develop, together with the leaders, a communication strategy by providing suitable communication material or by directly communicating relevant changes to the workers. For workers directly affected by the implementation of novel technologies, offering suitable, customized training is favorable. The content of such training might include (i) the development of new skills and expertise, (ii) the identification of one's own use cases within the respective work environment, (iii) instructions on the proper application of specific technologies, or (iv) explanations of underlying technological logics. Besides, it is essential to conduct effective stakeholder management by engaging with key stakeholders and ensuring their involvement in driving the digital transformation agenda. Members of the project team and IT departments should act as role models for digital transformation initiatives and promote such initiatives at the top management level, as they are the digitalization experts within the organization. Finally, selecting the correct application areas for new data-driven technologies is highly relevant. Based on our findings, it is evident that specific task characteristics (e.g., task complexity) should be considered during AM implementation. This consideration is crucial to fully exploit the capabilities and benefits offered by emerging data-driven technologies.

12 Limitations

The selection of the appropriate research approach and the corresponding study design within the individual publications imposes some limitations on the present work. Although we try to avoid potential issues, assessing our findings within the overall context of these limitations is essential. In the following paragraph, we provide an overview of the limitations to consider.

For most of our studies, we follow a **qualitative research approach** as we apply the case study design (P1) and grounded theory methodology (P2 & P3). As mentioned in the previous chapters, qualitative methods are selected for their exploratory nature to generate a deep understanding of complex research phenomena and to develop new theoretical insights (Venkatesh et al., 2013; Walsham, 1995). Nevertheless, qualitative research raises several concerns, such as (i) the limited generalizability of the findings, (ii) a possible researcher bias, or (iii) a lack of rigor.

In general, qualitative studies are criticized for their *inability to generalize* findings beyond the specific context of the study. Hence, insights from qualitative studies can hardly be transferred to the entire population due to the small sample sizes (Myers, 2000). However, the criteria to determine generalizability in qualitative studies vary from those in quantitative investigations. For instance, each interview participant in our rather small samples (P2, P3 & P5) is carefully selected considering different positions, hierarchical levels, or work experience, and, hence, their contributions to the emerging theory (Morse, 1999). This selection approach ensures a comprehensive and complete theory, as theoretical saturation is achieved (Suddaby, 2006). Moreover, we choose a multiple-case design (P1) and include three cases from varied circumstances in our sample. In this way, we expand our results' external generalizability compared to the single-case design (Yin, 2010).

Furthermore, qualitative research is vulnerable to *researcher bias*, which is displayed by either (a) the impact of the researcher on the case or (b) the effects of the case on the researcher. Bias (a) shows up at the moment when the researcher enters the organizational setting as an “outsider”, which might disrupt ongoing relationships and influence the established behavior of the local actors (Miles et al., 2020). We involve ourselves deeply in the investigated organizational setting for several years as a countermeasure. Hence, the entire data collection is conducted by the author of the present work, who is also a member of the investigated organization. Bias (b) appears if the researcher is accepting the assumed interpretation of the observed incidents. We engage in several discussions within the research group, at conferences or workshops, in order to challenge our findings and counterbalance possible effects from the case. Moreover, one co-author always adopts the outsider perspective so that we can avoid being too close to the research field (Gioia et al., 2013; Miles et al., 2020). In addition to these two sources of bias, it needs to be considered that the entire data collection and data analysis are prone to subjectivity and individual interpretation by the researchers (Buber & Holzmüller, 2009). Researchers could observe and interpret data based on anticipated outcomes (Morse, 2015). Hence, regular self-reflection is necessary to ensure awareness and mitigation of personal bias (Suddaby, 2006). Furthermore, we triangulate with various data collection methods such as interviews, internal documents, presentations, and observations within every qualitative study to rely on various data sources and enhance our overall understanding (Miles et al., 2020).

Finally, qualitative inquiry is often seen as *less rigorous* when compared to quantitative methods. Therefore, we apply several methodologies to improve reliability and validity and enhance the rigor of qualitative research (Morse, 2015). For example, we utilize the systematic grounded theory approach (P2 & P3) by following theoretical sampling and substantive coding procedures (Eisenhardt, 1989; Glaser & Strauss, 1967; Holton, 2007; Strauss & Corbin, 1998). Moreover, we develop a comprehensive interview guide for our semi-structured interviews (Appendix B) and generate a thick description to provide deep insight into the study design and execution (Gioia et al., 2013; Morse, 2015).

For our publication P4, we build on linear mixed modeling as a **quantitative method**, representing an extension of the general linear regression model. The name of the linear regression model already indicates the basic assumption of the model, namely the linear relationship between the dependent and independent variables. As we violate the linearity assumption, we perform a logarithmic transformation and select the LMM as it is less sensitive to a non-linear dataset. Nevertheless, our results might be biased and contain missing or incorrect information (Fahrmeir et al., 2013). Moreover, the analyzed dataset is limited to a timeframe of nine months (January 2023 to September 2023), due to restrictions within the organization that hinder us from gathering manufacturing data for a more extended period. Consequently, we can only investigate the first months of the AM implementation and cannot capture long-term trends. We made an effort to address this issue by enriching the manufacturing dataset within the provided timeframe with supplementary information, such as team and shift details. We further conduct several informal interviews with organizational members to receive additional background information and to discuss our results (Table 17).

This procedure significantly contributes to enhancing our understanding of the process. Additionally, it is essential to mention that the dataset is restricted to error types addressed using AM. However, most error records are not subjected to the usage of AM and thus are excluded from the analysis. As this might bias our results, we conduct a robustness check and analyze the excluded errors separately (X. Lu & White, 2014).

In addition to the limitations associated with the chosen qualitative or quantitative methodology, it is important to consider some overall limitations of the present work. The primary objective of the present work is to explore the implications of data-driven technologies on work and workers in incumbent firms. However, it is vital to note that all the studies we conduct in the present work are based on data collection from a single international supplier operating in the automotive industry. Therefore, gaining insights from additional organizations and diverse industrial sectors could significantly enhance our understanding of the phenomenon being studied. Furthermore, our exploratory research strategy leads to the selection of three focus topics, each centered around a distinct data-driven technology: (i) data science, (ii) AI, and (iii) AM. Since we do not restrict ourselves to a single technology, the synthesized results of the present work may be affected by the combination of the individual findings. Consequently, we examine each of the three focus topics and technologies separately.

13 Future Research

Several open questions emerge throughout our study on implementing data-driven technologies within incumbent firms and their impact on work and workers. In the following paragraph, we outline potential areas for future research.

The role of generative AI for knowledge-intensive work and trust.

The present work sheds light on the implications for incumbent firms related to the implementation of data-driven technologies such as data science, AI, and AM. However, technological advancements introduce new technologies on a regular basis. Just recently, generative AI has evolved as a tool to increase productivity and drive innovations across multiple industries. For example, it can write documents, develop software code, or interact with humans, e.g., in the form of a chat (Benbya et al., 2024). Various incumbent firms have already started to introduce generative AI within their organizations, such as Bosch across its international production network (Christmann, 2023). As generative AI is capable of conducting tasks that previously needed human involvement, it offers advancements in knowledge-intensive work, including creating new content, identifying patterns, and the decision-making process (M. Alavi et al., 2024). Consequently, generative AI enormously impacts work and workers, also within areas that require creative thinking (Benbya et al., 2024). Based on this, it would be of great interest to analyze the effects of generative AI on knowledge workers such as engineers. Insights from such an analysis would provide additional insights related to the evolution of new work practices or the disruption of traditional roles.

Moreover, it might be promising to investigate the building of trust upon the introduction of generative AI tools such as ChatGPT (Huy et al., 2024). In this context, generative AI might pose additional challenges concerning trust calibration. Some researchers argue that generative AI is particularly susceptible to overestimation, which exhibits an urgent need for additional measures in order to prevent trust miscalibration (Tomitza et al., 2023). Besides, using generative AI and the generated output compromises a new dimension related to ethical challenges. For instance, the generated content might be harmful, biased, or could violate data privacy and security (Nah et al., 2023). Therefore, future research could give evidence of our suggested model on the dynamic evolvement of trust in AI and provide additional details related to our derived organizational measures.

Multifaceted outcomes of AM implementation within incumbent firms.

In the present work, we offer several insights into the performance impact of AM implementation by measuring workers' efficiency (P4 & P5). However, additional quantitative measurements for analyzing organizational outcomes could be considered, such as customer satisfaction or cost effectiveness. Furthermore, we analyzed a large archival data set of manufacturing data from an international automotive supplier. It could harm the generalizability of our results, as further quantitative metrics, such as cycle time or lead time, could be used for measuring the performance impact (Banker et al., 2006). Moreover, detailed information related to a possible negative effect of AM on workers and managers within the traditional work context remains unclear. Our confirmatory semi-structured interviews (P5) offer relevant insights into soft organizational outcomes such as the situational optimization within the team or the supportive role of human management for AM implementation. However, further research could investigate the challenging consequences for human managers, such as the decreasing relevance of middle management (Baiocco et al., 2022) or the impact of union power (Dupuis, 2025). Moreover, a quantitative survey could be conducted to assess the impact of AM on workers' satisfaction and their well-being. Consequently, a deeper understanding of the potential drawbacks of AM in incumbent firms can be gained. Insights from such analysis could contribute to the ongoing discussions on the dark sides of AM, such as dehumanization (Möhlmann & Henfridsson, 2019), privacy and data protection issues (Giermindl et al., 2022), as well as ethical concerns (Jarrahi et al., 2023). Finally, we did not take into account the development process of the AM system, including the impact of specific technological configurations and design choices. Emerging research already highlights the importance of data scientists with their domain-specific knowledge for the successful implementation of AM (Krzywdzinski, Schneiß, & Sperling, 2024) or the critical role of managerial design choices (Alizadeh et al., 2025). Further research should build on this to investigate how the development of the AM system might influence workers' perception. In this context, additional recommendations for successfully implementing AM in incumbent firms could be deduced.

Beyond digital transformation: incumbent firms vs. digital natives.

To summarize, the present work contributes to a comprehensive understanding of different dimensions of the digital transformation process within incumbent firms. However, questions about what lies beyond the digital transformation process still need to be answered. Some researchers already postulate that the status “beyond digital transformation” might only be reserved for start-ups or digital natives. While digital natives are companies founded in the digital age, incumbent firms have operated before the digital era (Carroll, Conboy, et al., 2023). Hence, it is questionable how and whether incumbent firms can achieve this state at all. Literature suggests that “beyond digital transformation” might only be achieved with a “digital defined organization”, which is oriented towards the recurring challenges of emerging data-driven technologies (Hess, 2022). Therefore, future research is necessary to enhance the understanding of a potential post-digital transformation state and to explore the distinctiveness among incumbent firms and digital natives in this context.

14 Conclusion

Incumbent firms need to implement data-driven technologies to retain their future competitive position. The present work investigates implications for work and workers in the digital age. We derive three distinct research areas that contribute to enhancing our current understanding, and we utilize a multi-method approach to analyze these fields. First, we apply a case study methodology to deepen our understanding of how workers adapt their work practices to a changing work environment. Due to the increasing utilization of data science, engineers combine engineering work practices and data science work practices to perform hybrid data science work. Second, we apply grounded theory methodology to empirically investigate how workers reconfigure their attitude towards AI-based systems, such as possible mistrust and concerns related to the trusting belief "reliability". The present work provides detailed insights into the dynamic process of AI implementation. It shows that workers are willing to accept a lower level of reliability without a negative impact on building trust in AI. In this context, the relevance of an ethical framework for trust calibration is further illustrated. Finally, we explore the performance outcomes of AM in the traditional work context through a quantitative analysis, as well as its impact on workers and human managers, using confirmatory semi-structured interviews. Our results show that AM increases work performance in incumbent firms. Nevertheless, socio-technical factors such as task complexity and worker engagement need to be considered. Moreover, the successful use of AM in incumbent firms depends on collaborative dynamics among workers and human managers, as AM fundamentally impacts established work relationships and team dynamics.

To conclude, we identify three building blocks that are relevant to the complex digital transformation process: (i) the reconfiguration of work practices, (ii) technology usage, and (iii) new management forms. Combining these three aspects is essential for bridging the gap between the implementation of data-driven technologies and the desired outcomes, thereby ensuring the long-term success of incumbent firms in the future.

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Appendix

Appendix A: List of Interview Partners

Table 15: Interview partners – data science work

Interview	Date	Role	Brief description
#01	03.12.2021	Senior expert organizational development	• Responsible for digital culture initiatives and communication • Coordination of implementation of digital roles
#02	08.12.2021	Director	• Leader of an international engineering department • Driver of digitalization activities within engineering
#03	14.12.2021	Senior expert organizational development	• Support of change management activities in the context of digital transformation
#04	13.12.2021	Data visualization engineer	• Responsible for graphical user interface- and user experience design • Creation of a common platform for all data science project
#05	20.12.2021	Internal consultant	• Consultant for digitalization in engineering
#06	21.12.2021	Internal consultant	• Consultant for data management and data engineering • Former software development engineer
#07	22.12.2021	Data engineer	• Development of data pipelines for manufacturing data
#08	07.01.2022	Data scientist	• Responsible for data processing of engineering data as well as enabling colleagues in China • Former mechanical engineer, developed towards data expert within engineering unit
#09	07.01.2022	Executive director	• Responsible for the overall digitalization strategy of the company • 30 years at the company in different positions
#10	07.01.2022	Program manager	• Coordination of digitalization activities within manufacturing
#11	10.01.2022	Group leader	• Leader of an engineering group with limited digital experts • Drives digital transformation within the group
#12	11.01.2022	Group leader	• Leader of a software development group • Responsible for software development for internal customers
#13	12.01.2022	Process engineer	• Focus on manufacturing quality and problem-solving • Creating dashboards for quality management of plant

#14	13.01.2022	Project leader	• Product owner for digitalization in manufacturing
#15	17.01.2022	Data architect	• Responsible for the automatization of product testing and reliability engineering
#16	18.01.2022	Data modeler	• Simulations engineer • Product leader for data modeling in the engineering area
#17	01.02.2022	Machine learning expert	• Creating the machine learning algorithm for image recognition and enhancement of engineering processes
#18	02.02.2022	Engineer	• Product development and design • Data architect within the group
#19	05.02.2022	Executive director	• Product team leader • Responsible for the manufacturing process
#20	04.02.2022	Engineer	• Development engineer for assembly and interconnect technology
#21	04.02.2022	Engineer	• Project leader for mechanical components • Responsible data architect within the group
#22	09.02.2022	Simulation engineer	• Development engineer for assembly and interconnect technology • One year within the company
#23	11.02.2022	Project leader	• Responsible for digitalization in the engineering area
#24	11.02.2022	Internal consultant	• Consultant for data engineering and modeling • Responsible for IT architecture
#25	14.02.2022	Process engineer	• Process expert for bonding • Builds up data science knowledge in engineering
#26	01.03.2022	Engineer	• Coordination of data science projects in Hungary • Implementation of data science in engineering, interface towards manufacturing
#27	02.03.2022	Team leader	• Mechanical engineer • Responsible for data science projects in Portugal
#28	15.03.2022	Team leader	• Responsible for the reduction of internal defect costs • Scaling of digitalization activities from China toward global level
#29	15.03.2022	Project leader	• Responsible for digitalization activities in the purchasing unit • Purchasing contact person for engineering and manufacturing areas

#30	16.03.2022	Engineer	• Responsible for three use cases regarding digitalization • Coordination of the big data stream project in engineering

Table 16: Interview partners – AI project

Interview	Date	Role	Brief description
#01	28.10.2022	Project leader	• Main project leader of the AI project • Coordination of the local teams
#02	28.10.2022	Process expert	• Labeling of data for AI model training • Implementation of AI at pilot plant in Germany
#03	02.11.2022	Engineer	• Support from an engineering perspective • Support in the AI release process
#04	03.11.2022	Director	• Leader of quality management at the pilot plant • Responsible for process release, following quality standards
#05	03.11.2022	Director	• Support process release and implementation from an engineering perspective
#06	04.11.2022	Director	• Responsible for overall strategy in manufacturing • Coordination of global roll-out and management persuasion
#07	07.11.2022	Executive director	• Project representation on top management level
#08	07.11.2022	Expert	• Responsible for building up the AI data pipeline • Technical support of plants
#09	07.11.2022	Project leader	• Local project leader in Mexico • AI implementation at the local plant
#10	10.11.2022	Executive director	• Responsible for the overall digitalization strategy of the company • Internal consulting
#11	11.11.2022	Director	• Responsible for digitalization in manufacturing and quality assurance in Mexico
#12	14.11.2022	Expert	• Responsible for AI training • Central coordination of domain experts
#13	14.11.2022	Director	• Responsible for process release and quality assurance in Romania
#14	15.11.2022	Project leader	• Responsible for digitalization activities in manufacturing • Central digitalization coordinator
#15	15.11.2022	Data expert	• Central data pipeline support
#16	15.11.2022	Data expert	• Central data pipeline support

#17	16.11.2022	Expert	• Former main project leader
#18	18.11.2022	Expert	• Organizational support from an engineering perspective

Table 17: Interview partners – AM project phase 1

Interview	Date	Role	Brief description
#01	07.12.2022	Group leader	• Responsible for several digitalization projects
#02	12.12.2022	Project leader	• Project leader of the AM project
#03	12.12.2022	Director	• Manufacturing manager in Mexico
#04	14.12.2022	Process expert	• Product owner for a process at the manufacturing line
#05	15.12.2022	Expert	• Industry 4.0 coordinator in Hungary
#06	16.12.2022	Process expert	• Product owner for a process at the manufacturing line
#07	11.01.2023	Expert	• Coordination of digitalization activities within one plant
#08	10.02.2023	Expert	• Industry 4.0 coordinator in Hungary
#09	22.03.2023	Digitalization expert	• Central coordinator of the AM project
#10	09.05.2023	Process expert	• Product owner for a process at the manufacturing line
#11	11.05.2023	Process expert	• Product owner for a process at the manufacturing line
#12	03.05.2023	Process expert	• Product owner for a process at the manufacturing line
#13	03.05.2023	Operator	• Operator at the manufacturing line

Table 18: Interview partners – AM project phase 2

Interview	Date	Role	Brief description
#01	18.02.2025	Operator	• Worker on the shopfloor, using AM
#02	18.02.2025	Operator	• Worker on the shopfloor, using AM
#03	18.02.2025	Operator	• Worker on the shopfloor, using AM
#04	18.02.2025	Operator	• Worker on the shopfloor, using AM
#05	18.02.2025	Operator	• Worker on the shopfloor, using AM
#06	18.02.2025	Operator	• Worker on the shopfloor, using AM
#07	18.02.2025	Operator	• Worker on the shopfloor, using AM
#08	08.01.2025	Project leader	• Project leader AM project
#09	15.01.2025	Project leader	• Co-project leader AM project
#10	30.01.2025	Digitalization expert	• Central project coordinator

#11	05.02.2025	Process expert	• Project leader at respective plant
#12	11.05.2023	Manager	• Production supervisor
#13	12.02.2025	Manager	• Deputy team coordinator on the shop floor
#14	18.02.2025	Process expert	• IT coordinator in manufacturing
#15	18.02.2025	Manager	• Team coordinator on the shop floor

Appendix B: Interview Guidelines

Table 19: Interview guideline for publication 1

<table>
<tr><th colspan="2">Personal background</th></tr>
<tr><td>Position / Role</td><td></td></tr>
<tr><td>Time within position and / or company</td><td>__ years within position / __ years within company</td></tr>
<tr><td>Degree</td><td></td></tr>
<tr><td>Assignment of the interview group (Data XY refers to digital roles such as data engineer or data scientist)</td><td>☐ Group 1: Persons who are directly employed as "Data XY"
☐ Group 2: Persons who are currently qualifying for "Data XY"
☐ Group 3: Persons who work as "Data XY" after further training
☐ Group 4: People who work with "Data XY"</td></tr>
<tr><th colspan="2">Main part</th></tr>
<tr><td>Intro questions for everyone</td><td>Current tasks and role
Please describe your current job.
What does a typical day look like for you?
Changes in tasks and role
How has your work changed as a result of the increasing use of data?
What new tasks have been added?</td></tr>
<tr><td>Groups 1-3: Questions for people in a digitalization role (e.g., data scientist)</td><td>Organizational design
How is the activity embedded/integrated into the area?
…from the point of view of leadership?
…from the point of view of colleagues?
…from the point of view of collaboration (with other areas)?
What are your responsibilities? Who do you depend on to deliver them?
In which areas of your work do you have contact with
…Management?
…direct colleagues?
…further areas outside your department?
How are decisions made on digitalization topics?
Amount of work
Is it an additional qualification? Why (not)?
What % of your working time do you spend as "Data XY"?
Implementation & transformation of the role (if applicable)
Why did you decide to take on this further qualification/take on the role?
What support did you receive during the process? By whom?
Where do you see the biggest challenges in implementation?</td></tr>
</table>

	Non-technical contribution of digitalization roles • What organizational activities do you take on besides the purely technical tasks? • What non-technical activities do you take on as part of your role, e.g., in decision-making? • In addition to the technical task, what other challenges do you face? • Where do you take on tasks you would not have expected when you started your job?
Group 4: Questions for people in an established role (e.g., development engineer)	**Collaboration with groups 1-3** • How does the collaboration with colleagues who are "Data XY" work? • What expectations do you have of "Data XY" regarding your work? • How can you be supported by "Data XY"? **Implementation & transformation of work** • Where do you see the biggest challenges in implementing the digitalization roles?
Conclusion	
All groups	• Was there any topic you expected us to cover that we did NOT talk about? • Is there anything else you would like to add to the discussed topics?

Table 20: Interview guideline for publication 5

<table>
<tr><th colspan="2">Personal background</th></tr>
<tr><td>Position / Role</td><td></td></tr>
<tr><td>Time within position and / or company</td><td>__ years within position / __ years within company</td></tr>
<tr><td>Working with AM</td><td>Since</td></tr>
<tr><td>Team</td><td>☐ Team 1 ☐ Team 2 ☐ Team 3 ☐ Team 4</td></tr>
<tr><th colspan="2">Main part</th></tr>
<tr><td colspan="2">Current tasks and role

Please describe your current job.
How do you use smart watches in your daily work?
To what extent/when are you currently in contact with your team leader?

Changes in tasks and role / in interaction with team leader

How has the use of smart watches changed your work and your interaction with your team leader?
In what ways has your work become more efficient?

Type of work

For which tasks are smart watches particularly helpful?

Why do you think smart watches are particularly useful for tasks of medium complexity?
Why do you think smart watches are particularly useful during night shifts?

For which tasks are smart watches not helpful?
Do you think AM has improved your efficiency in performing your tasks?

Implementation of smart watches

To what extent were you involved in the implementation of the smart watch use cases?
How important was your involvement in the introduction to you?
Can you explain why involvement is not always relevant to the outcome?
What support did you receive during implementation? From whom?

Experience with use

What problems did you encounter at the beginning? Or did everything work right from the start?
How has the use of smart watches developed/improved/deteriorated?

Usage behavior

How does AM affect your job satisfaction?
How often do you receive feedback on your work? Is it more often than before?
What are the advantages and disadvantages of using smart watches?
Where do you see the biggest challenges in using smart watches?
</td></tr>
<tr><th colspan="2">Conclusion</th></tr>
<tr><td colspan="2">
Was there any topic you expected us to cover that we did NOT talk about?
Is there anything else you would like to add to the discussed topics?
</td></tr>
</table>