Navigating the Bright and Dark Sides: Four Essays on Stakeholder Reactions to Algorithmic Decision-Making in Organizations and the Role of Boundary Conditions

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List of Abbreviations

ADM	Algorithmic decision-making
AI	Artificial intelligence
AIC	Akaike Information Criterion
AM	Algorithmic management
ANOVA	Analysis of variance
AOM	Academy of Management
APPI	Act on the Protection of Personal Information
ARM	Affective response model
ASEAN	Association of Southeast Asian Nations
B	Unstandardized regression coefficient
BIC	Bayesian Information Criterion
CASA	Computers-are-social-actors
CEO	Chief Executive Officer
CFI	Comparative fit index
CFA	Confirmatory factor analysis
CI	Confidence interval
CMO	Chief Marketing Officer
CPTPP	Comprehensive and Progressive Agreement for Trans-Pacific Partnership
Corr.	Corrected
CSO	Chief Sales Officer
CV	Curriculum vitae
Df	Degrees of freedom
Dr.	Doctor

EI	Entrepreneurial identity
EPEAI	Economics Perspective on Artificial Intelligence
ETP	Entrepreneurship Theory and Practice
EU	European Union
EURAM	European Academy of Management
e.V.	eingetragener Verein [English: registered association]
F	F-test
GEM	Global Entrepreneurship Monitor
GenAI	Generative artificial intelligence
GDPR	General Data Protection Regulation
HDM	Human decision-making
HICSS	Hawaii International Conference on System Sciences
HM	Human management
HR	Human resources
HRM	Human resource management
HRMR	Human Resource Management Review
IECER	Interdisciplinary European Conference on Entrepreneurship Research
I^2_b	Percentage of true heterogeneity in observed heterogeneity between studies
I^2_w	Percentage of true heterogeneity in observed heterogeneity within studies
ISJ	Information Systems Journal
ISO	International Organization for Standardization
k	Number of independent samples

LLM	Large language model
M	Mean
m	Number of effect sizes
MBA	Master of Business Administration
MANOVA	Multivariate analysis of variance
M.Sc.	Master of Science
N	Total sample size
n	Subgroup sample size
Neg.	Negative
NRC	National Research Council of Canada
Org.	Organizational
p	Probability value (significance level)
Ph.D.	Doctor of Philosophy
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-analyses
Psych.	Psychological
Q_M	Cochran's Q-test for heterogeneity
r	Correlation coefficient
RCEP	Regional Comprehensive Economic Partnership
RENT	Research in Entrepreneurship and Small Business
RMSEA	Root mean square error of approximation
SaaS	Software as a Service
SD	Standard deviation
SE	Standard error
SEM	Structural equation modeling

SJR	Scientific Journal Ranking
SME	Small and medium-sized enterprise
SRMR	Standardized root mean square residual
t	t-test
TEA	Total early-stage entrepreneurial activity
TÜV	Technischer Überwachungsverein [English: Technical Supervisory Association]
u	Residual
U.S.	United States
VIF	Variance inflation factor
vs.	Versus
x	Predictor
α	Threshold for statistical significance
β	Standardized regression coefficient
ε	Error term
Δ	Difference
$\times$	Interaction term
$\hat{\rho}$	Weighted average effect size
τ_w	Estimate of the true heterogeneity within studies
τ_b	Estimate of the true heterogeneity between studies
χ^2	Chi-squared test

1 Introduction

1.1 Relevance and Research Gaps

With the development of artificial intelligence (AI), many organizational and managerial decisions traditionally made by humans are now augmented or automated by algorithms (Fügener et al., 2022; Jussupow et al., 2024; Meijerink & Bondarouk, 2023). *AI* refers to technologies designed to perform cognitive functions, such as learning, reasoning, and problem-solving, typically associated with human intelligence (Prikshat et al., 2023; Rai et al., 2019). The term *algorithm* falls under the umbrella of AI and comprises structured sets of rules or statistical models that analyze data (Beer, 2017). *Algorithmic decision-making* (ADM) denotes the use of algorithms to assist decisions that were traditionally made only by humans (Langer & Landers, 2021). ADM systems can range from simple rule-based decision trees to more complex, adaptive systems which evolve over time as they process increasing volumes of data (Zerilli et al., 2019). When ADM is introduced in managerial processes, such as monitoring performance or allocating tasks, this is referred to as *algorithmic management* (AM; Möhlmann et al., 2021).[1]

The implementation of ADM is steadily expanding across organizational contexts. A recent McKinsey (2025) report showed that 78% of organizations currently use AI in at least one business function, for example, in marketing and sales, operations, or human resources (HR). One in three companies worldwide expects to invest over 25 million dollars in AI in 2025 (Boston Consulting Group, 2025), which reflects the immense potential organizations attribute to ADM. This trend is not limited to established or large organizations. New or small ventures and entrepreneurs are increasingly adopting AI tools to gain competitive

[1] This dissertation primarily uses the term ADM, occasionally referring to related terms, such as AM, AI, or algorithms. The use of these terms varies across the essays, depending on the specific literature streams they are embedded in. All essays examine algorithm-based tools or systems, either for decision-making (as in the management-focused essays) or for content generation and task support (as in the entrepreneurship-focused essay).

advantages. For example, a survey by the U.S. Chamber of Commerce (2024) found that nearly all small businesses in the United States (U.S.; i.e., 98%) are utilizing AI-enabled tools, with 40% employing generative AI tools such as chatbots. According to the European Commission (2009), small enterprises have fewer than 50 employees and an annual turnover of no more than 10 million euros.

ADM is applied across a range of organizational functions, particularly in human resource management (HRM), operations, and strategic decision-making (Bankins et al., 2024; Jussupow et al., 2024). For example, in HRM, ADM can be used to screen job applicants by parsing CVs, ranking candidates, or using predictions to estimate future performance (Köchling & Wehner, 2023; Langer et al., 2021; Oostrom et al., 2024). ADM may also support the interview process through asynchronous video interviews, where applicants answer interview questions via video recording instead of talking to an HR representative directly (Canagasuriam & Lukacik, 2025). These videos can then be analyzed based on specific criteria, for example, verbal or nonverbal (e.g., smiling, eye movements) cues that the algorithm detects (Langer, König, & Hemsing, 2020; Park & Jung, 2025). In the employee lifecycle, ADM can support performance evaluation by monitoring behavior and productivity (e.g., how many tasks are completed within a given timeframe) or generating feedback (e.g., notifying the employee if they are working too slowly; Benlian et al., 2022; Möhlmann et al., 2021). In operations, ADM systems optimize the allocation of work tasks to employees by scheduling their time and coordinating workflows (Lee, 2018; Parent-Rocheleau & Parker, 2022). Moreover, organizations rely on ADM for forecasting, analysis of potential investments, and for creating pricing strategies (Nunan & Di Domenico, 2022). Importantly, ADM systems are often introduced with the intention of enhancing objectivity, consistency, and efficiency (Budhwar et al., 2022; Malik et al., 2023).

ADM usage may differ depending on the maturity of the organization. Established organizations typically have more resources to embed ADM (e.g., funds to purchase ADM systems, dedicated departments for transformation, or established data infrastructures) compared to new ventures (Antolín-López et al., 2015). In contrast, new ventures often face resource constraints (i.e., constraints in finances and human capital; Bauer et al., 2024) and may therefore adopt ADM tools in a more ad hoc or experimental manner as a means to overcome these limitations. According to the OECD (2025), new ventures are typically no more than five years old. Moreover, the needs that ADM should fulfill may vary across maturity stages. While established firms may focus on using ADM to optimize internal operations, such as performance management, new ventures may prioritize ADM for tasks to overcome their resource constraints and liabilities of newness (Stinchcombe, 1965), such as supporting funding acquisition or identifying market opportunities. ADM implementation in established firms often requires alignment with existing workflows and organizational structures (Jöhnk et al., 2021), which may slow down its integration. In contrast, new ventures may benefit from more flexibility, allowing them to experiment with ADM more quickly.

While the organizational context shapes ADM implementation, it is crucial to consider how individuals respond to ADM systems. These reactions have been primarily studied in contexts where ADM systems make decisions about people or have direct consequences for individuals (Kern et al., 2022). Thus, scholars particularly investigated ADM implementation in domains, such as HRM or operations, as these areas involve decisions about (potential) employees[2] (e.g., hiring, layoffs, performance evaluation), which may have important consequences for these individuals (Bankins et al., 2024; Langer & Landers, 2021).

[2] (Potential) employees comprise applicants and employees.

To investigate ADM reactions, this dissertation adopts the computers-are-social-actors (CASA) framework (Nass & Moon, 2000) as an overarching theoretical lens. CASA posits that individuals respond to digital systems using the same social scripts, heuristics, and interpersonal norms they would apply in human–human interaction (Nass & Moon, 2000). Previous research extended CASA to the context of ADM and found that individuals perceive ADM systems as autonomous identities rather than as an extension of their human developers (Gambino et al., 2020). Individuals tend to anthropomorphize systems when they mimic social roles or have their own agency, which is the case when an ADM system makes a decision. As such, CASA provides a fitting overarching theoretical framework to explain why individuals transfer evaluation criteria from human–human to human–algorithm contexts. Drawing on CASA, this dissertation creates a bridge between theories and findings traditionally applied to human–human contexts (e.g., justice theory; Colquitt, 2001) and transfers them to human–algorithm contexts. This allows for creating an overarching theoretical understanding of how varying stakeholders (e.g., entrepreneurs, employees) react to ADM systems in different organizational contexts (i.e., established organizations, new ventures) and how these reactions are shaped by specific boundary conditions (e.g., type of task, psychological distance).

Previous research applied CASA to investigate individuals' reactions to ADM (Gambino et al., 2020) and found algorithm aversion and algorithm appreciation to be prevalent (Dietvorst et al., 2015; Logg et al., 2019; Mahmud et al., 2022). *Algorithm aversion* refers to the rejection of ADM systems in favor of human decision-making (HDM), even when the algorithm performs equally well or better (Dietvorst et al., 2015). Algorithm aversion rather emerges in emotionally sensitive or high-stakes contexts, such as hiring (Langer et al., 2019), promotion (Köchling et al., 2025), or layoffs (Newman et al., 2020). In these situations, individuals typically want to be treated with empathy and expect moral reasoning from the decision entity (Glikson & Woolley, 2020; Liefooghe et al., 2023). Furthermore, aversion to ADM is apparent when ADM systems operate autonomously without human oversight (De Cremer & McGuire, 2022), are perceived as opaque (Langer & König, 2023), or when individuals feel depersonalized and reduced to data points (Binns et al., 2018). In contrast, *algorithm appreciation* is defined as the preference of ADM over HDM and tends to emerge in objective, repetitive, or data-intensive tasks, such as work or task allocation (Castelo et al., 2019; Lee, 2018; Logg et al., 2019). Algorithm appreciation further increases when ADM systems are introduced in a transparent way (Jussupow et al., 2024) or used to augment decisions rather than replace HDM (De Cremer & McGuire, 2022). In doing so, ADM may be perceived as more consistent, impartial, and efficient than HDM, leading to more positive stakeholder reactions (Jussupow et al., 2024). The tension of algorithm aversion and appreciation in the literature suggests that stakeholders (e.g., entrepreneurs, employees, applicants) react differently to ADM and that their reactions depend on certain boundary conditions, such as the type of task or decision, the implementation process of ADM, and the perceived objectivity of the outcome.

Whether individuals are averse or appreciative toward ADM has important consequences for organizations. Currently, many organizations face labor shortages and competition for talent, which increases the importance of selecting well-fitting candidates and retaining their talent (Collings et al., 2019). When ADM is introduced, potentially negative reactions (e.g., perceptions of lower justice or fairness) can jeopardize organizational attractiveness (Acikgoz et al., 2020; Mirowska & Mesnet, 2022) and compliance with ADM decisions (Choi & Chao, 2024). In the worst case, employees may consider leaving the organization (Köchling et al., 2025) or applicants may withdraw from the recruitment process (Oostrom et al., 2024). Conversely, when stakeholders perceive ADM positively, this may improve ADM adoption and efficiency and may lead to a higher chance of retaining the organization's talent. Previous research showed that individuals are more likely to accept and comply with decisions they perceive as procedurally just and trustworthy (Lind, 2001), which underscores the importance of understanding the boundary conditions under which ADM elicits algorithm aversion or appreciation.

In addition, this dissertation differentiates five key stakeholders who react to and partially use ADM (i.e., entrepreneurs, HR professionals, employees, applicants, and observers). Consistent with CASA and previous work on human–human interaction, each stakeholder group may react differently to ADM introduction (Matthews et al., 2025). Langer and Landers (2021) propose a distinction of stakeholders into first, second, and third parties. *First parties* are those who directly interact with ADM and are involved in its application. For example, HR professionals who use ADM systems to make a hiring decision or entrepreneurs who employ ADM to optimize their resource allocation. *Second parties* are those who are confronted with algorithmic decisions, but do not use ADM themselves. For example, applicants receiving a hiring decision or employees getting feedback on their performance. *Third parties* are those who observe ADM use, but are not directly affected by its decisions or its usage. For example, individuals reading about ADM introduction in the news or talking to their friends who had experiences with ADM. Each party differs in whether they interact with ADM (i.e., first parties), are only confronted with its decisions (i.e., second parties), or are not affected at all (i.e., third parties), which may impact how they view the introduction of ADM systems. Thus, a combination of the level of psychological distance to the decision and the level of interaction (i.e., users vs. non-users) sets them apart. Although previous literature acknowledges the differences between stakeholders (Langer & Landers, 2021; Matthews et al., 2025), knowledge about how their reactions to ADM truly differ, is underdeveloped. Accordingly, this dissertation introduces five stakeholder groups to derive potential variations in ADM reactions. These stakeholder groups relate to all three parties: entrepreneurs and HR professionals as first parties, (potential) employees as second parties, and observers as third parties.[3]

Despite the findings from previous literature, four critical research gaps remain unaddressed. First, the tension between algorithm aversion and appreciation remains unresolved. Previous findings on stakeholder reactions to ADM are often inconsistent and inconclusive, which makes it difficult to develop a coherent theoretical framework guiding the research field. Previous studies used a large number of different theories and models, such as justice theory (Colquitt, 2001) or the integrative model of organizational trust (Mayer et al., 1995). As a result, the theoretical landscape remains fragmented, making it difficult to draw meaningful comparisons across studies. Moreover, insights on which boundary conditions affect ADM reactions remain underdeveloped. Although previous literature proposed several study-level moderators (e.g., the type of task or the level of decision stakes; Langer et al., 2019; Lee, 2018), the findings are not always consistent, and many overarching boundary conditions remain unexplored. This ambiguity complicates ADM implementation in organizations on a practical level: If it is not clear when algorithm aversion or appreciation occurs, organizations risk the consequences of adverse reactions (e.g., reduced organizational attractiveness). Therefore, it is essential to understand when and how algorithm aversion arises.

Second, much of the literature on algorithm aversion has focused on negative cognitive and emotional reactions, such as reduced fairness or trust (Höddinghaus et al., 2021; Ochmann et al., 2024), while largely neglecting the advantages that ADM systems have to offer. These advantages could also lead to positive ADM stereotypes, including perceptions of innovativeness, efficiency, and performance. Thus, it is questionable whether

[3] It is important to note that not all roles are set in place. For instance, HR professionals do not inherently hold the position of first parties. In other situations, outside of the organization, they can also switch to third parties when they observe the usage of ADM. Thus, the roles they are assigned to in this dissertation relate to the primary roles they have in the organization that employs ADM.

individuals are always either averse or appreciative depending on outside factors (i.e., in which task or in which country ADM is introduced; Kleinlogel et al., 2023; Lee, 2018), or if they can hold positive and negative evaluations at the same time.

Moreover, prior literature did not consider how psychological distance impacts these stereotypes. Drawing on construal level theory (Trope & Liberman, 2010), psychological distance refers to the perceived closeness of an event or a decision on the dimensions of time, space, social distance, and hypotheticality. Relating ADM introduction to the social distance of the decision, individuals who are psychologically close to an ADM decision (e.g., applicants directly evaluated by an algorithm) may focus more on their own consequences of the decision. This may lead to a more critical or in-depth evaluation of ADM. In contrast, psychologically distant individuals (e.g., third parties) are more likely to think in abstract terms, and may rely on broader positive associations, such as efficiency. Nevertheless, previous literature has yet to integrate psychological distance as a key mechanism of ADM reactions. Theoretically, without realistic insights into ADM reactions, scholars struggle to develop generalizable theoretical models. As a result, some frameworks may conclude that individuals either exhibit algorithm aversion or appreciation, without accounting for the possibility that both can coexist simultaneously. Practically, organizations may hesitate to implement ADM, even where employee reactions could be positive, thereby missing its potential benefits.

Third, previous studies found that transparency regarding ADM can lead to algorithm appreciation, as stakeholder reactions improve compared to non-transparent ADM introduction (Chowdhury, Joel-Edgar, et al., 2023; Grimmelikhuijsen, 2023). As a result, prior research has reached a consensus that transparency is a recommended practice when implementing ADM. However, scholars have not specified which type of information or how much information is beneficial when ADM is introduced. There are first indications that transparency can also backfire when there is too much information given about the algorithm (Hu et al., 2024). Individuals may experience information overload when particularly technical or overly detailed explanations of the algorithm are presented, which hinders successful ADM adoption (Bauer & Gill, 2024). This reflects the *transparency paradox*, the idea that greater transparency does not necessarily improve ADM reactions (Ananny & Crawford, 2018).

In addition, ADM transparency may not be equally well received in all types of tasks. Some tasks include rather objective and rational decision components (e.g., work allocation), whereas others require more intuitive and emotional judgements (e.g., performance evaluation; Lee, 2018). Therefore, individuals may appreciate information about ADM and its implementation more so in mechanical tasks, as ADM introduction is congruent with the expected skills to make a decision (Langer et al., 2019; Lee, 2018). In contrast, ADM transparency in tasks where "human" skills are needed, may evoke more negative reactions, as feelings of observation and invasion of privacy may become more important.

Fourth, previous research and also the three aforementioned gaps focused on ADM reactions in established organizations, leaving the context of entrepreneurs underrepresented. However, entrepreneurs deal with a distinct set of challenges and dynamics which cannot be easily transferred from established organizations (Shepherd et al., 2021). Entrepreneurial ventures typically operate with limited resources, face higher uncertainty, and lack formalized structures and procedures (Chalmers et al., 2021; Townsend & Hunt, 2019). These conditions can largely shape how and why AI systems are introduced. Entrepreneurs may adopt AI in response to constrained resources or in pursuit of gaining legitimacy (Shepherd & Majchrzak, 2022). While prior research explores how AI disrupts business models and opportunity exploitation (Jorzik et al., 2024), it overlooks the institutional forces impacting AI adoption. Institutional theory (Scott, 2014) differentiates between three pillars which guide organizational behavior: the regulative pillar (e.g., laws, formal policies), the normative pillar (e.g., social expectations, professional standards), and the cultural–cognitive pillar (e.g., taken-for-granted beliefs, shared understandings). These institutional pillars lead to certain pressures, which can be subsumed under isomorphism. Isomorphism refers to the process by which organizations in a shared environment become similar over time and can take the form of coercive (e.g., regulative demands), normative (e.g., expectations from investors or customers), and mimetic pressures (e.g., emulation of peers; DiMaggio & Powell, 1983). Empirical research is limited regarding how entrepreneurs perceive and respond to these AI-related pressures, particularly across diverse regulatory and cultural settings. This is problematic as it limits our understanding of the broader institutional impact in entrepreneurial decision-making. Theoretically, this gap calls for an integration of institutional theory (Scott, 2014) to understand how entrepreneurs perceive and respond to different institutional demands. Practically, failing to consider institutional factors may lead to overly narrow or ineffective support structures or policy interventions. This may undermine the success of new ventures and may have detrimental effects at the individual level for entrepreneurs.

These research gaps lead to the overarching research question of this dissertation: ***How do stakeholders react to ADM, and how do these reactions vary depending on interaction and system characteristics, company types, and institutional contexts?***

1.2 Research Questions of the Essays and Contributions

This dissertation investigates the overarching research question through four essays, each addressing specific sub-questions. Table 1-1 provides a summary of these essays, outlining their theoretical perspectives, methodologies, objectives, and contributions, as well as their current status. Figure 1-1 visualizes the conceptual structure and interrelationships of the four essays in this dissertation.

Table 1-1. Characteristics of the Four Essays

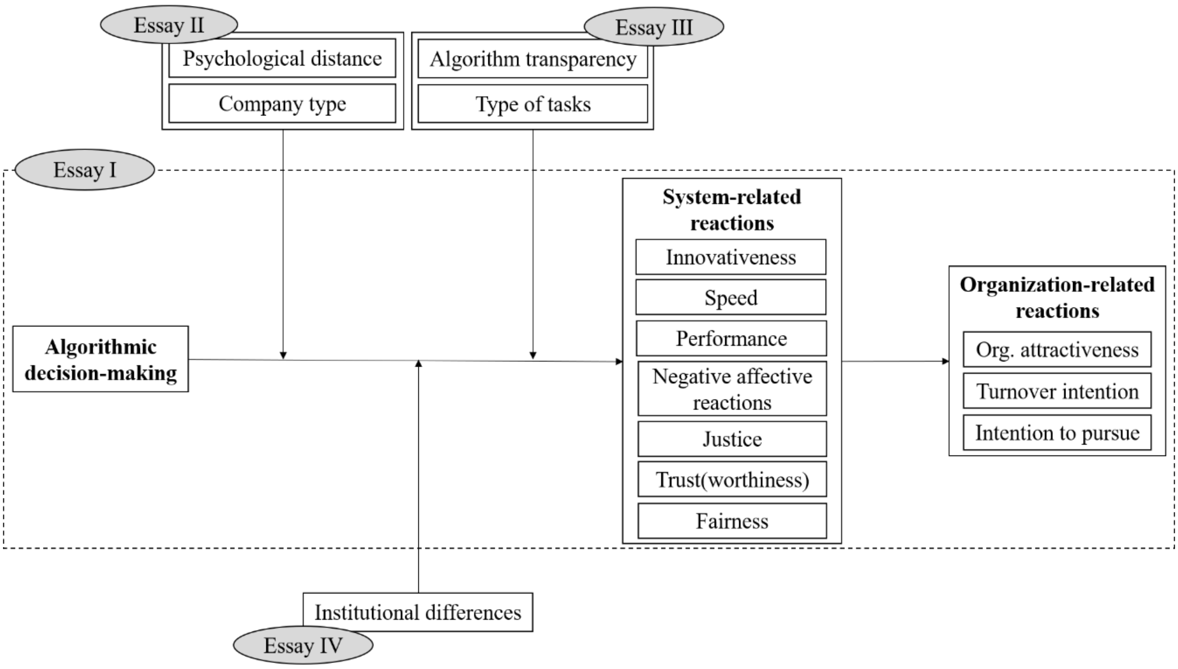
No.	**Title**	**Theoretical perspectives**	**Research objectives**	**Method and sample**	**Results and contributions**	**Current status**	**Conferences**	**Share of contri-butions**
I	A meta-analysis on reactions to algorithmic decision-making in human resource management	Computers-are-social-actors (CASA; Nass & Moon, 2000) Proposed overarching theoretical framework	This study provides a synthesis of reactions to ADM usage and their boundary conditions in the context of HRM. This study uses CASA as a meta-theoretical framework in order to propose an overarching theoretical framework, which is aimed to guide future research.	Meta-analysis including 73 samples in 53 studies (N = 24,578)	ADM is negatively associated with system-related (i.e., justice, fairness, trust, trustworthiness) and organization-related (i.e., organizational attractiveness, job pursuit intention) reactions, which depend on boundary conditions (i.e., type of interaction, type of decision). The overarching theoretical framework explains the relationships between ADM, reactions, and boundary conditions and provides future research avenues.	Moderate revision (2nd round) in *Human Resource Management Review (HRMR)*	**Presented at:** *84th Annual Meeting of the Academy of Management (AOM)*, Chicago, U.S., 2024. *83rd Annual Meeting of the Academy of Management (AOM)*, Boston, U.S., 2023. *AI in Business and Economics – The Economics Perspective on Artificial Intelligence (EPEAI)*, Mülheim, Germany, 2023.	J. M. Moritz 50% L. Pomrehn 30% H. Steinmetz 10% M. C. Wehner 10%
II	The bright and dark sides of algorithmic decision-making (ADM): The role of stereotypes and psycho-	Stereotype theory (Oakes & Turner, 1990) Construal level theory (Trope &	This study examines how ADM evokes both positive (i.e., innovativeness, performance, speed) and negative (i.e., unfairness, distrust, creepiness) stereotypes. In addition, this study	Data scraping of newspaper articles (5,947,814 words) Study 1 – between-subjects	ADM evokes both positive (i.e., innovativeness, performance, speed) and negative (i.e., unfairness, distrust, creepiness) stereotypes compared to HDM. Psychological distance significantly impacts both positive and	Under review in *Information Systems Journal (ISJ)*	**Accepted at:** *Research in Entrepreneurship and Small Business (RENT)*, Enschede, Netherlands, 2025.	L. Pomrehn 85% M. C. Wehner 10% V. Göttel 5%

No.	Title	Theoretical perspectives	Research objectives	Method and sample	Results and contributions	Current status	Conferences	Share of contri-butions
	logical distance of ADM in organiza-tional attraction	Liberman, 2010)	analyzes the role of psychological distance to the algorithmic decision regarding ADM stereotypes. This study also explores how these stereotypes mediate the relationship between ADM and organizational attractiveness as well as between psychological distance and organizational attractiveness.	vignette experiment (n = 405) Study 2 – between-subjects vignette experiment (n = 317)	negative stereotypes: those directly affected show fewer positive and more negative stereotypes. This study highlights that ADM stereotypes can be both positive and negative at the same time, which allows the introduction of the term *algorithm ambivalence*. In addition, this study presents psychological distance as an important predictor in ADM stereotypes.			
III	Too much information? The role of algorithm transparency and type of task in employee reactions to algorithmic management	Affective response model (ARM; Zhang, 2013)	This study explores how algorithm transparency and the type of managerial task (i.e., work allocation, training allocation, performance evaluation) shape employee reactions (i.e., perceived data security, opportunity to perform,	One between-subjects vignette experiment (n = 354)	AM reduces perceived data security and opportunity to perform, while increasing emotional creepiness. High algorithmic transparency of AM leads to increased negative employee responses, especially in managerial tasks that involve emotional and intuitive decision	Previous version published in the *Proceedings of the Hawaii Inter-national Conference on System Sciences (HICSS)*	**Presented at:** *58th Hawaii International Conference on System Sciences (HICSS),* Big Island, Hawaii, U.S., 2025. (Nominated for the Best Paper Award in the track "AI and the Future of Work") *83rd Annual Meeting of the Academy of*	L. Pomrehn 80% M. C. Wehner 10% F. Strich 10%

No.	Title	Theoretical perspectives	Research objectives	Method and sample	Results and contributions	Current status	Conferences	Share of contri-butions
			emotional creepiness) to algorithmic management (AM).		components (i.e., task allocation, performance evaluation). This study extends the ARM and prior work on the transparency paradox.	Under review in *European Management Review*	*Management (AOM)*, Boston, U.S., 2023. *23rd European Academy of Management Conference (EURAM)*, Dublin, Ireland, 2023. *AI in Business and Economics – The Economics Perspective on Artificial Intelligence (EPEAI)*, Mülheim, Germany, 2023.	
IV	Navigating institutional pressures in the age of artificial intelligence: A typology of entre-preneurial responses	Institutional theory (Scott, 2014)	This study examines how entrepreneurs from different institutional environments (i.e., Germany and Japan) perceive AI-related institutional pressures (i.e., regulative, normative, cultural–cognitive), how this affects their own AI usage, and how they strategically	32 semi-structured qualitative interviews	Entrepreneurs perceive AI as a driver of institutional change across the regulative, normative, and cultural–cognitive pillars which affect their usage. They respond with a range of strategies (e.g., complying or resisting pressures) and a transformation of their entrepreneurial identity. This study presents a framework and develops a typology of entrepreneurial profiles	Submitted to *Entrepre-neurship Theory and Practice (ETP)*	**Presented at:** *Annual Interdisciplinary Conference on Entrepreneurship, Innovation, and SMEs (G-Forum)*, Ingolstadt, Germany, 2024. **Accepted at:** *Interdisciplinary European Conference on Entrepreneurship Research (IECER)*, Reykjavik, Iceland, 2025. *85th Annual Meeting of the Academy of*	L. Pomrehn 95% T. Yoshikawa 5%

No.	Title	Theoretical perspectives	Research objectives	Method and sample	Results and contributions	Current status	Conferences	Share of contri-butions
			respond to these pressures.		which differ in their compliance with institutional pressures and the level of their identity transformation.		*Management (AOM)*, Copenhagen, Denmark, 2025.	
Total contribution of the author								290%

Figure 1-1. Research Model and Overview of the Four Essays



Note. Org. = organizational. Dotted lines indicate that Essay I primarily focuses on the depicted main relationship. Algorithmic decision-making is always compared to human decision-making. Not all investigated boundary conditions of the essays are shown, but rather the ones which made up the main focus of the essays.

The structure of this dissertation is as follows: This subsection explains the research questions and contributions of each essay. Chapters 2 to 5 present the four essays in full. Chapter 6 concludes the dissertation by discussing the theoretical and practical implications, limitations, and directions for future research.

Essay I presents a meta-analysis of stakeholder reactions to ADM in the HRM domain. In doing so, this essay directly addresses the first research gap which includes (1) inconsistent and inconclusive findings of the literature, (2) limited insights into boundary conditions which affect ADM reactions, and (3) a fragmented theoretical landscape. Drawing on the CASA framework (Nass & Moon, 2000), this essay synthesizes data from 73 samples in 53 studies (N = 24,578). Essay I focuses on how ADM impacts system-related (i.e., justice, fairness, trust, trustworthiness, negative affective reactions) and organization-related (i.e., organizational attractiveness, job pursuit intention) reactions. In doing so, Essay I aims to investigate whether algorithm aversion or appreciation is prevalent in primary studies. In addition, the meta-analysis examines the role of boundary conditions, including type of stakeholder ([potential] employees vs. HR professionals), type of interaction (confrontation vs. collaboration), type of task (screening vs. interviews vs. career development), extent of decision (augmentation vs. automation), and psychological distance (personally affected vs. not personally affected). Therefore, Essay I examines the following research question:

Research question 1: ***How do individuals react to the use of ADM in the HRM domain and which boundary conditions impact these reactions?***

In answering this research question, the essay contributes to the literature in three ways: First, Essay I shows that algorithm aversion is prevalent in the literature as both system-related and organization-related reactions are negative on an aggregated level. Therefore, the essay synthesizes findings from previous literature. Second, this meta-analysis incorporates several boundary conditions (i.e., type of stakeholder, type of interaction, type of task, extent of decision, psychological distance) to shed light on how ADM reactions vary between them. Third, the study builds a bridge between theories applied in human–human contexts and extends them to human–algorithm contexts by means of CASA as a meta-theoretical lens and the development of an overarching framework. Future research avenues are derived from the framework to guide future scholars.

The following three essays are derived from the findings from Essay I. Essay II builds upon the finding that overall algorithm aversion was prevalent in the research field. This may be due to the constructs that researchers employed for their studies, which were mainly focused on potentially negative emotional and cognitive reactions (e.g., fairness, justice). This essay introduces positive stereotypes (i.e., innovativeness, performance, speed) alongside more established negative stereotypes (i.e., unfairness, distrust, creepiness) to directly answer the second research gap. Accordingly, Essay II aims to derive whether individuals hold positive and negative stereotypes simultaneously. In addition, this essay investigates the role of psychological distance (i.e., the degree to which individuals feel personally affected by a decision) in shaping ADM stereotypes. The study is grounded in stereotype theory (Oakes & Turner, 1990) and construal level theory (Trope & Liberman, 2010), proposing that individuals form stereotypes about ADM to simplify the evaluation of such systems. Accordingly, Essay II deals with the following research questions:

Research questions 2: *Does ADM also lead to positive stereotypes and if so, do these stereotypes coexist with negative ones? What role does psychological distance play in shaping these stereotypes?*

This essay identifies positive and negative stereotypes of ADM through triangulation of prior literature, newspaper article analysis, and qualitative interviews. Specifically, previous research provided initial indications of negative stereotypes, while an analysis of newspaper articles on AI and ADM (5,947,814 words) and ten short semi-structured interviews offered insights into positive stereotypes and helped validate negative ones. Accordingly, innovativeness, performance, and speed were found to be the most prevalent positive stereotypes individuals form about ADM, and unfairness, distrust, and creepiness as the most prevalent negative ones. Overall, this analysis showed that ADM is not only perceived in a negative light. In the newspaper analysis, most articles were framed positively, talking about the potentials of AI and ADM. Across two pre-registered vignette-based experiments (Study 1: n = 405; Study 2: n = 317), this study introduces the stereotypes by comparing ADM to HDM (Study 1) and examines the impact of psychological distance (i.e., low and high; Study 2). The findings show that ADM leads to more positive and more negative stereotypes compared to HDM, and importantly, these stereotypes coexist within individuals. In addition, high psychological distance to an ADM decision (e.g., reading about it in the news) leads to more favorable reactions than low distance (e.g., being directly affected in a recruiting scenario).

With these findings, Essay II offers two main contributions. First, it urges future scholars to not only investigate emotional and cognitive reactions to ADM, but also to examine positive stereotypes which individuals associate with ADM, as these significantly impact organizational attractiveness and therefore have important implications for organizations. Accordingly, this essay introduces the term *algorithm ambivalence* to describe the simultaneous perception of ADM as both positive and negative. This concept contrasts with earlier research, which has typically examined algorithm aversion and algorithm appreciation as separate and mutually exclusive reactions. Second, the study introduces psychological distance as an important predictor of ADM stereotypes, which has been largely overlooked by previous research. In doing so, this study provides insights into the boundary conditions that shape ADM reactions and helps organizations with context-dependent implementation and communication of ADM systems in the workplace.

Essay III, again, builds upon the call for research in Essay I to investigate the boundary conditions of ADM implementation in more detail. Thus, this essay analyzes how algorithm transparency and the type of managerial task shape employee reactions to AM and directly answers the third research gap. Drawing on the affective response model (ARM; Zhang, 2013), this essay introduces perceived data security, opportunity to perform, and emotional creepiness as a conceptualization of employee reactions. Moreover, the study argues that algorithm transparency does not uniformly enhance employee reactions, but that the reactions depend on the type of information that is given and the type of managerial task in which AM is introduced. The essay distinguishes AM introduction in “mechanical” (i.e., work allocation) and “human” tasks (i.e., training allocation, performance evaluation). Information about the algorithm in “human” tasks may trigger stronger negative employee reactions, as individuals may expect a human to make the decisions and additional information on this process may further highlight this dissonance. Accordingly, the research question addressed is:

Research question 3: ***How do employee reactions to AM vary across levels of algorithm transparency (i.e., high vs. low) and managerial tasks (i.e., work allocation, training allocation, performance evaluation)?***

The findings of Essay III highlight that AM is associated negatively with perceived data security and opportunity to perform and positively with emotional creepiness compared to human management. In addition, multigroup structural equation modeling (SEM) reveals that algorithm transparency in work allocation does not change employee reactions, but significantly decreases reactions in training allocation and specifically in performance evaluation.

With these insights, Essay III contributes to the literature in two ways. First, the essay shows that transparency in the process of AM introduction does not always improve employee reactions, but that the type of information given plays a significant role. When the information given is too excessive or difficult to understand, employees react more negatively due to information overload and confusion. This provides insights into the transparency paradox (Ananny & Crawford, 2018), which denotes that transparency is not universally beneficial, but has its limits. Second, by distinguishing different managerial tasks where AM is introduced, this essay shows that employee reactions to transparent AM introduction are task-dependent and that organizations should be cautious about introducing transparent AM systems in tasks that are associated with human skills. In addition, this study finds that boundary conditions do not change ADM reactions in a vacuum: For instance, analyzing the level of algorithm transparency and type of task together brought additional insights which would have been lost when analyzing their effects individually. Therefore, this essay calls for a broader investigation of different boundary conditions within studies as this also represents a more realistic view of how ADM is implemented in organizations.

Finally, Essay IV also builds upon the findings from Essay I and explores a distinct organizational setting for AI introduction: new ventures led by entrepreneurs, in contrast to the earlier essays, which focused on ADM in more established organizations. However, AI adoption may differ for entrepreneurs compared to other stakeholders, such as employees or applicants, due to the unique characteristics they face (e.g., dealing with uncertainties; Townsend & Hunt, 2019). In addition, institutional theory (Scott, 2014) has not been integrated in previous studies of AI adoption in entrepreneurship, despite its potential to explain how regulatory, normative, and cultural–cognitive pressures influence entrepreneurial behavior. Accordingly, the research question addressed is:

Research question 4: ***How do entrepreneurs integrate AI into their practices on an individual level, and how do they perceive and respond to institutional pressures brought about by AI?***

Essay IV answers this question by analyzing 32 semi-structured interviews with entrepreneurs in Germany and Japan to explore the institutional demands that entrepreneurs face in both countries. The essay derives enabling and constraining processes and mechanisms for each institutional pillar that entrepreneurs perceive. For example, regarding the regulative pillar, entrepreneurs in Japan perceived rather loose regulations regarding AI as an enabler as they were relatively free in their AI adoption. In terms of the normative pillar, entrepreneurs reported that using AI has become the new norm and that they feel pressured to adopt AI as much as they can. On the cultural–cognitive level, entrepreneurs from Japan in particular said that they grew up with AI depicted as something positive (e.g., AI displayed in a cute way in famous anime shows), which in turn encourages their adoption.

The identified barriers lead to specific pressures, which can be subsumed under isomorphism (e.g., pressure to adhere to AI regulations). Entrepreneurs react differently to these demands: Some adhere to all of the pressures, others are more critical and resist some of these demands (e.g., not feeling pressured by their peer group and developing their own strong opinion). In addition, this essay shows that the adoption of AI leads to a shift in the entrepreneurial identity (EI); however, not all entrepreneurs experienced the same level of identity shift. To better visualize the differences in compliance with institutional demands and the level of identity shift, this study presents four profiles which differ in both: the visionary, the conformer, the skeptic, and the rebel. The visionary shows the highest levels of identity transformation and compliance to institutional demands, whereas the skeptic shows the lowest levels in both. The conformer puts a particular emphasis on conforming to external demands, without changing their identity much. In contrast, the rebel does not fully engage in compliance to the pressures, but rather goes through a large identity transformation.

Hence, Essay IV contributes to the literature in three important ways: First, this study advances institutional theory (Scott, 2014) by demonstrating how entrepreneurs perceive AI as a driver of institutional change across the regulative, normative, and cultural–cognitive pillars. They face evolving laws, stakeholder expectations, and societal norms, leading to coercive (e.g., EU AI Act), normative (e.g., investor demands), and mimetic pressures (e.g., peer imitation). In doing so, the study directly responds to Obschonka and Audretsch’s (2020) call to examine institutional influences in AI development. Second, it shows how entrepreneurs strategically respond to these pressures, while often reconfiguring their professional identity. This gives insights into how such strategies form. They depend largely on the type of person (e.g., personality traits) but also on the institution itself (in this case, Germany or Japan). Third, the study proposes an integrative framework, which links institutional pressures, strategic responses, and identity transformation. From this framework, a typology of entrepreneurial profiles is created, which extends institutional theory by capturing variation in how entrepreneurs navigate AI-related demands.

In summary, the four essays in this dissertation offer a comprehensive analysis of stakeholder reactions to ADM across organizational contexts. By integrating CASA as an overarching theoretical lens, the dissertation bridges insights and theories from human–human to human–algorithm contexts. In particular, this dissertation investigates certain system-related (i.e., justice, fairness, trust, trustworthiness, negative affective reactions, innovativeness, performance, speed) and organization-related reactions (i.e., organizational attractiveness, turnover intention, intention to pursue) to ADM. *System-related reactions* refer to reactions directed at the ADM system itself, whereas *organization-related reactions* are linked to the organization that employs the ADM system. In doing so, this dissertation focuses on the potentially positive and negative ADM reactions and implications for organizations (e.g., increase or decrease of organizational attractiveness). In addition, this dissertation presents important boundary conditions that shape ADM reactions. Essay I investigates psychological distance, type of task, extent of decision, type of stakeholder, and type of interaction as boundary conditions. Essay II builds on this and introduces psychological distance as well as company types as boundary conditions. Essay III combines algorithm transparency with type of tasks as boundary conditions and Essay IV identifies institutional differences as a boundary condition.

Overall, this dissertation advances ADM research by synthesizing prior findings, identifying key boundary conditions, and developing a theoretical framework. This work contributes to management literature while integrating insights from information systems and psychology, highlighting the value of interdisciplinary research on ADM. In particular, this dissertation addresses how different stakeholders (i.e., entrepreneurs, HR professionals, employees, applicants, and observers) in different organizational settings (i.e., established vs. new organizations) react to ADM introduction and how these reactions differ between them. This way, this dissertation offers important theoretical and practical implications that help future scholars, organizations, managers, and policymakers alike.

2 Essay I: A Meta-Analysis on Reactions to Algorithmic Decision-Making in Human Resource Management[4]

Abstract

In this meta-analysis, we assess reactions to algorithmic decision-making (ADM) in human resource management. Drawing on the computers-are-social-actors (CASA) paradigm as a meta-theoretical framework, we offer an overarching theoretical framework to explain the relationships between ADM and (1) system-related reactions (e.g., justice, trust) as well as between ADM and (2) organization-related reactions (e.g., organizational attractiveness, turnover intention). Based on our overarching theoretical framework, we examine boundary conditions impacting these reactions. Our meta-analysis includes 365 effect sizes from 73 samples in 53 studies (N = 24,578) and reveals that ADM is negatively associated with system-related (i.e., justice, fairness, trust, trustworthiness) and organization-related (i.e., organizational attractiveness, job pursuit intention) reactions, which depend on boundary conditions (i.e., type of interaction, extent of decision). Based on our overarching theoretical model, we provide an empirical and theoretical synthesis of primary studies and outline avenues for future research.

Keywords: algorithmic decision-making, stakeholder reactions, human resource management, meta-analysis

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2.1 Introduction

Organizations increasingly use algorithmic decision-making (ADM) to optimize and accelerate the tasks of their human resource management (HRM; Chowdhury, Dey, et al., 2023; Meijerink & Bondarouk, 2023), specifically in recruitment and selection processes (Bankins et al., 2022; Campion et al., 2024; Koenig et al., 2023), career development and training (Köchling et al., 2025), and performance management of employees (Zhang & Amos, 2024). ADM refers to systems that use advanced computational techniques and falls under the umbrella term artificial intelligence (AI; Langer & Landers, 2021; Meijerink et al., 2021). Artificial intelligence (AI) refers to the ability of machines to analyze large datasets to make predictions and solve problems within complex environments and includes machine learning (Koenig et al., 2023; Prikshat et al., 2023). In this context, machine learning is a method through which systems analyze large sets of data, learn patterns from it, and apply these patterns to make decisions or predictions without being explicitly programmed for each task (Koenig et al., 2023). ADM systems can benefit managers by augmenting or automating HRM tasks, such as screening resumes or predicting employee turnover, thereby improving efficiency and potentially reducing human bias in decision-making (Daugherty & Wilson, 2018).

While the rapid growth of ADM holds significant promise for HRM, its benefits can only be fully realized if all stakeholders in the decision-making process accept and effectively engage with the ADM technology (Langer & Landers, 2021). However, if individuals respond negatively to ADM systems (e.g., with feelings of distrust or unfairness), these individual reactions may negatively affect the entire organization, for example, by diminishing organizational attractiveness or increasing turnover intentions (Koch-Bayram et al., 2023; Köchling et al., 2025). In times of labor shortages and the ongoing war for talent, it is crucial for organizations to understand how individual reactions to ADM emerge and whether they are able to positively influence these reactions to effectively manage their human capital and achieve competitive advantages. Prior literature has subsumed negative ADM reactions under the term *algorithm aversion* that is often applied when algorithms make mistakes (Castelo et al., 2019; Dietvorst et al., 2015) and positive ADM reactions under the term *algorithm appreciation*, which is often demonstrated for tasks such as forecasting (Logg et al., 2019). In addition, these reactions depend on boundary conditions, such as type of task (Lee, 2018) or included stakeholders (Langer & Landers, 2021). Furthermore, although several empirical papers (Bedemariam & Wessel, 2023; Kleinlogel et al., 2023) and qualitative reviews (e.g., Bankins et al., 2024; Basu et al., 2023; Budhwar et al., 2023; Cheng & Hackett, 2019; Langer & Landers, 2021; Pan & Froese, 2023) depicted the landscape of ADM and AI usage in organizations, the theoretical basis to explain reactions to ADM is rather scattered.

Following a thorough literature review of studies on ADM usage in the HRM domain, we identified three gaps in this field. First, although research often highlights negative reactions to ADM, findings from previous studies are controversial and inconclusive (e.g., Acikgoz, 2019; Feldkamp et al., 2024). On the one hand, prior research demonstrated algorithm aversion when (1) the decision or task is expected to require social or emotional skills (Castelo et al., 2019; Lee, 2018), (2) decisions are made by an algorithm with little or no human interaction or human-in-the-loop (De Cremer & McGuire, 2022), and (3) decisions involve high stakes for individuals (Langer et al., 2019). On the other hand, studies report algorithm appreciation when (1) it is used for tasks considered mechanical (i.e., forecasting; Logg et al., 2019), (2) it is considered transparent (Suen & Hung, 2023), or (3) participants experienced prior discrimination by humans and hence prefer ADM (Koch-Bayram et al., 2023; Schulte Steinberg & Hohenberger, 2023). From a theoretical point of view, this polarization hinders the development of a coherent framework for understanding reactions to ADM, as inconsistent results make it difficult to establish generalizable mechanisms. Practically, this ambiguity can complicate ADM implementation in organizations, especially when stakeholder reactions are not considered, thereby risking employee disengagement and reducing trust in ADM and the organization itself. Addressing this ambiguity is essential for advancing the research field and supporting organizations to implement ADM in a manner that is perceived as fair and trustworthy by stakeholders.

Second, research on boundary conditions is mixed and there is no quantitative synthesis to date, although several systematic and narrative reviews do examine the consequences of AI and ADM usage (e.g., Bankins et al., 2024; Basu et al., 2023; Budhwar et al., 2023; Bujold et al., 2024; Cheng & Hackett, 2019; Langer & Landers, 2021; Pan & Froese, 2023). Additionally, previous research on boundary conditions often focuses on individual moderators (e.g., type of task, cultural differences; Lee, 2018; Kleinlogel et al., 2023), but findings on study-specific moderators, such as type of interaction, are lacking across primary studies. The lack of focus on study-specific moderators and absence of a quantitative synthesis is concerning as it leaves critical boundary conditions underexplored, yet these factors are essential for understanding how ADM reactions vary across contexts. This gap hinders the ability to adapt ADM systems to specific stakeholder needs, which is crucial for ensuring successful adoption.

Third, theoretical approaches used in previous literature lack a coherent foundation, as prior studies focused on specific aspects of ADM reactions rather than making use of one overarching theoretical framework (see Table 2-1). While existing theories such as the computers-are-social-actors (CASA) framework (Nass & Moon, 2000; Reeves & Nass, 1996) address human–technology interactions, other theories emphasize specific variables, for example, justice theory (Colquitt, 2001; Greenberg, 1987; Leventhal, 1980), Gilliland’s (1993) model of applicant reactions, or Mayer et al.’s (1995) integrative model of organizational trust. These different theoretical approaches could lead to various challenges, such as difficulty in developing a unified understanding of reactions to ADM. Without such understanding, researchers may struggle to identify patterns across studies, as inconsistent use of theoretical constructs can undermine the validity of empirical research and complicate efforts to build cumulative knowledge in this field.

Table 2-1. Overview of Utilized Theories to Explain ADM Reactions in HRM

Theories	Description/main argument	Articles
	Theories to explain system-related reactions	
Advice Response Theory (ART; Feng & MacGeorge, 2010)	People react to advice depending on the message, the advisor, and the receiver.	(Chacon et al., 2024)
Affective Response Model (Zhang, 2013)	(Unconscious) evaluation processes lead to affective responses, which guide cognition and action.	Köchling et al. (2023), Pomrehn and Wehner (2025)
Applicant Attribution-Reaction Theory (Ployhart & Harold, 2004)	Job applicants interpret/attribute reasons behind recruitment decisions and these interpretations influence their reactions.	Oostrom et al. (2024)
Automation Model (Parasuraman et al., 2000)	Guides automation design by matching system functions with appropriate automation types and levels.	Langer, König, and Papathanasiou (2019), Langer, König, Sanchez, et al. (2019)
Attachment Theory (Mikulincer & Shaver, 2005)	Assumes that individuals internalize early interactions with primary caregivers and that resulting emotions guide their social behavior.	Deriu et al. (2024)
CASA (computers-are-social-actors)/Social Response Theory (Nass & Moon, 2000)	Suggests that people tend to treat computers and other technology as if they were human, applying social norms to their interactions with machines.	Moritz and Schmidt (2024), Moritz et al. (2024), Moritz et al. (2025), Suen and Hung (2023), Suen et al. (2019)
Explanation-for-Trust-Theory (Pieters, 2011)	Transparent explanations for system behavior can build trust in automated systems.	Suen and Hung (2023)
Exposure Theory (Zajonc, 1968)	Repeated exposure to a stimulus increases an individual's preference for it.	Koch-Bayram et al. (2023)
Fairness Heuristics Theory (Lind, 2001)	People rely on fairness heuristics to decide how to respond to organizational decisions.	Bedemariam and Wessel (2023), Choi and Chao (2024), Luo and Zhang (2023)

Theories	Description/main argument	Articles
Integrative Model of Organizational Trust (Mayer et al., 1995)	Defines trust as a willingness to be vulnerable to another party, whereas trustworthiness includes ability, benevolence, and integrity.	Höddinghaus et al. (2021), Kares et al. (2023), Lacroux and Martin-Lacroux (2022), Langer et al. (2023), Moritz and Schmidt (2024), Moritz et al. (2024), Sondern et al. (2025)
Media Richness Theory (Daft & Lengel, 1986)	Explains how the effectiveness of communication depends on the medium's ability to convey rich information.	Köchling and Wehner (2023), Langer, König, and Hemsing (2019), Suen et al. (2019)
Model of Applicants' Reactions to Employment Selection Systems (Gilliland, 1993)	Procedural and distributive justice impact applicants' fairness perceptions during selection.	Acikgoz et al. (2024), Acikgoz et al. (2020), Langer, König, and Papathanasiou (2019), Langer, König, Sanchez et al. (2019), Lavanchy et al. (2023), Noble et al. (2021), Oostrom et al. (2024), Suen and Hung (2023), Suen et al. (2019)
Model of Justice Expectation (Bell et al., 2004)	Individuals form expectations about justice based on prior experiences and adjust their behavior according to whether these expectations are met.	Koch-Bayram et al. (2023), Moritz and Schmidt (2024)
Model of Social Validity (Schuler & Stehle, 1983)	Information, participation, transparency, and feedback are used to evaluate whether a selection procedure is socially acceptable.	Koch-Bayram et al. (2023)
Organizational Justice Theory (Colquitt, 2001)	Justice comprises distributive, procedural, interpersonal, and informational justice, which impact workplace behavior.	Bankins et al. (2022), Bedemariam and Wessel (2023), Gonzalez et al. (2022), Koch-Bayram et al. (2023), Köchling et al. (2025), Köchling and Wehner (2023), Lavanchy et al. (2023), Moritz and Schmidt (2024), Moritz et al. (2024), Moritz et al. (2025), Nagtegaal (2021), Noble et al. (2021), Oostrom et al. (2024), Schlicker et al. (2021), Zhang and Amos (2024)
Self-Determination Theory (Deci & Ryan, 2012)	Suggests that motivation is driven by the fulfillment of three basic needs: autonomy, competence, and relatedness.	Gonzalez et al. (2022)

Theories	Description/main argument	Articles
Social Exchange Theory (Blau, 1964)	People assess relationships by weighing costs and benefits in exchanges.	Dutta and Mishra (2025), Oostrom et al. (2024)
Social Information Processing Theory (Walther, 2011)	Individuals infer characteristics of other individuals based on implicit and explicit cues.	Suen et al. (2019)
Social Interface Theory (Long, 2003)	Humans interact with computer interfaces similarly to human–human interaction.	Suen and Hung (2023), Suen et al. (2019)
Social Monitoring System (Pickett & Gardner, 2005)	Individuals have a heightened sensitivity to social cues when their belonging is threatened.	Lavanchy et al. (2023)
Stereotype Content Model (Fiske et al., 2002)	Individuals distinguish others according to warmth and competence.	Sondern et al. (2025)
Stereotype Theory (Oakes & Turner, 1986)	Stereotypes are cognitive shortcuts that help individuals categorize people or things.	Pomrehn, Göttel, et al. (2024)
Task-Technology Fit Theory (Furneaux, 2012)	Technology is used effectively when its capabilities match the requirements of the task.	Acikgoz et al. (2024)
Technology Acceptance Model (Davis et al., 1989)	Perceived ease of use and usefulness are the primary factors influencing technology adoption.	Choung et al. (2024), Suen and Hung (2023)
Theory of Planned Behavior (Ajzen, 1991)	Behavioral intention is shaped by an individual's attitude towards the behavior, the influence of social norms, and perceived control.	Mirowska (2020)
Three-Factor Theory of Anthropomorphism (Epley et al., 2007)	Anthropomorphism depends on anthropocentric knowledge, motivation to explain and understand the other agent, and desire for social motivation.	Liu et al. (2023)
Trust in Automation (Lee & See, 2004)	Trust in automation develops over time and impacts human reliance on automated systems.	Lacroux and Martin-Lacroux (2022)
Uncanny Valley Theory (Mori et al., 2012)	People feel discomfort when a digital representation appears almost human, creating a sense of eeriness.	Suen and Hung (2023)
Theories to explain organization-related reactions		
HR Attribution Framework (Nishii et al., 2008)	Suggests that employees' perceptions of HR practices are influenced by the attributions they make about the organization's intentions.	Koch-Bayram and Kaibel (2024)
Signaling Theory (Spence, 1973)	Explains how signals (such as qualifications or organizational practices) convey information in situations of uncertainty.	Acikgoz et al. (2024), Acikgoz et al. (2020), Bedemariam and Wessel (2023), Gonzalez et al. (2022), Keppeler (2023),

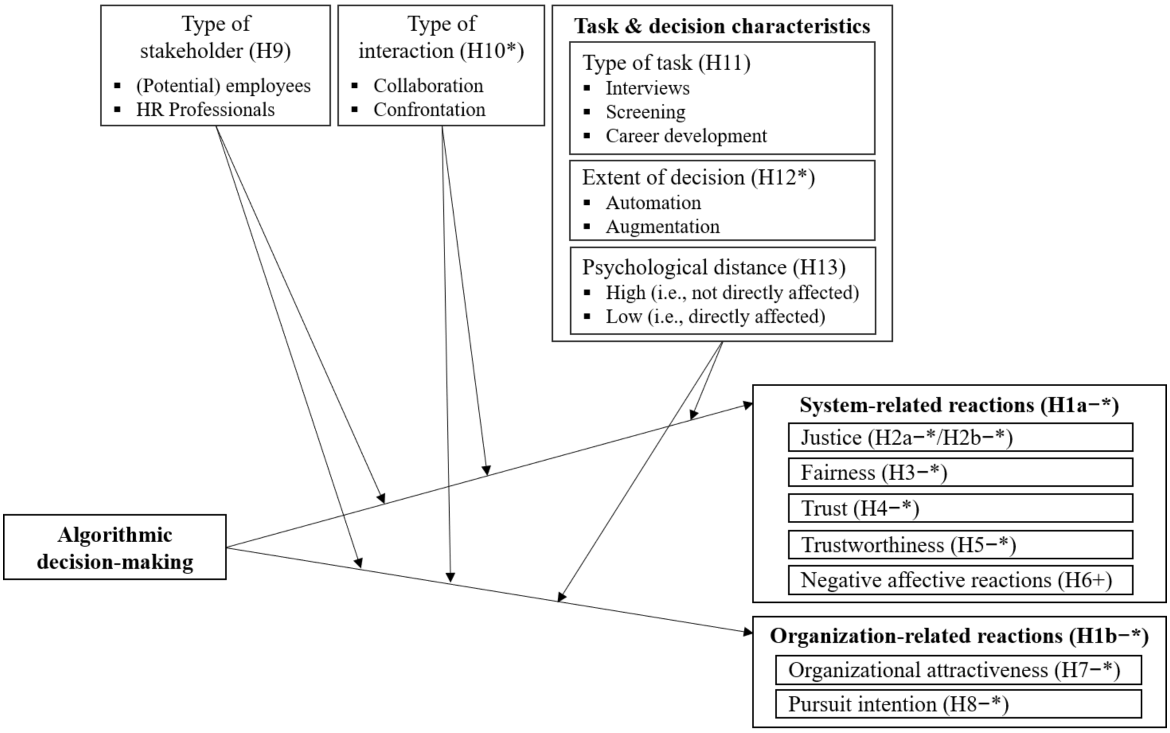
Theories	Description/main argument	Articles
		Koch-Bayram et al. (2023), Koch-Bayram and Kaibel (2024), Köchling et al. (2023), Luo and Zhang (2023), Mirowska (2020), Moritz et al. (2025), Oostrom et al. (2024), Suen and Hung (2023), Yan et al. (2024)
Social Identity Theory (Highhouse et al., 2007)	Proposes that people derive part of their self-concept from their membership in social groups.	Keppeler (2023)

To address the aforementioned gaps, we conducted a meta-analysis of reactions to the use of ADM in the HRM domain. We analyzed 53 studies consisting of 73 individual samples (N = 24,578) published between 2019 and 2025. We offer three main contributions:

First, given the mixed results of previous research, this meta-analysis offers a synthesis of initial findings. We differentiate two reactions to ADM: *System-related reactions* include those reactions directly related to the system used for decision-making (e.g., justice, fairness, trust, trustworthiness, negative affective reactions). *Organization-related reactions* are linked to the respective organization which uses ADM systems (e.g., organizational attractiveness, job pursuit intention). By quantitatively synthesizing prior research on ADM in HRM, we provide the most robust evidence to date on reactions to ADM, thereby contributing to the creation of a new consensus in the field. This is a crucial step towards understanding reactions to ADM due to the inevitable adoption of these systems in organizations, as highlighted by Del Giudice et al. (2023).

Second, we follow the call by Colquitt et al. (2023) to provide evidence about relevant boundary conditions of the effects of ADM in HRM. Thus, the present meta-analysis examines study-specific moderators as boundary conditions, which include type of stakeholder (i.e., applicants, employees, and human resource [HR] professionals), type of interaction (i.e., confrontation vs. collaboration), type of task (i.e., interviews vs. screening applications vs. career development tasks), extent of decisions (i.e., automation vs. augmentation) as well as psychological distance concerning the decision (i.e., being personally affected by the decision vs. others being affected). Figure 2-1 depicts our theoretical framework.

Figure 2-1. Overarching Theoretical Framework and Brief Summary of Results



Note. Algorithmic decision-making is always compared with human decision-making. The corresponding hypotheses are given in parentheses with an asterisk (*) if $p < .05$. For direct effects on system-related and organization-related reactions, we included the proposed positive or negative direction of the hypotheses. H9–H13 include sub-hypotheses for (a) system-related and (b) organization-related reactions; however, for brevity, only the main hypotheses are presented. (Potential) employees include current employees and applicants.

Third, we adopt CASA (Nass & Moon, 2000; Reeves & Nass, 1996) as a meta-theoretical framework to integrate and extend the diverse theories that have been applied in ADM research within HRM. CASA posits that individuals apply social norms and expectations to interactions with technology, including ADM systems, particularly when these systems simulate human characteristics (Gambino et al., 2020; Nass & Moon, 2000). This makes CASA well-suited to serve as a meta-theoretical framework: It allows us to build bridges between theories developed in human–human contexts—such as justice theory (Colquitt, 2001) or the integrative model of organizational trust (Mayer et al., 1995)—and their application in human–algorithm contexts. Table 2-1 illustrates the theoretical heterogeneity in prior ADM research and underscores the lack of synthesis across studies. By situating these constructs within CASA as a meta-theoretical framework, our overarching theoretical framework advances the field by clarifying which types of reactions are most relevant in ADM contexts and by specifying key boundary conditions, such as type of stakeholder or type of task. In doing so, our framework helps reconcile previous theoretical inconsistencies and outlines avenues for future research.

2.2 Current Research, Framework, and Hypotheses Development

2.2.1 Theoretical Framework

Current literature on human–algorithm interaction is scattered, with studies drawing on various theories to explain reactions to ADM use. Table 2-1 illustrates the fragmented use of theories, which gives rise to several challenges. A central challenge lies in the fact that most of the theories and frameworks were originally developed to understand human–human interactions and are now being adapted to the context of ADM. Theories, such as justice theory (Colquitt, 2001; Greenberg, 1987), social exchange theory (Blau, 1964), the integrative model of organizational trust (Mayer et al., 1995), and signaling theory (Spence, 1973), assume interpersonal dynamics, yet are frequently used to understand reactions to ADM (e.g., Feldkamp et al., 2024; Schlicker et al., 2021). Even models intended for human–computer interaction, such as Zhang ’s (2013) affective response model, are rooted in assumptions about emotional and social responses that originate from human–human contexts.

We propose that the CASA framework (Nass & Moon, 2000; Reeves & Nass, 1996) can be used as a meta-theoretical framework to explain the application of theories from human–human contexts to human–algorithm contexts. Here, CASA suggests that individuals perceive a computer as an independent entity, distinct from its programmer, and as possessing its own source of information (Sundar & Nass, 2000). Following this, people respond to technologies as they would to human beings, attributing human-like characteristics to these systems (Gambino et al., 2020), which allows the application of human–human theories in this context. By adopting CASA, we build a bridge between theories from human–human contexts, extend these theories to the ADM field, and offer an overarching theoretical framework for understanding how stakeholders react to ADM in HRM settings (see Figure 2-1). This integration offers a comprehensive theoretical foundation for analyzing how stakeholders perceive and engage with ADM systems in HRM.

2.2.2 System-Related and Organization-Related Reactions

System-related reactions reflect how individuals respond to ADM itself, based on their expectations of human-like behaviors, such as accountability, transparency, and responsiveness. We use system-related reactions as an umbrella term for all reactions relating to the ADM system including justice, fairness, trust, trustworthiness, and affective reactions. All of these specific variables are introduced separately as they offer a theoretical lens (i.e., justice theory, model of applicant reactions to employment selection systems, organizational trust, affective reactions; Colquitt, 2001; Gilliland, 1993; Greenberg, 1987; Leventhal, 1980; Mayer et al., 1995; Zhang, 2013) through which they can be investigated.

As ADM systems grow more interactive, expectations for human-like behaviors increase (Chandra et al., 2022). However, key differences between human–human and human–algorithm interactions remain. While ADM may offer advantages, such as increased objectivity, availability, efficiency, and feedback (Campion & Campion, 2023), it can also lead to unfulfilled social expectations (Glikson & Woolley, 2020). When individuals apply inappropriate norms from human interactions, they may experience negative system-related reactions to ADM, stemming from the system's inability to fully replicate human-like accountability and social responsiveness (Castelo et al., 2019; Zerilli et al., 2019). This gap reflects current limitations in the capacity of ADM systems to meet these expectations.

Beyond system-related reactions, we propose that transferring HRM tasks from humans to ADM can shape *organization-related reactions*. Drawing on signaling theory (Spence, 1973), we argue that ADM use sends observable cues, "signals," about the organization's values, priorities, and work culture to stakeholders such as applicants, employees, and HR professionals. For example, using ADM may signal innovation and efficiency (Van Esch & Black, 2019) or a lack of personal engagement (Bedemariam & Wessel, 2023), impacting how stakeholders view the organization itself. In HRM, humans typically signal aspects of the organization through their behavior and communication. Based on the CASA framework (Nass & Moon, 2000), ADM becomes a "social actor" and thus a representative of the organization. However, algorithms may fail to meet expectations associated with human interaction, such as offering explanations or personal interactions (Gambino et al., 2020; Glikson & Woolley, 2020; Gursoy et al., 2019). This can result in a negative view on the organization, which may manifest in higher turnover intention or decreased organizational attractiveness. These reactions extend beyond the system itself, because ADM is perceived as a proxy for the organization (Acikgoz et al., 2019; Köchling et al., 2025). Thus, signaling theory and CASA jointly explain why ADM may negatively affect both system-related and organization-related reactions. We thus hypothesize:

Hypothesis 1: Compared to human decision-making (HDM), the use of ADM is negatively associated with (a) system-related reactions (e.g., justice, trust) and (b) organization-related reactions (e.g., organizational attractiveness, perceived organizational support).

2.2.2.1 Justice and Fairness

Within the organizational justice literature, justice is characterized as "the degree to which one's company […] is perceived to act consistently, equitably, respectfully, and truthfully in decision contexts” (Colquitt & Rodell, 2015, p. 188). Whereas scholars oftentimes use the terms fairness and justice interchangeably (Beugré, 2009), Goldman and Cropanzano (2015) distinguish between both terms by stating that justice rules precede fairness perceptions. Hence, individuals draw on procedural, interactional (i.e., consisting of interpersonal and informational justice), and distributive justice to determine whether they feel fairly treated (Colquitt, 2001; Cropanzano et al., 2015; Goldman & Cropanzano, 2015).

Justice and fairness play a pivotal role in organizational decision-making, because higher levels of justice and fairness are associated with higher job performance (Cohen-Charash & Spector, 2001). Additionally, individuals are more likely to follow a decision when it is perceived to be fair (Lind, 2001), whereas low levels of justice and fairness are associated with counterproductive work behaviors (Cohen-Charash & Spector, 2001). Unlike HDM, ADM systems lack human intuition and the ability to assess an individual’s social context, a critical factor in shaping perceptions of justice (Köchling et al., 2025; Lee, 2018; Suen et al., 2019). Wiblen and Marler (2021) highlighted that ADM systems may be less effective when addressing subjective factors that cannot be objectively quantified. Thus, drawing on organizational justice theory (Colquitt, 2001), we propose that ADM usage in HRM is associated with lower justice evaluations and hence lower fairness perceptions. Due to inappropriate social expectations (Nass & Moon, 2000), ADM is often viewed as lacking transparency (Suen & Hung, 2023) or being less responsive to individual circumstances (Glikson & Woolley, 2020). When ADM does not meet expectations for transparency (i.e., informational justice), personal and adequate treatment (i.e., interpersonal justice), and consistent procedures (i.e., procedural justice), these limitations together lower perceptions of justice and fairness. We thus hypothesize:

Hypothesis 2*:* Compared to HDM, the use of ADM is negatively associated with (a) overall justice evaluations, (b) interactional justice, and (c) procedural justice.[5]

Hypothesis 3*:* Compared to HDM, the use of ADM is negatively associated with perceived fairness.

2.2.2.2 Trust and Trustworthiness

Trust is defined as the willingness to expose oneself to the actions of another party, driven by the belief that "the other will carry out a specific action of importance to the trusting party, regardless of the ability to observe or control that party" (Mayer et al., 1995, p. 712). Mayer and colleagues (1995) suggest that trustworthiness precedes trust. Trustworthiness refers to the qualities or attributes of the trustee that make them worthy of trust and comprises three factors: ability, benevolence, and integrity (Mayer et al., 1995). Cabiddu et al. (2022) propose that ADM may be perceived as more trustworthy due to higher precision and objectivity, which has been supported by empirical evidence (Logg et al., 2019; Wang & Benbasat, 2016). In the HRM context, however, the use of ADM might be associated with lower perceived trustworthiness and trust compared to HDM due to the nature of tasks and decisions, which are often associated with emotional or social skills, and the perceived lack of high morals and values (i.e., integrity and benevolence; Lacroux & Martin-Lacroux, 2022; Langer et al., 2023). Additionally, Cabiddu et al. (2022) propose that trust in algorithms will develop over time. However, the use of ADM systems in HRM is still rather uncommon, which indicates that individuals might generally have lower trust perceptions. Furthermore, prior research demonstrates ADM is associated with a lack of human warmth (Lee, 2018), responsibility (Binns et al., 2018), and familiarity (Cabiddu et al., 2022), resulting in lower perceived trustworthiness and trust by individuals. We thus hypothesize:

[5] Due to the limited availability of primary studies, we were unable to test for distributive justice.

Hypothesis 4*:* Compared to HDM, the use of ADM is negatively associated with perceived trust.

Hypothesis 5: Compared to HDM, the use of ADM is negatively associated with perceived trustworthiness.

2.2.2.3 Affective Reactions

Extant research focused on emotional or affective responses as consequences of ADM (Köchling et al., 2023; Langer et al., 2019). Based on Zhang's (2013) affective response model, affective responses to technology, such as anxiety or emotional creepiness, arise from (unconscious) evaluation processes. These evaluation processes impact how individuals think about technology and shape their subsequent behavior by prompting specific actions, such as engaging with or avoiding technology, depending on whether the emotions are positive or negative (Zhang, 2013). One of the most common measurements assessing affective responses to ADM is emotional creepiness (Köchling & Wehner, 2023; Langer & König, 2018; Oostrom et al., 2024), referring to the "potentially negative and uncomfortable emotional response paired with perceptions of ambiguity toward a person, technology or even during a situation" (Langer & König, 2018, p. 2). Emotional creepiness oftentimes occurs when individuals experience uncertainty or unpredictability (Langer & König, 2018). As ADM systems are relatively new to the HRM field, stakeholders might experience uncertainty and, hence, exhibit stronger negative affective reactions towards ADM usage. We thus hypothesize:

Hypothesis 6*:* Compared to HDM, the use of ADM is positively associated with negative affective reactions (e.g., emotional creepiness, creepy ambiguity).

2.2.2.4 Organizational Attractiveness and Job Pursuit Intention

Drawing on signaling theory (Spence, 1973), ADM also impacts (potential) employees' and HR professionals' perceptions of the organization, which we operationalize with the most common measurements for organizational reactions within the ADM–HRM field, namely organizational attractiveness and job pursuit intention (Qu et al., 2023). While organizational attractiveness describes the general positive attitude or affect towards an organization reflecting a desire to establish a relationship (Highhouse et al., 2003), job pursuit intention describes the "intention to pursue a job or to remain in the applicant pool" (Chapman et al., 2005, p. 929). When organizations use ADM systems for recruitment and selection processes, such as using asynchronous video interviews evaluated by ADM systems, applicants may interpret this as a signal of what it is like to work for the potential employer or how the organization will treat them in the future. Here, individuals may perceive the company as modern, data-driven, and efficient. Conversely, individuals could perceive this as an indication of being treated impersonally (Hunkenschroer & Luetge, 2022; Lee, 2018), a violation of reciprocity norms (Oostrom et al., 2024), and a signal of an organizational culture that devalues personal contact (Mirowska & Mesnet, 2022). The direction of reactions (i.e., either positive or negative) ultimately impacts organizational attractiveness and job pursuit intention, as individuals use observable signals (i.e., such as ADM usage) to infer unobservable information about the potential employer.

Drawing on CASA, we suggest that reactions to ADM are more negative than those of HDM, as individuals may sense an absence of interpersonal interaction and reasoning (Binns et al., 2018), potentially leading to feelings of dehumanization (Bankins et al., 2022). For current employees and HR professionals, the use of ADM for career development (Köchling et al., 2025) or performance measurements (Zhang & Amos, 2024) introduces novel work dynamics. This shift may evoke a sense of continuous electronic surveillance, dehumanization, or the assumption that evaluations by algorithms might be disadvantageous (Bankins et al., 2022). We thus hypothesize:

Hypothesis 7: Compared to HDM, the use of ADM is negatively associated with organizational attractiveness.

Hypothesis 8: Compared to HDM, the use of ADM is negatively associated with job pursuit intention.

2.2.3 Boundary Conditions Affecting Reactions to ADM

Following our meta-theoretical framework based on CASA (Nass & Moon, 2000), we propose that the relationship between ADM usage and reactions is impacted by boundary conditions. Based on theories and findings from human–human and human–algorithm contexts, we differentiate between type of stakeholder (Langer & Landers, 2021), type of interaction (Burton et al., 2020), as well as task and decision characteristics (i.e., type of task, extent of decision, psychological distance; Deci & Ryan, 2012; Höddinghaus et al., 2021; Lee, 2018).[6]

2.2.3.1 Type of Stakeholder

We propose that ADM usage involves different *types of stakeholders* (i.e., HR professionals, line managers, and [potential and/or current] employees; adapted from the HR triad; Jackson & Schuler, 2003) in the HRM context. The HR triad emphasizes the shared responsibility of the involved stakeholders: HR professionals offer HR expertise (e.g., training, bonus payments, and promotions; Budhwar et al., 2022), line managers implement HR practices, and current employees actively participate in shaping their own development. We also include potential employees (i.e., applicants from the labor market and current employees applying for internal positions), because they represent key stakeholders who are directly affected by ADM decisions but have limited influence over them.

In accordance with self-determination theory (Deci & Ryan, 2012), which posits that individuals are motivated to grow when their basic psychological needs for autonomy,

[6] We acknowledge that it was not possible to include all boundary conditions identified in the literature. Instead, we focused on those conditions that could be empirically tested based on the available primary studies.

competence, and relatedness are fulfilled, we argue that competence is an important factor in differentiating stakeholder reactions to ADM. In particular, HR professionals may fulfill their need for competence by learning new skills and overcoming challenges when using ADM systems over time compared to (potential) employees who are more interested in shaping their own development (Deepa et al., 2024). This aligns with the differentiation of stakeholders related to the HR triad and the classification into *first, second,* and *third parties* by Langer and Landers (2021), which highlights that stakeholders have distinct roles and levels of involvement in HRM. Here, first parties use ADM to make decisions affecting others (i.e., HR professionals), second parties are directly impacted by ADM (i.e., applicants, employees), and third parties observe ADM use and may be indirectly affected in the near future (Langer & Landers, 2021). Therefore, HR professionals can use ADM to enhance decision-making and support daily tasks, whereas employees and applicants (i.e., which are focused on personal outcomes) may feel more threatened by ADM, as its (lack of) communication may fail to meet expectations compared to human interaction. Specifically, in hiring, HR professionals may value ADM for its efficiency in screening applicants, whereas applicants might perceive automated decisions as impersonal or unfair. We thus hypothesize:

Hypothesis 9: Type of stakeholder moderates the relationship between the use of ADM and (a) system-related reactions and (b) organization-related reactions, such that negative reactions to ADM usage are stronger for (potential) employees than for HR professionals.[7]

2.2.3.2 Type of Interaction

Our framework distinguishes stakeholders' *type of interaction*, and we categorize this as confrontation or collaboration. Confrontation refers to a type of interaction in which individuals are subjected to decisions made by ADM systems without any opportunity to

[7] We were not able to include line managers here as none of the primary studies included line managers as a stakeholder group.

provide input (e.g., applicants receiving a hiring decision). Collaboration means that stakeholders are actively involved in decision-making (e.g., HR professionals using ADM insights; Daugherty & Wilson, 2018). Following our distinction, the same task, for example, automated CV screening, can involve both collaboration and confrontation, depending on the individuals' perspective. In our example, HR professionals could use automated CV screening to decide who to invite for an interview (i.e., collaboration), whereas applicants may be rejected by ADM based on CV screening (i.e., confrontation). When individuals are confronted with ADM, they may perceive a lack of agency or control over the process, which can increase negative reactions such as lower trust, frustration, or feelings of unfairness (Burton et al., 2020). In contrast, collaborating with ADM systems allows individuals to retain a sense of control and agency, as they are actively involved in the decision-making process (Langer et al., 2025). This interaction can foster trust and acceptance, as the ADM system is perceived as a tool that enhances, rather than replaces, human judgment (Burton et al., 2020). We thus hypothesize:

Hypothesis 10: Type of interaction moderates the relationship between the use of ADM and (a) system-related reactions and (b) organization-related reactions, such that negative reactions are stronger when individuals are confronted with ADM than when they collaborate with it.

2.2.3.3 Type of Task

We argue that tasks that require tacit knowledge or social skills, such as interviews or career development, could be perceived as less suitable for ADM and are likely to evoke more negative reactions compared to mechanical tasks, such as resume screening or work scheduling (Castelo et al., 2019; Lee, 2018). Following the cognitive psychology and human factors literature, it is generally assumed that certain skills or types of knowledge, such as procedural and tacit knowledge, are not suitable for programming in computer programming languages (Lee, 2018; Reber, 1989). These types of knowledge and respective skills are typically acquired through experiences and practices, encompassing intuitive judgments and the understanding of emotions (Lee, 2018). Consequently, ADM is often considered more appropriate for tasks that are structured, quantifiable, and less dependent on human judgment, such as resume screening or data analysis, where standardized processes are prioritized over interpersonal interaction (Lee, 2018). We thus hypothesize:

Hypothesis 11: Type of task (interviews, screening, and career development) moderates the relationship between the use of ADM and (a) system-related reactions and (b) organization-related reactions, such that negative reactions to ADM usage are stronger when it is used for interviews and career development compared to screening.

2.2.3.4 Extent of Decision

Extent of decision comprises whether ADM automates or augments human decisions (Langer & Landers, 2021). Here, researchers differentiate between ADM systems that autonomously make decisions without human involvement (i.e., automation), and those that serve as decision support, namely augmentation (Candrian & Scherer, 2022). ADM systems that fully automate decisions may evoke more negative responses (e.g., reduced justice or trust) due to a perceived loss of autonomy (Deci & Ryan, 2012). In contrast, using ADM for decision support—where human intervention is possible—may result in less negative reactions (e.g., higher perceptions of justice or trust), because individuals perceive that a human retains control over final decisions (Burton et al., 2020). We thus hypothesize:

Hypothesis 12: Extent of decision moderates the relationship between the use of ADM and (a) system-related reactions and (b) organization-related reactions, such that negative reactions to ADM usage are stronger when it is used for automation compared to augmentation.

2.2.3.5 Level of Psychological Distance

We argue that the *level of psychological distance* can affect stakeholders' reactions to ADM. When individuals are directly affected by ADM decisions (e.g., applicants, second parties), they may experience stronger negative reactions due to a perceived loss of control by themselves or humans (Langer & Landers, 2021). These individuals might feel psychologically closer to the situation as the outcomes of the decisions affect their lives directly in the long run (e.g., getting a job or being laid off; Langer et al., 2019; Trope & Liberman, 2010). In such contexts, individuals may evaluate the introduction of ADM more critically as the decision process becomes more salient due to its potential impact on their lives. In contrast, individuals who use ADM in the decision-making process (e.g., HR professionals; first parties) may respond less negatively, because they feel less personally connected to ADM and are less likely to be significantly impacted by its outcomes (Deci & Ryan, 2012; Trope & Liberman, 2010). In turn, reactions from less affected stakeholders could be more positive as they include a broader, rather distant decision rationale. We thus hypothesize:

Hypothesis 13: Level of psychological distance moderates the relationship between the use of ADM and (a) system-related reactions and (b) organization-related reactions, such that negative reactions are stronger when psychological distance is low compared to when it is high.

2.3 Method

2.3.1 Literature Search and Data Extraction

We conducted a literature search of articles published between January 2010 and March 2025. The search process consisted of four steps drawn from the PRISMA protocol (preferred reporting items for systematic reviews and meta-analyses; Liberati et al., 2009; Page et al., 2021): identification, screening, eligibility, and inclusion. A flow diagram of the search process is provided in Appendix A1 and an overview of included studies is provided in Appendix A2.

As the first step (i.e., identification), the sample collection was based on two complementary search strategies (i.e., database search and manual search). We used two databases for our initial search, specifically, EBSCO Business Source Premier and Web of Science (Social Sciences Citation Index). We applied search terms used in previous studies (Hunkenschroer & Luetge, 2022; Köchling & Wehner, 2020) and extended these by adding additional synonyms. We searched for articles by applying the following combination of search terms: “algorithm,” “artificial intelligence,” or “algorithmic decision,” potential reactions, such as “fairness” or “trust,” and our context “human resources” or “HRM,” whereas we extended all search words with further terms and synonyms (i.e., fairness was extended by justice terms).

The initial search resulted in 8,790 studies. After eliminating duplicates, we kept 8,107 unique studies for further evaluation. Additionally, following the approach by Ravid et al. (2023), we applied an issue-by-issue search of journals and conference proceedings,[8] resulting in 34 additional articles for initial screening. We identified relevant journals by using the FT50 ranking and by using those journals most frequently represented in the initial database search. Further, we compared our findings with samples from recently published reviews (Bankins et al., 2024; Basu et al., 2023; Budhwar et al., 2022; Cheng & Hackett, 2019; Giermindl et al., 2022; Kaushal et al., 2023; Köchling & Wehner, 2020; Pan & Froese, 2023; Votto et al., 2021; Vrontis et al., 2022) on the topic of ADM use in organizations. We identified one article from this step of the search process. Discrepancies between our meta-

[8] Academy of Management Journal, Academy of Management Proceedings, Big Data and Society, Computers in Human Behavior, Human Resource Management, Information Systems Frontiers, Information Systems Research, International Journal of Selection and Assessment, Journal of Applied Psychology, Journal of Business Ethics, Journal of Management, Journal of Management Information Systems, Journal of Management Studies, Management Information Systems Quarterly, Management Science, Organizational Behavior and Human Decision Processes, Personnel Psychology, Research Policy, Technovation.

analysis and the reviews were often due to the methods used in the primary studies (e.g., qualitative approaches), but more importantly, they resulted from differences in the context, as our analysis focused specifically on the HRM context. As an additional step, we used AI-based tools, such as Connectedpapers, ResearchRabbit, and Litmaps, to identify other articles that would fit our inclusion criteria. However, no additional articles were identified through this process. We contacted authors of papers already included for additional published and unpublished articles, resulting in 15 additional articles. To complement our manual search, we conducted a forward search for articles (i.e., screening articles that cited the articles included in the analysis), resulting in three additional articles.

In the second step (i.e., screening), two of the authors independently examined titles, key words, and abstracts of the identified studies and excluded all studies that did not fit into the scope of the meta-analysis (i.e., studies not focused on HRM). Here, we used the tool Rayyan (Ouzzani et al., 2016). While we did not use Rayyan's automation features, we did use it to conduct blinded and independent screening. Consistent with previous meta-analyses, we calculated intercoder agreement as a measurement for reliability (Ravid et al., 2023). Initial intercoder agreement was 99.42%, corresponding to 47 disagreements among 8,107 articles. The authors discussed and resolved all disagreements collaboratively.

For the third and fourth step (i.e., eligibility and inclusion), two authors examined the full text of the studies according to our a priori inclusion criteria: Included publications should report (a) at least one quantitative study, (b) the reaction to ADM in comparison to HDM, and (c) at least one correlation coefficient between the use of ADM and system-related reactions (e.g., fairness, emotional creepiness) or organization-related reactions (e.g., organizational attractiveness, litigation intention, turnover intention). For this step, we read 84 full-text articles stemming from the initial database search and 53 articles stemming from our manual search. The most common reason for article exclusion was that the studies did not compare HDM to ADM but rather compared different ADM systems or assessed general ADM reactions (e.g., Edwards et al., 2024). When studies fit our inclusion criteria but did not report the data needed, we contacted authors to ask for further information. Studies were excluded if the authors did not respond or were unable to provide the requested data. Our final dataset consists of 53 studies and 73 samples (*N* = 24,578; 52.97% female, mean age = 34.32 years).

2.3.2 Included Studies

As we required studies to compare ADM to HDM for the analysis, most of the included studies used an experimental approach (except for Dutta & Mishra, 2025; Keppeler, 2023; Suen & Hung, 2023, who all employed field experiments). Typically, participants in the experimental group were presented with a scenario—such as a job application—in which an ADM-based system made a decision (e.g., regarding their hiring). Participants in the control group were presented the same scenario with one difference: The decision was made by a human entity (e.g., a HR professional). Consequently, the studies measured differences between the two groups in their reactions to the scenario. The effect sizes coded in each study reflected the mean differences. We coded the correlation coefficient, such that the treatment (i.e., ADM) group was coded as 1 and the control (i.e., HDM) group was coded as 0 (HDM = 0, ADM = 1). A positive correlation coefficient indicated a higher mean in the outcome variable for the ADM group versus the HDM group. We were not able to apply Cohen's *d*, an effect size measure traditionally used in meta-analyses, as most of the primary studies did not provide sufficient information (e.g., missing information on standard deviations or group sizes).

2.3.3 Aggregation Levels and Coding

To address the heterogeneity of primary studies (Steel et al., 2021), we analyzed different aggregation levels of the dependent variables. First, we aggregated all variables subsumed under the *main relationship* (i.e., including both system-related and organization-related constructs). Second, we grouped the effect sizes in two broad aggregates of system-related and organization-related variables to understand and to address differences between both types of reactions. Third, we grouped the effect sizes according to the specific constructs, namely *justice, fairness, trust, trustworthiness, negative affective reactions, organizational attractiveness,* and *job pursuit intention*. For justice, we were able to further differentiate between *procedural* and *interactional justice*. Two of the authors independently coded the 365 effect sizes of the first model according to the guidelines by Steel et al. (2021). We calculated the intercoder agreement, which was 96.44% (13 disagreements) for all coded relationships. All disagreements were resolved through discussions.

2.3.4 Coding of Reactions and Moderators

System-related reactions comprise all constructs that refer to reactions directly linked to the system used for decision-making, such as perceived fairness or justice. For organization-related reactions, we grouped the effect sizes of variables that were related to organizational parameters. To identify the respective correlations, we examined the research model and the descriptions of the variables in the studies. In addition to the effect sizes reported in the primary studies, we included study-level moderators. We used information on *stakeholders* targeted in the respective primary study, *type of interaction* and *type of task*, *extent of decision*, and *psychological distance*. Here, we report on the first two levels of aggregation (i.e., main relationships, system-related reactions, and organization-related reactions) because the lowest aggregation level separated into specific constructs (e.g., justice, fairness) did not allow meaningful investigation due to the low number of available samples.

2.3.5 Analytical Procedure

To address multiple correlation coefficients per study and the inherent dependability of effect sizes, we used three-level random and mixed effects models (Assink & Wibbelink, 2016; Cheung, 2019). A three-level model analysis has the advantage over a two-level random effect model to add a third variance component to understand the differences in correlation coefficients within the respective studies (Assink & Wibbelink, 2016; Hox et al., 2017). Furthermore, this model acknowledges that the multiple correlation coefficients are nested (within each primary study) and not statistically independent. Three-level models can be used to create averages per study and—in contrast—enable the investigation of the extent of heterogeneity within (and between) studies, while addressing nonindependence. The random effects model is a simplified version of a regression model without predictors:

$$y_{ij} = \beta_0 + u(2)_{ij} + u(3)_j + \varepsilon_{ij}$$

with y_{ij} representing the correlation coefficient i in study j that, in our case, is the relationship between the use of ADM and system-related or organization-related reactions. The intercept β_0 reflects the weighted correlation coefficient, $Var(u(2)_{ij}) = \tau^2(2)$ reflects the true within-study variance, $Var(u(3)_j) = \tau^2(3)$ represents the true between-study variance, and $Var(\varepsilon_{ij})$ reflects random sampling error. Following Aguinis et al.'s (2011) recommendations, we report the square root of the two tau-squares, representing an estimate of the "true" (i.e., nonrandom) heterogeneity in the form of an easily interpretable standard deviation of the effect size. We refer to the within-study heterogeneity as τ_w and to the between-study heterogeneity as τ_b.

When analyzing moderators (i.e., type of stakeholder, type of interaction, type of task, extent of decision, psychological distance), the model is expanded to a mixed effects regression model by including these as predictors, potentially allowing the prediction of portions of the between-study or within-study variance. In this model, one or several predictors, x_j, are added. When analyzing categorical moderators (e.g., type of task), we used dummy coding. For these categorical moderators, we estimated the model as a mixed effects model, excluding the intercept β_0. As a result, the reported coefficients of the model represent the weighted average in each category of the moderator depicted by $\hat{\rho}$. To investigate differences across levels of the moderator, we report the result of an omnibus χ^2-test (i.e., the Q_M test), which assesses whether significant differences exist in the average effect sizes across the levels of the moderator, thereby indicating whether the moderator explains variability in the respective effect size. A significant Q_M value suggests that the moderator contributes to differences in the observed relationships. For this test, the selection of the reference category (determined by the first alphabetical occurrence) is inconsequential, as the test examines differences across all included categories collectively. The analyses were conducted with the open-source software R (R Core Team, 2025). Packages used were tidyverse (Wickham et al., 2019) for data management, and metaphor (Viechtbauer, 2010) and metaSEM (Cheung, 2019) for the meta-analytical procedures.

2.4 Results

2.4.1 Main Relationships between ADM and Reactions

Table 2-2 presents the results for the bivariate correlation analysis of the main effects. Regarding the main relationship, findings reveal that ADM was perceived negatively, including system-related and organization-related reactions ($\hat{\rho}$ = −.13, p < .001). In addition, ADM was negatively related to system-related reactions ($\hat{\rho}$ = −.12, p < .001), including justice ($\hat{\rho}$ = −.17, p < .001), and more specifically, also to procedural ($\hat{\rho}$ = −.14, p < .001) and interactional justice ($\hat{\rho}$ = −.21, p < .001), fairness ($\hat{\rho}$ = −.13, p = .002), trust ($\hat{\rho}$ = −.20, p < .001), and trustworthiness ($\hat{\rho}$ = −.13, p = .033). We found no significant relationship between ADM and negative affective reactions ($\hat{\rho}$ = .08, p = .099).

Table 2-2. Results of the Bivariate Meta-Analysis

Dependent variable	k	m	N	$\hat{\rho}$	SE	p-value	95% CI		τ_w (I^2_w)	τ_b (I^2_b)	Publication bias	Outlier
Main relationship	73	365	24,578	−.13***	.02	< .001	−.16	−.09	.19 (.66)	.13 (.30)	No	Yes (Corr. $\hat{\rho}$ = −.14, p < .001)
System-related reactions	69	286	23,601	−.12***	.02	< .001	−.16	−.08	.22 (.75)	.12 (.21)	No	Yes (Corr. $\hat{\rho}$ = −.13, p < .001)
Justice	29	88	7,015	−.17***	.03	< .001	−.23	−.10	.16 (.57)	.13 (.36)	Yes (Corr. $\hat{\rho}$ = −.15, p < .001)	Yes (Corr. $\hat{\rho}$ = −.14, p < .001)
Procedural justice	26	61	6,191	−.14***	.03	< .001	−.20	−.07	.16 (.58)	.12 (.34)	Yes (Corr. $\hat{\rho}$ = −.11, p < .001)	No
Interactional justice	12	23	2,993	−.21***	.05	< .001	−.32	−.11	.15 (.51)	.14 (.42)	No	No
Fairness	33	40	14,109	−.13**	.04	.002	−.21	−.05	.16 (.44)	.17 (.52)	No	No
Trust	21	28	5,619	−.20***	.06	< .001	−.31	−.09	.15 (.35)	.20 (.60)	No	No
Trustworthiness	5	16	1,069	−.13*	.06	.033	−.25	−.01	.15 (.68)	.08 (.21)	No	No
Neg. affective reactions	16	38	6,811	.08	.05	.099	−.02	.18	.06 (.09)	.20 (.86)	No	Yes (Corr. $\hat{\rho}$ = .12, p < .001)
Organization-related reactions	34	79	11,230	−.15***	.02	< .001	−.19	−.10	.04 (.06)	.13 (.79)	No	No
Organizational attractiveness	22	39	5,572	−.16***	.03	< .001	−.22	−.11	.06 (.20)	.11 (.59)	No	No
Pursuit intention	10	20	2,813	−.12**	.04	.003	−.20	−.04	.07 (.26)	.10 (.56)	No	No

Note. *** p < .001, ** p < .01, * p < .05; k = number of independent samples; m = number of effect sizes; N = number of analyzed individuals; $\hat{\rho}$ = weighted average effect size; SE = standard error; CI = confidence interval (lower and upper bound of a 95% CI given); τ_w and τ_b = estimate (standard deviation) of the true heterogeneity within and between studies; I^2_w and I^2_b = percentage of true heterogeneity in observed heterogeneity; Corr. = corrected; Neg. = negative. Whenever the estimate is zero, the random effects model was reduced to a fixed effects model. Independent variable is HDM versus ADM for all relationships (HDM = 0, ADM = 1).

Overall, our results supported hypotheses 1a and 2 to 5, demonstrating a negative relationship between ADM and system-related reactions, justice, fairness, trust, and trustworthiness, but did not support hypothesis 6 related to negative affective reactions. Further, we found that ADM was negatively related to organization-related reactions ($\hat{\rho}$ = −.15, p < .001), including organizational attractiveness ($\hat{\rho}$ = −.16, p < .001) and job pursuit intention ($\hat{\rho}$ = −.12, p = .003), supporting hypotheses 1b, 7, and 8.

2.4.2 Moderator Analysis

2.4.2.1 Type of Stakeholder and Type of Interaction

Results of the moderator analysis for type of stakeholder and type of interaction are reported in Table 2-3. For type of stakeholder, we found a significant relationship between ADM on the main relationship for applicants ($\hat{\rho}$ = −.14, p < .001) and employees ($\hat{\rho}$ = −.13, p < .001), but not for HR professionals ($\hat{\rho}$ = −.07, p = .222). Similarly, on the level of system-related reactions, we found significant effects for applicants ($\hat{\rho}$ = −.12, p < .001) and employees ($\hat{\rho}$ = −.13, p < .001), but not for HR professionals ($\hat{\rho}$ = −.08, p = .207). Results showed a significant relationship between ADM and organization-related reactions for applicants ($\hat{\rho}$ = −.17, p < .001) and for employees ($\hat{\rho}$ = −.10, p = .012), but not for HR professionals ($\hat{\rho}$ = −.19, p = .196). The difference tests showed no significant differences for all aggregation levels; hence, we cannot confirm our hypothesis 9. For type of interaction, results indicated that on the main relationship, confrontation has significant effects ($\hat{\rho}$ = −.14, p < .001) compared to collaboration ($\hat{\rho}$ = −.04, p = .417). A similar pattern emerges for system-related reactions (collaboration: $\hat{\rho}$ = −.04, p = .360; confrontation: $\hat{\rho}$ = −.13, p < .001) and organization-related reactions (collaboration: $\hat{\rho}$ = −.02, p = .881; confrontation: $\hat{\rho}$ = −.16, p < .001). The difference tests indicated significant differences on the main relationship ($\chi^2(1)$ = 4.64, p = .030), but not on the level of system-related or organization-related reactions, leading us to reject our hypothesis 10.

Table 2-3. Results of the Bivariate Meta-Analysis Including Type of Stakeholder and Type of Interaction as Moderators

Dependent variable	*k*	*m*	*N*	$\hat{\rho}$	*SE*	*p*-value	95% *CI*		$Q_M(df)$
Main relationship									
Type of stakeholder									$\chi^2(2) = 0.84$, $p = .660$
Applicants	42	254	11,521	$-.14^{***}$	.03	< .001	−.18	−.09	
Employees	22	91	7,736	$-.13^{***}$	.04	< .001	−.20	−.05	
HR profession.	9	29	5,321	−.07	.06	.222	−.19	.04	
Type of interaction									$\chi^2(1) = 4.64^{*}$, $p = .030$
Collaboration	14	63	7,405	−.04	.04	.417	−.12	.05	
Confrontation	55	294	16,432	$-.14^{***}$	.02	< .001	−.18	−.10	
System-related reactions									
Type of stakeholder									$\chi^2(2) = 0.50$, $p = .780$
Applicants	39	183	10,736	$-.12^{***}$	.03	< .001	−.17	−.07	
Employees	21	75	7,544	$-.13^{***}$	.04	< .001	−.20	−.05	
HR profession.	9	28	5,321	−.08	.06	.207	−.20	.04	
Type of interaction									$\chi^2(1) = 3.28$, $p = .070$
Collaboration	14	61	7,405	−.04	.04	.360	−.13	.05	
Confrontation	51	219	15,455	$-.13^{***}$	.02	< .001	−.17	−.08	
Organization-related reactions									
Type of stakeholder									$\chi^2(2) = 2.18$, $p = .340$
Applicants	21	62	5,495	$-.17^{***}$	.03	< .001	−.23	−.12	
Employees	12	16	5,530	$-.10^{*}$	.04	.012	−.18	−.02	
HR profession.	1	1	205	−.19	.15	.196	−.48	.10	
Type of interaction									$\chi^2(1) = 2.10$, $p = .150$
Collaboration	2	2	1,384	−.02	.10	.881	−.21	.18	
Confrontation	31	75	9,430	$-.16^{***}$	.02	< .001	−.21	−.11	

Note. *** $p < .001$, ** $p < .01$, * $p < .05$; k = number of independent samples, m = number of effect sizes, N = number of analyzed individuals; profession. = professionals; $\hat{\rho}$ = weighted average effect size; *SE* = standard error; *CI* = confidence interval (lower and upper bound of a 95% CI given). Differences were tested with a Q_M test, which is a χ^2-test with the depicted degrees of freedom. Independent variable is HDM versus ADM for all relationships (HDM = 0, ADM = 1).

2.4.2.2 Type of Task, Extent of Decision, and Psychological Distance

Table 2-4 summarizes the findings of the moderator analysis for type of task, extent of decision, and psychological distance. Regarding the type of task on the main relationship, ADM was perceived negatively in interviews ($\hat{\rho} = -.17$, $p < .001$), screening ($\hat{\rho} = -.15$, $p <$

.001), and career development ($\hat{\rho}$ = −.18, p < .001). Similarly, for system-related reactions, results indicated that ADM in interviews ($\hat{\rho}$ = −.15, p < .001), screening ($\hat{\rho}$ = −.14, p = .002), and career development ($\hat{\rho}$ = −.18, p < .001) was perceived negatively. In terms of organization-related reactions, we could not confirm this relationship for career development ($\hat{\rho}$ = −.11, p = .116), compared to interviews ($\hat{\rho}$ = −.26, p < .001) and screening ($\hat{\rho}$ = −.16, p = .004). The difference tests were not significant; therefore, we reject our hypothesis 11.

For the extent of the decision, we found a significant relationship between ADM on the main relationship when decisions were automated ($\hat{\rho}$ = −.16, p < .001) compared to when decisions where augmented ($\hat{\rho}$ = −.04, p = .220). On the level of system-related reactions, we found associations between ADM and automation ($\hat{\rho}$ = −.16, p < .001), but not between ADM and augmentation ($\hat{\rho}$ = −.04, p = .217). Regarding organization-related reactions, the relationships between ADM and automation ($\hat{\rho}$ = −.13, p < .001) as well as between ADM and augmentation ($\hat{\rho}$ = −.16, p < .001) were significant. Our results revealed significant differences for the main relationship and system-related reactions, but not for organization-related reactions, thereby confirming H12a and rejecting H12b.

Table 2-4. Results of the Bivariate Meta-Analysis Including Type of Task, Extent of Decision, and Psychological Distance as Moderators

Dependent variable	***k***	***m***	***N***	$\hat{\rho}$	***SE***	***p*-value**	**95% *CI***		$Q_M(df)$
Main relationship									
Type of task									$\chi^2(3) = 3.78$, $p = .290$
Interviews	18	86	3,317	−.17***	.04	< .001	−.24	−.09	
Screening	18	64	8,006	−.15***	.04	< .001	−.23	−.07	
Career development	8	34	3,111	−.18***	.05	< .001	−.28	−.07	
Extent of decision									$\chi^2(2) = 7.13^*$, $p = .030$
Automation	48	201	17,276	−.16***	.02	< .001	−.21	−.11	
Augmentation	21	137	6,171	−.04	.04	.220	−.11	.03	
Psychological distance									$\chi^2(1) = 0.85$, $p = .360$
Low distance	55	299	17,473	−.14***	.02	< .001	−.18	−.09	
High distance	18	66	7,105	−.10*	.04	.029	−.17	−.01	
System-related reactions									
Type of task									$\chi^2(3) = 4.00$, $p = .260$
Interviews	17	71	3,133	−.15***	.04	< .001	−.22	−.07	
Screening	16	46	7,405	−.14**	.04	< .001	−.22	−.05	
Career development	8	28	3,111	−.18***	.06	< .001	−.29	−.07	
Extent of decision									$\chi^2(2) = 6.88^*$, $p = .030$
Automation	44	164	16,299	−.16***	.03	< .001	−.21	−.11	
Augmentation	20	104	6,270	−.04	.03	.217	−.11	.03	
Psychological distance									$\chi^2(1) = 2.30$, $p = .130$
Low distance	53	228	16,947	−.13***	.02	< .001	−.18	−.09	
High distance	16	58	6,654	−.06	.04	.182	−.14	.03	
Organization-related reactions									
Type of task									$\chi^2(3) = 4.46$, $p = .220$
Interviews	7	15	1,735	−.26***	.05	< .001	−.36	−.16	
Screening	6	18	1,532	−.16**	.06	.004	−.27	−.05	
Career development	4	6	2,146	−.11	.07	.116	−.24	.03	
Extent of decision									$\chi^2(2) = 0.53$, $p = .770$
Automation	19	37	6,579	−.13***	.03	< .001	−.20	−.07	
Augmentation	11	33	3,742	−.16***	.04	< .001	−.24	−.08	
Psychological distance									$\chi^2(1) = 2.69$, $p = .100$
Low distance	30	71	10,368	−.13***	.02	< .001	−.18	−.09	
High distance	4	8	862	−.26***	.07	< .001	−.39	−.12	

Note. *** $p < .001$, ** $p < .01$, * $p < .05$; k = number of independent samples, m = number of effect sizes, N = number of analyzed individuals; $\hat{\rho}$ = weighted average effect size; *SE* = standard error; *CI* = confidence interval (lower and upper bound of a 95% CI given). Differences were tested with a Q_M test, which is a χ^2-test with the depicted degrees of freedom. Independent variable is HDM versus ADM for all relationships (HDM = 0, ADM = 1).

For the level of psychological distance, our results indicated that ADM was perceived negatively in low psychological distance ($\hat{\rho}$ = −.14, p < .001) and high psychological distance scenarios ($\hat{\rho}$ = −.09, p = .029) on the main relationship. Regarding system-related reactions, ADM was significantly related to low psychological distance ($\hat{\rho}$ = −.13, p < .001), but not to high psychological distance ($\hat{\rho}$ = −.06, p = .182). In terms of organization-related reactions, we found significant associations between ADM and low distance ($\hat{\rho}$ = −.13, p < .001) as well as between ADM and high distance ($\hat{\rho}$ = −.26, p < .001). The difference tests suggested that there are no significant differences between low or high levels of psychological distance, leading us to reject hypothesis 13.

2.4.3 Robustness Checks and Assessment of Study Quality

To ensure robustness of our results, we tested for outliers and publication bias. For the outlier analysis, we combined the studentized residuals and Cook's distance to analyze if outliers with a high leverage were present in the sample (Viechtbauer & Cheung, 2010). When this was the case, the three-level model was re-estimated without the outlier, and the resulting correlation coefficient and significance level are reported in Table 2-2. Additionally, we analyzed publication bias by testing for funnel plot asymmetry by Egger et al. (1997) and by conducting the rank test by Begg and Mazumdar (1994). If both tests showed significance, we acknowledged the presence of publication bias. Similarly to the outlier test, we used the trim-and-fill procedure and estimated a corrected correlation coefficient (see Table 2-2). In summary, we found several instances of publication bias and outliers, but these had no impact on the results' significance or the study's implications.

Furthermore, as a robustness check, we incorporated mean age (conceptualized by the mean age of the participants in the study) and gender (conceptualized by the percentage of female participants in the studies) in our bivariate meta-analysis to check for potential effects. For the main relationship and the levels of system-related as well as organization-related reactions, our results revealed no significant difference effects for mean age and gender. In addition, we controlled for the terminology used in the scenarios regarding the automated decision entity (i.e., AI, algorithm, automation). These results indicated that there were no significant differences in reactions to the three terms across all aggregation levels. We introduced the experimental approach (between vs. within designs) as a robustness check, and again found no differences at any level of aggregation. Additionally, we used country of origin as a robustness check. We operationalized country of origin based on the country specified in the sample description. We found no significant differences for the main relationship and system-related reactions. However, we did find significant differences between countries for organization-related reactions ($\chi^2(2) = 8.98$, $p = .010$) with positive reactions in India ($\hat{\rho} = .13$, $p = .276$) compared to Germany ($\hat{\rho} = -.14$, $p < .001$) and the U.S. ($\hat{\rho} = -.21$, $p < .001$).

In addition, we controlled for study quality by analyzing both the journal quality as well as the differences between study approaches (true experiments vs. quasi-experiments) according to PRISMA guidelines (Page et al., 2021). Journal quality was assessed using the Scientific Journal Ranking (SJR) from 2023. No significant differences were found between higher ranked versus lower ranked journals neither for the main relationship nor for the division into system-related and organization-related reactions. In terms of the differences of the study approaches, two authors engaged in coding whether the included studies randomized (or reported on randomizing) the allocation of participants to scenarios. Results indicated that randomized or nonrandomized approaches did not differ significantly in terms of the main relationship and on the level of system-related reactions. However, a significant difference emerged at the level of organization-related reactions, as confirmed by the difference test, indicating that careful interpretation of organization-related reactions is needed.

2.5 Discussion

To advance the understanding of reactions to ADM usage in the HRM domain, we conducted a meta-analysis on system-related and organization-related reactions and their boundary conditions. Overall, we found significant negative reactions towards ADM use in general, and particularly regarding system-related reactions (i.e., procedural, interactional, and overall justice, fairness, trust, trustworthiness) and organization-related reactions (i.e., organizational attractiveness, job pursuit intention). In addition, we found differences in the proposed relationships depending on certain boundary conditions, namely, the type of interaction and the extent of decision. Specifically, negative effects occurred when individuals were confronted with ADM compared to HDM, but not when they collaborated with the system. Similarly, ADM use led to more negative reactions when it automated rather than augmented decisions. Although not significant in the difference test, our results indicated that employees and applicants responded more negatively to ADM than HR professionals, and reactions were more negative when individuals were personally affected by decisions. We did not find differences regarding type of task, indicating that context sensitivity might not be as pronounced as initially assumed (e.g., Lee, 2018). However, all included tasks focused on the HRM domain due to the scope of this meta-analysis, so it is possible that the tasks might have been too similar.

2.6 Theoretical Implications

We expand the growing literature on reactions to ADM systems by (1) synthesizing existing heterogeneous findings on ADM usage and related reactions, (2) explaining these findings through an examination of boundary conditions that impact them, and (3) proposing an overarching theoretical framework to account for these findings. Our initial synthesis revealed that ADM is generally perceived negatively, confirming the presence of algorithm aversion in the existing literature. However, our findings indicate that algorithm aversion is not a static phenomenon, but rather depends on boundary conditions (e.g., extent of decision).

First, our findings revealed negative associations between ADM usage and perceptions of both fairness and justice. Notably, the negative relationship was stronger for justice than for fairness, with the largest differences between interactional justice and fairness perceptions, supporting organizational justice theory (Colquitt et al., 2001; Greenberg, 1987). This posits that individuals apply justice rules to form their fairness perceptions, emphasizing that justice and fairness are distinct concepts (Goldman & Cropanzano, 2015). However, fairness and justice are often used interchangeably in primary studies; we thus urge researchers to clarify whether they are assessing rule-based justice or subjective fairness perceptions. Notably, interactional justice showed the strongest negative correlation with ADM usage, suggesting that such systems may particularly undermine expectations of informational and interpersonal treatment (Binns et al., 2018). This highlights the importance of analyzing justice dimensions separately to better understand reactions to ADM.

Second, these main results vary according to specific boundary conditions as proposed in our overarching theoretical framework. Even though our difference test did not reveal significant differences across stakeholder types, our results suggested that applicants and employees evaluated the introduction of ADM more negatively than HDM—a trend that was not evident among HR professionals. This finding aligns with the differentiation proposed by Langer and Landers (2021), who argue that HR professionals often occupy the position of first parties (i.e., actively using ADM systems) whereas applicants and employees are more likely to be positioned as second parties (i.e., individuals directly affected by decisions) or third parties (i.e., external observers). As first parties, HR professionals may possess greater familiarity with the system’s functionalities and potential benefits, which could reduce skepticism and promote a more neutral or even positive evaluation of ADM (Binns et al., 2018).

Third, drawing on CASA (Nass & Moon, 2000; Reeves & Nass, 1996), we offer an overarching theoretical framework to clarify why theories from human–human contexts are relevant in human–algorithm contexts, building a bridge between both contexts. Since people often engage with ADM systems as if interacting with humans, we can apply theories, such as organizational justice theory (Colquitt, 2001; Greenberg, 1987), to explain reactions to ADM. However, CASA also suggests that ADM may prompt negative reactions when human-like expectations remain unmet, which may be particularly strong in HR contexts that inherently imply human interactions. Focusing solely on the HRM domain, this could also explain why we observed no task-specific effects. Additionally, we suggest that considering the various boundary conditions affecting ADM reactions may help account for prior inconsistent findings.

2.7 Practical Implications

The results of this study provide several practical implications for organizations. First, ADM might offer advantages from a business perspective (e.g., increased efficiency, reduction of human bias). However, our study indicates that individuals tend to react negatively to ADM usage. Here, the proposed boundary conditions of our overarching theoretical framework might help to guide organizations. Specifically, individuals' negative reactions were strengthened in cases where ADM was used as automation and when they were confronted with ADM decisions and had no opportunity to interact with the system. Taking this into consideration, organizations might introduce human oversight to facilitate trust as well as fairness and justice perceptions. Additionally, organizations might increase interactivity when incorporating ADM systems. However, the responsible decision-making entity should be clearly defined in advance to prevent HR professionals from placing blame on the algorithm for morally difficult decisions (Maasland & Weißmüller, 2022). Furthermore, it is important to note that human-in-the-loop designs are not a panacea for all concerns of ADM usage in this context, and several studies point out the difficulties of combining HDM and ADM. Langer et al. (2024), for instance, suggest that humans need to learn how to detect errors in ADM before intervening. Consequently, organizations are challenged to train their employees to work with ADM systems efficiently. Additionally, HRM should create clear guidelines to ensure that the introduction and application of ADM work as intended.

Moreover, we found no significant negative relationships associated with HR professionals interacting with ADM systems. This suggests that HR professionals may view ADM systems as tools to enhance efficiency and decision quality. To support this potential benefit, organizations could offer training to strengthen HR professionals' competencies in ADM usage.

Lastly, when individuals were not affected by a decision, they reacted more positively to ADM use. Hence, current employees might not experience lower levels of organizational attractiveness simply because their employer uses ADM. However, when potential employees are targeted, organizations should introduce interventions to increase positive reactions specifically for affected individuals, for example, by providing more detailed information and transparency about the algorithm in use (Suen & Hung, 2023).

2.8 Future Research Avenues

2.8.1 Main Relationship

We found that ADM is negatively associated with system-related and organization-related reactions. These negative reactions are typically measured by assessing fairness, trust, or justice. However, some studies report that they found perceptions of unfairness or distrust to be apparent (despite measuring fairness and trust), although previous literature established that low levels of fairness or trust do not necessarily equate to unfairness or distrust (Lewicki et al., 1998). Instead, previous studies suggest that, for example, trust and distrust are independent constructs which need to be viewed separately (Kramer, 1999). Future research could examine whether fairness, justice, and trust reactions are distinguishable from constructs such as unfairness, injustice, or distrust, thus leading to our first research avenue:

Research avenue 1: What roles do constructs such as distrust, injustice, and unfairness play in shaping responses to ADM? How are these constructs distinct from negative perceptions of trust, justice, and/or fairness?

2.8.2 Type of Stakeholder

Primary studies have included HR professionals, current employees, and applicants as participants, while generally overlooking other potential stakeholders. Line managers' reactions to ADM remain underexplored, although they play a key role in implementing HR practices as established by the HR triad (Jackson & Schuler, 2003). We argue that line managers may act as both first and second parties in ADM-related HR decisions: they are involved in making decisions, while also being affected by HR decisions in which ADM is used, such as performance evaluations or promotions.

In addition, most scenarios for HR professionals have been framed from the perspective of HR managers. We define HR professionals as all staff involved in developing formal HR policies and processes (Jackson & Schuler, 2003), noting that while HR managers are included, they also hold additional management responsibilities. Following this, we propose that HR managers are more likely to occupy the role of first parties (i.e., individuals using ADM and making decisions), whereas HR professionals may simultaneously serve as both first and second parties (Langer & Landers, 2021) similar to line managers. Due to the potentially overlapping roles, HR professionals and line managers may respond differently than other stakeholders.

Furthermore, we urge future research to empirically examine the underlying mechanisms differentiating stakeholders (i.e., differing tasks according to the HR triad, Jackson & Schuler, 2003; competence based on self-determination theory, Deci & Ryan, 2012), as this area of research is currently underdeveloped. In addition, the dynamic between HR managers and their subordinates introduces an important yet underexplored influencing factor. Investigating how these groups jointly evaluate ADM implementation (e.g., dealing with conflicting interests) offers a promising avenue for future research. We thus propose our second research avenue:

Research avenue 2: How do line managers/HR professionals (not on the management level) react to ADM systems in comparison to other stakeholder groups (e.g., employees, applicants)? Which underlying mechanisms play a role in the differences in stakeholder reactions?

2.8.3 Type of Interaction

We showed that the type of interaction (i.e., either collaboration or confrontation) impacts ADM reactions. Building on this, researchers could examine how ADM reactions might be improved when individuals are confronted with these decisions (i.e., second parties; Langer & Landers, 2021). Therefore, we suggest our third research avenue:

Research avenue 3: How can organizations improve perceptions of ADM for individuals that are confronted with algorithmic decisions? How can decision processes become more interactive for second parties?

2.8.4 Type of Task

In terms of our moderator type of task, we were able to include a differentiation of interviews, screening, and career development in ADM. However, other tasks, such as payroll, remain underexplored. Therefore, we propose our fourth research avenue:

Research avenue 4: Which HR tasks beyond interviews, screening, and career development may be suitable for ADM implementation? How do reactions differ between these tasks?

2.8.5 Extent of Decision

We found differences between ADM used for automation versus augmentation. However, it remains questionable whether human and ADM in collaboration yield better results than HDM or ADM alone (Langer et al., 2025), as previous literature indicates that results could become more or less accurate depending on situational aspects (Vaccaro et al., 2024). Furthermore, the factors that underpin successful collaboration remain unclear, leading to our next research avenue:

Research avenue 5: How can successful human–ADM collaboration be achieved? How can human–ADM collaboration create better results compared to HDM or ADM alone?

2.8.6 Psychological Distance

We found indications that psychological distance plays a role in shaping ADM reactions; however, there were no significant effects in the difference test. Thus, we urge future researchers to investigate psychological distance in more detail to derive the importance of this boundary condition. Moreover, the level of psychological distance was coded into two categories: low or high. However, we argue that future studies could differentiate this further to understand the specific differences arising from the proximity of the decision to the respective stakeholder. In addition, we stress the importance of examining the subjective severity of decisions for individuals (i.e., important vs. unimportant decisions).

Research avenue 6: How do different levels of psychological distance affect reactions to ADM? Which role does the subjective importance of the decision play for affected stakeholders?

2.8.7 Country of Origin

While our meta-analysis only included country of origin as a robustness check (i.e., due to the limited availabilities of different countries), we see potential for future research in this area. Country of origin can act as a proxy for formal and informal institutions (North, 1990) that shape how individuals perceive ADM. Formal institutions (i.e., laws, regulations) such as the EU AI Act (European Commission, 2021) or the U.S. Algorithmic Accountability Act (Mökander et al., 2022), may foster trust and perceived fairness or, when absent, raise concerns about bias and lack of control (Fessenko & Jasperse, 2024). Informal institutions, including cultural norms and values (North, 1990), might also impact ADM reactions. As prior research on informal institutions is mixed (e.g., Kleinlogel et al., 2023; Mahmud et al., 2022), this might be a particularly relevant future research avenue. Given that most studies in our meta-analysis were conducted in the U.S. and Germany, we encourage future research to explore ADM reactions in diverse institutional contexts to broaden theoretical insights beyond Western perspectives. This leads us to our final research avenue:

Research avenue 7: How do informal (e.g., norms, traditions) and formal (e.g., political standards, legislation, regulation) institutions in different countries shape reactions to ADM?

2.9 Limitations

This meta-analysis has limitations in terms of study inclusion and methodology. First, meta-analyses are always limited by the availability of primary studies. Due to the absence of primary studies (in our case: studies including line managers' reactions to ADM and studies including severity of the decision), some effects could not be tested adequately

($k < 3$). Hence, the results need to be interpreted carefully. However, as Schmidt et al. (1985) argued, even with a small number of studies and sample sizes, meta-analyses remain the optimal method for synthesizing findings.

Second, most of the included primary studies tested their research models in hypothetical experimental scenarios. This creates a dependency on the participants to be able to realistically imagine themselves being evaluated by a human or an algorithm in the HRM domain. Furthermore, it might be difficult to compare the studies and consequently the reported effect sizes, as some scenarios were more realistic and sophisticated than others. We therefore invite future researchers to investigate real-life scenarios or conduct field experiments that analyze actual introductions of ADM in organizations. Further, one of our inclusion criteria was to only include studies comparing HDM and ADM directly, a strategy that contained the possibility of leaving out any studies that investigated differences between two algorithms that differed in certain functionalities. Therefore, scholars could analyze differing reactions towards ADM in the future to clarify and synthesize the current research landscape even further. This might be particularly important due to the proposed boundary conditions that could be explored by comparing different ADM systems.

3 Essay II: The Bright and Dark Sides of Algorithmic Decision-Making (ADM): The Role of Stereotypes and Psychological Distance of ADM in Organizational Attraction[9]

Abstract

While algorithmic decision-making (ADM) is increasingly used in organizations due to its expected benefits, prior research has mainly focused on its negative stereotypes (e.g., unfairness, distrust). This leaves the following questions unanswered: (1) Does ADM also lead to positive stereotypes? (2) If so, do these stereotypes coexist with negative ones? (3) What role does psychological distance play in shaping these stereotypes? To answer these questions, we identified positive (i.e., innovativeness, performance, speed) and negative (i.e., distrust, unfairness, creepiness) stereotypes of ADM by scraping and analyzing German newspaper articles (2019–2024) and conducting qualitative interviews (n = 10) in a pre-study. In Study 1 (n = 405), we found that ADM elicits both positive and negative stereotypes during recruitment. In Study 2 (n = 317), we found that lower psychological distance to ADM (i.e., high personal consequences of ADM decisions) leads to fewer positive and stronger negative stereotypes. Across Studies 1 and 2, we analyzed inter-organizational (i.e., established vs. new firms) and intra-organizational (i.e., bonus payments, recruitment, layoffs) contexts as boundary conditions, but found no significant variation in the main relationships. We offer a more nuanced understanding of ADM stereotypes by introducing the concept of algorithm ambivalence.

Keywords: algorithmic decision-making, algorithm ambivalence, stakeholder reactions, psychological distance

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3.1 Introduction

In times of talent shortages and increased war for talent, organizations need to be perceived as attractive employers by both new hires and current employees to ensure a sufficient supply of talent, to retain it, and to achieve sustainable competitive advantages (Dineen & Allen, 2016; Onken-Menke et al., 2018; Schüler et al., 2023). At the same time, organizations are increasingly implementing algorithms into various managerial processes (Bankins et al., 2024; Gal et al., 2022; Langer & Landers, 2021; Ochmann et al., 2024), which either augment (i.e., support) or automate (i.e., replace) human decisions (Langer & Landers, 2021). Such use of algorithms is known as *algorithmic decision-making* (ADM) and has consequences for new and current employees. For new hires, organizations implement ADM in digital recruitment channels, applicant screening, or automated video interviews; for current employees, it is used to assign training or work tasks, evaluate employee performance, and recommend promotions (Kelan, 2024; Park et al., 2021; Votto et al., 2021). By implementing ADM, organizations expect to reduce costs, increase the speed and efficiency of tasks and processes, minimize potential human biases, and remain at the forefront of digital innovation (Kellogg et al., 2020; Lamers et al., 2024; Lee, 2018).

However, ADM turns out to be a double-edged sword for organizations in managing their workforce and attracting talent. Most previous studies have compared applicant or employee reactions to ADM with human decision-making (HDM) and found that ADM is mainly associated with negative reactions, such as reduced fairness, diminished trust, and increased feelings of creepiness (Höddinghaus et al., 2021; Hyun Baek & Kim, 2023; Köchling et al., 2023; Langer & König, 2018; Ochmann et al., 2024). This has led to the prevalent assumption that ADM triggers algorithm aversion (Dietvorst et al., 2015; Turel & Kalhan, 2023), with individuals favoring human decision-makers over ADM.

In contrast, positive reactions of ADM have also been reported, such as its potential to enhance objectivity and consistency, reduce human biases, and increase the transparency of decision-making processes—often described as algorithm appreciation (Jussupow et al., 2024; Logg et al., 2019; You et al., 2022). With ongoing advancements in artificial intelligence (AI), benefits of ADM, such as enhanced speed (Duan et al., 2019) and potential for innovation (Haefner et al., 2021; Olan et al., 2022), may also positively affect new and current employees. However, the extent of these positive reactions and how they relate to negative reactions remain unclear. This gap limits a comprehensive and nuanced understanding of ADM's broader effects on organizations.

Hence, this study addresses the following research questions: (1) Does ADM also lead to positive stereotypes? (2) If so, do these stereotypes coexist with negative ones? (3) What role does psychological distance play in shaping these stereotypes? To answer these questions, we conducted a pre-study and two experimental studies with a sample of the working population in Germany, examining the coexistence of positive and negative ADM stereotypes and their role in shaping organizational attractiveness. In doing so, we offer three major contributions to the current debate on ADM.

First, by employing categorization theory (Oakes & Turner, 1990; Turner & Oakes, 1986), we extend existing ADM literature by examining both its positive and negative stereotypes, thereby extending the focus beyond negative reactions of ADM and algorithm aversion. Specifically, we distinguish between positive (i.e., innovativeness, performance, speed) and negative (i.e., distrust, unfairness, creepiness) stereotypes of ADM and examine their impact on organizational attractiveness. As a result, we propose a new concept, *algorithm ambivalence*, which refers to the simultaneous perception of ADM as both positive and negative. This concept serves as a bridge between algorithm aversion and appreciation and calls for greater caution in the binary classification of these reactions in future research. Using this concept, we aim to provide more realistic and comprehensive insight into how ADM should be embedded in organizational theory and practice.

Second, we build on construal level theory (Trope & Liberman, 2010) to explore the influence of high vs. low psychological distance in ADM decisions. This involves investigating divergent stereotypes toward ADM between individuals directly exposed to it and those who encounter it only through external sources (i.e., the media). As media coverage of ADM adoption in organizations increases, individuals who only read about it (e.g., in news articles) may form opinions that differ significantly from those directly affected (Braun et al., 2022; DiMaggio et al., 2001). Indirect exposure to ADM only through the media creates high psychological distance, leading individuals to form abstract and generalized stereotypes based on external narratives (Braun et al., 2022). In contrast, direct exposure (i.e., being directly affected by ADM decisions) lowers psychological distance, leading to more concrete evaluations shaped by personal consequences (Kirshner, 2024). This distinction is crucial for organizations, as psychological distance may influence acceptance of ADM systems and ultimately affect their benefits and drawbacks.

Third, we consider inter-organizational (i.e., established vs. new ventures) and intra-organizational (i.e., bonus payments, recruitment, layoffs) contexts as boundary conditions for the proposed relationships, thereby offering insights into how ADM stereotypes may vary across organizational contexts. At the inter-organizational level, new ventures are often associated with innovation and agility and may benefit from ADM integration, as it aligns with their tech-forward image (Trocin et al., 2021). In contrast, because established firms are typically associated with greater rigidity (Antolín-López et al., 2015), introducing ADM may lead to skepticism due to its incongruence with employees' expectations of the organization. At the intra-organizational level, the specific managerial context (i.e., bonus payments, recruitment, layoffs) may also affect the perception of ADM. High-stakes decisions, such as recruitment and layoffs, often involve subjective and emotional considerations, heightening concerns about fairness when delegated to ADM (Lee, 2018; Yan et al., 2024). In contrast, bonus payments, which typically follow standardized criteria, may elicit more neutral or even positive responses (Höddinghaus et al., 2021; Newman et al., 2020). Moreover, intra- and inter-organizational contexts have so far mainly been examined from the perspective of negative perceptions, rather than both positive and negative stereotypes. Ignoring these boundary conditions could lead to one-size-fits-all ADM implementation strategies, increasing resistance or misalignment with stakeholder expectations and ultimately reducing organizational attractiveness.

3.2 Theoretical Background and Hypotheses Development

3.2.1 Stereotypes of Algorithmic Decision-Making

Categorization theory (Turner & Oakes, 1986) explains how individuals classify others and phenomena using cognitive shortcuts when facing uncertainty or incomplete information. Stereotypes emerge from these categorizations, shaping perceptions of new or unfamiliar entities (Taylor, 1982). People rely on such shortcuts to form stereotypes and reduce cognitive load (DiMaggio et al., 2001). Given that ADM represents a novel decision entity distinct from human managers, individuals are likely to form stereotypes based on available information rather than direct experience. In this study, we differentiate between positive and negative stereotypes to explore their varying effects based on the decision entity (i.e., HDM vs. ADM) and the psychological distance of an algorithmic decision (i.e., low vs. high).

On the positive side (i.e., algorithm appreciation), ADM may be associated with efficiency, accuracy, and innovation—qualities often attributed to data-driven processes (Duan et al., 2019; Olan et al., 2022). Unlike HDM, ADM relies on structured logic and statistical models, enabling faster decision-making, improved performance, and reduced bias in, for example, candidate selection (Ferreira et al., 2020). Organizations adopting ADM may be perceived as forward-thinking and technologically progressive, reinforcing its association with innovativeness and performance (Alon-Barkat & Busuioc, 2022).

At the same time, ADM is subject to negative stereotypes (i.e., algorithm aversion), particularly regarding fairness and trust (Glikson & Woolley, 2020; Ochmann et al., 2024). While ADM is often promoted for its objectivity, it lacks the contextual awareness, flexibility, and emotional intelligence that human decision-makers typically possess (Binns et al., 2018; Ghasemaghaei & Kordzadeh, 2024). As a result, ADM decisions may be perceived as opaque, rigid, and impersonal, fostering distrust and concerns about fairness (Kronblad et al., 2024). Moreover, ADM can exacerbate feelings of unease, triggering reactions of creepiness (Köchling et al., 2023; Langer & König, 2018).

However, previous research has tended to examine positive or negative reactions to ADM independently, and a comprehensive investigation is lacking. Existing studies have found differences in ADM stereotypes between contexts (e.g., type of task, country; Höddinghaus et al., 2020; Kleinlogel et al., 2023) or individual characteristics, such as attitudes toward AI (Schepman & Rodway, 2022). However, we argue that a single person may perceive ADM as innovative and efficient while simultaneously doubting its fairness, trustworthiness, or social appropriateness. Thus, we posit that, regardless of context or individual characteristics, ADM is perceived both positively and negatively at the same time.

We ground our argument in the concept of attitudinal ambivalence (Thompson et al., 1995), which posits that people can simultaneously hold multiple, sometimes conflicting attitudes—both positive and negative—toward a stimulus. To some extent, these differing stereotypes have been investigated in the AI field using the stereotype content model (Fiske et al., 2002), which categorizes perceptions into warmth and competence. AI is generally perceived as low in warmth (i.e., negative stereotype) but high in competence (i.e., positive stereotype; Peng et al., 2022). Nevertheless, these findings remain broad and do not offer a comprehensive picture of how ADM is perceived in organizational settings. Drawing on categorization theory (Turner & Oakes, 1986), we suggest that individuals use cognitive shortcuts when evaluating unfamiliar decision-makers, explaining why ADM may be simultaneously perceived both positively and negatively. As ADM is increasingly integrated into organizational processes, understanding this ambivalence becomes critical for designing strategies that maximize acceptance while mitigating skepticism. Thus, we hypothesize:

Hypothesis 1: Compared with HDM, ADM increases (a) positive stereotypes (i.e., innovativeness, performance, speed) and (b) negative stereotypes (i.e., distrust, unfairness, creepiness).

3.2.2 Psychological Distance of Algorithmic Decision-Making

The extent to which individuals are personally affected by ADM may play a critical role in shaping their stereotypes. Drawing on construal level theory (Trope & Liberman, 2010), we argue that individuals process ADM decisions differently depending on whether they experience high or low psychological distance, namely, their subjective perception of how near or far something or someone feels from their present self, location, or moment in time (Trope & Liberman, 2010).

Importantly, psychological distance does not always align with objective measures, as various cognitive and emotional factors shape perceptions of distance. For example, Han and Gershoff (2018) found that perceived control significantly influences psychological distance. When individuals feel low control over a situation, they tend to regard stimuli as psychologically closer. Conversely, when perceived control is high, stimuli are seen as more psychologically distant. When a stimulus is perceived as psychologically close (i.e., due to low perceived control), individuals tend to engage in more concrete, self-focused processing (Trope et al., 2007). In contrast, when a stimulus feels psychologically distant, individuals are more likely to process it abstractly, focusing on broader societal implications rather than personal consequences (Abbas et al., 2021; Marstand et al., 2024).

Psychological distance consists of multiple dimensions, including spatial, temporal, and social distance, as well as hypotheticality (Liberman et al., 2007a, 2007b; Liberman & Trope, 2014). We focus specifically on social distance, as it is most relevant in the context of ADM (Park et al., 2024). Social distance refers to the perceived closeness between individuals and a given stimulus (Magee & Smith, 2013; Trope & Liberman, 2010). The extent of social distance may vary depending on whether individuals are directly affected by ADM decisions (i.e., low psychological distance) or merely observe them without direct consequences (i.e., high psychological distance).

Langer and Landers (2021) differentiated first, second, and third parties involved when ADM is introduced. First parties refer to individuals who typically use ADM systems to make decisions for others. Second parties include individuals who are confronted with algorithmic decisions. Third parties are those who observe ADM being introduced. This differentiation helps explain why psychological distance impacts ADM stereotypes. We argue that second parties experience low psychological distance to ADM decisions, as they are directly confronted with the decisions and their consequences (Langer & Landers, 2021). This closeness may prompt them to process the decision in a self-focused manner (Trope et al., 2007). A key factor influencing this perception is perceived control (Han & Gershoff, 2018). When second parties are affected by ADM, they often lack control over the outcome, as ADM operates with minimal human intervention (Braun et al., 2022). This low perceived control intensifies feelings of scrutiny and uncertainty, leading individuals to critically evaluate the decision-making process (Li & Sung, 2021; Pronin et al., 2008).

As a result, individuals may focus on potential risks and limitations, engaging in detailed assessments of ADM's fairness and trustworthiness. Given the lack of human oversight and the perceived opacity of ADM systems (Bujold et al., 2022; Glikson & Woolley, 2020), low psychological distance may reduce positive stereotypes such as innovativeness, performance, and speed, because ADM is no longer viewed abstractly, but rather as something with direct, potentially unfavorable consequences. Additionally, negative stereotypes are likely to be heightened as second parties become more aware of how ADM decisions affect them personally and feel powerless to influence the outcome (Park et al., 2021).

Conversely, individuals with high psychological distance can be categorized as third parties, who only observe ADM decisions without being directly affected (Langer & Landers, 2021). For these individuals, ADM decisions remain psychologically distant, leading to more abstract and generalized perceptions (Trope et al., 2007). Crucially, this distance allows them to avoid a sense of lost control, as they are not personally subjected to ADM decisions and thus do not experience the same threat to their autonomy or agency (Han & Gershoff, 2018; Li & Sung, 2021). With no immediate personal consequences, they may feel detached from potential risks and instead focus on generalized narratives that highlight ADM's efficiency, objectivity, and innovation (Kirshner, 2024). As a result, third parties may be more inclined to endorse positive stereotypes (i.e., innovativeness, performance, speed), perceiving ADM as a promising technological advancement. At the same time, they may be less sensitive to negative stereotypes, as they do not experience the algorithm's consequences firsthand. Without a perceived loss of control, they may also be less likely to perceive ADM as creepy or threatening.

Thus, psychological distance shapes the extent to which individuals perceive ADM positively or negatively. When ADM is perceived as socially close (i.e., low psychological distance), individuals engage in more critical evaluations, reducing positive stereotypes and amplifying negative ones. When it is socially distant (i.e., high psychological distance), individuals rely on generalized perceptions, reinforcing positive stereotypes while downplaying potential risks. Accordingly, we hypothesize:

Hypothesis 2: Compared to decisions with high psychological distance, ADM in low psychological distance scenarios (a) decreases positive stereotypes (i.e., innovativeness, performance, speed) and (b) increases negative stereotypes (i.e., unfairness, distrust, creepiness).

3.2.3 Inter-Organizational and Intra-Organizational Boundary Conditions

3.2.3.1 The Impact of Company Type

Despite the growing adoption of ADM, research has largely overlooked inter-organizational factors (i.e., factors between organizations) that shape ADM stereotypes. One such factor is company type, which may play a key role in shaping applicant perceptions. Job descriptions and company websites often emphasize organizational values and culture, influencing perceptions of person–organization fit (Chapman et al., 2005). Applicants draw on various sources (i.e., company websites, marketing materials, and peer recommendations) to form expectations about an organization before applying (Braddy et al., 2006). Therefore, failing to consider the broader organizational context in which ADM is introduced overlooks an essential factor in how it is perceived.

Company type may influence how ADM aligns with existing organizational stereotypes. New ventures are often perceived as innovative and agile due to their lean structures (Antolín-López et al., 2015; Fini et al., 2012). Since ADM is commonly associated with innovation (Trocin et al., 2021), its implementation in new ventures may reinforce existing positive stereotypes, enhancing perceptions of innovativeness, performance, and efficiency. In contrast, established companies, often characterized as traditional and hierarchical (Antolín-López et al., 2015), may face resistance when implementing ADM, as it may be perceived as clashing with expectations of stability. Previous research suggests that when organizational practices misalign with established stereotypes, individuals experience cognitive dissonance, leading to negative reactions (Blum, 2004). Thus, applicants who expect personalized selection processes in established companies may find ADM use disconcerting, potentially diminishing positive perceptions.

Prior research on ADM reactions in different organizational contexts has yielded mixed results. Langer et al. (2020) found no significant differences between innovative and established companies in ADM perceptions. However, their study was conducted when ADM adoption was still emerging. Given its growing prevalence and visibility in recruitment, it is likely that stereotypes around ADM have evolved, necessitating a re-evaluation of its effects in different organizational contexts. In addition, the study considered only negative ADM stereotypes, which may not depict a realistic picture of how ADM is perceived. As ADM becomes more widely recognized, applicants may develop stronger positive and negative stereotypes depending on whether it aligns with existing company characteristics. Accordingly, we hypothesize:

Hypothesis 3a: Compared with established companies, the relationship between ADM and positive stereotypes is stronger for new ventures.

Hypothesis 3b: Compared with established companies, the relationship between ADM and negative stereotypes is weaker for new ventures.

3.2.3.2 The Impact of Managerial Context

According to construal level theory (Trope & Liberman, 2010), contexts influences perceptions based on psychological distance and perceived power asymmetry of the decision. Accordingly, high-stakes contexts, such as recruitment and layoffs, are psychologically closer due to their direct impact on individuals' careers and financial stability (Langer et al., 2019; Lee, 2018). In these situations, organizations hold significant power: Applicants have little power over the hiring decision other than through showing their own experience and performance. Employees facing layoffs often have little control over their employment outcomes, despite legal protections (Frick & Sadowski, 1995; Lam et al., 2023). This power imbalance increases perceived risks, potentially amplifying negative stereotypes of ADM (Höddinghaus et al., 2021; Pirson & Malhotra, 2011).

In contrast, allocating bonus payments represents a lower-stakes managerial context in which employees retain greater control over outcomes through their performance level (Locke & Latham, 2000; Pereira et al., 2023). Additionally, the consequences of a bonus allocation are less severe than those of being hired or laid off. The increased psychological distance (i.e., due to higher perceived control) in this context may lead to more neutral or even positive evaluations of ADM, as decision-making appears less intrusive and threatening. Thus, ADM may be judged more favorably when applied to bonus payments than to high-stakes decisions such as recruitment or layoffs.

Given these differences in psychological distance and power asymmetry, we propose that ADM implementation in high-stakes contexts (i.e., recruitment, employee layoff) intensifies negative stereotypes while diminishing positive ones compared with low-stakes contexts (i.e., bonus payments). To account for these variations across managerial contexts, we hypothesize:

Hypothesis 4: The relationship between psychological distance and positive stereotypes is weaker for (a) recruitment and (b) employee layoff than for bonus payments.

Hypothesis 5: The relationship between psychological distance and negative stereotypes is stronger for (a) recruitment and (b) employee layoff than for bonus payments.

3.2.4 Positive and Negative Stereotypes and Organizational Attractiveness

Previous research has emphasized the considerable impact of applicant and employee reactions on organizational outcomes (Ochmann et al., 2024; Tarafdar et al., 2023). One concept used to derive these outcomes is organizational attractiveness, which holds significance for organizational decision-making processes. This concept refers to how individuals perceive a company as an appealing workplace, reflecting its concern for and support of its employees (Highhouse et al., 2003). In line with categorization theory (Oakes & Turner, 1990), individuals' stereotypes about organizations influence subsequent decision-making. Thus, we propose that favorable stereotypes lead to higher attractiveness ratings, while negative stereotypes reduce them. Furthermore, we hypothesize that both positive and negative stereotypes mediate the relationship between the decision entity (i.e., HDM vs. ADM) and organizational attractiveness, as well as between psychological distance (i.e., high vs. low) and organizational attractiveness. Consequently, we propose the following hypotheses:

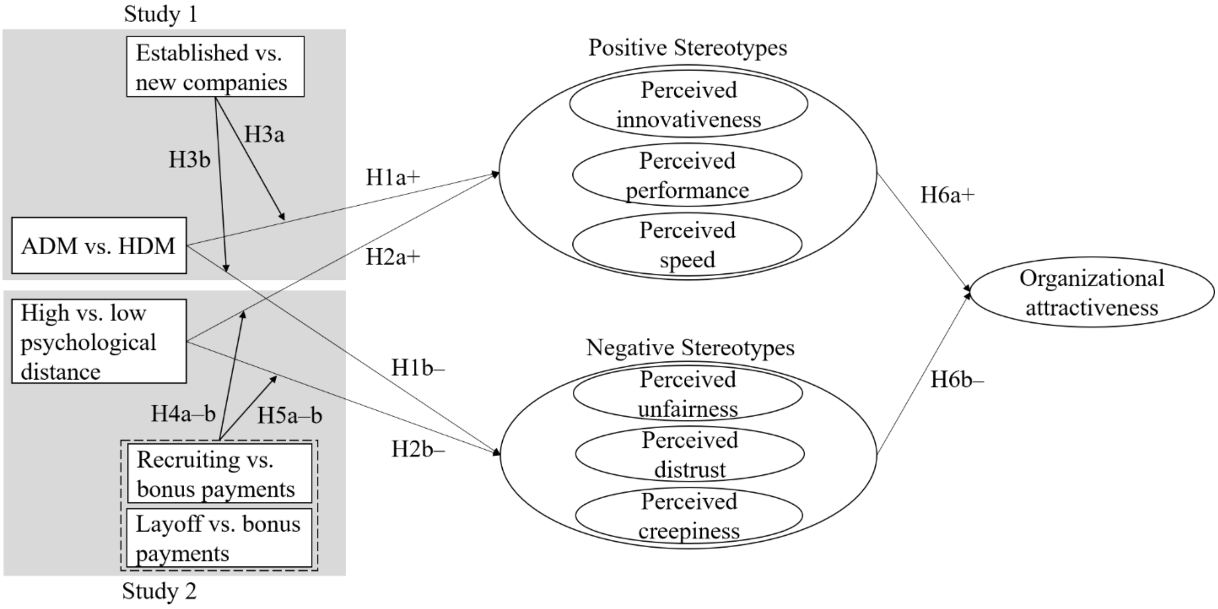
Hypothesis 6: (a) Positive stereotypes are positively associated with organizational attractiveness, and (b) negative stereotypes are negatively associated.

Hypothesis 7: (a) Positive and (b) negative stereotypes mediate the relationship between the decision entity (HDM vs. ADM) and organizational attractiveness.

Hypothesis 8: (a) Positive and (b) negative stereotypes mediate the relationship between psychological distance (high vs. low) and organizational attractiveness.

The hypothetical research model is depicted in Figure 3-1.

Figure 3-1. Hypothetical Research Model



Note. Latent constructs are depicted as ellipses, while the observed variables (i.e., treatments) are depicted as rectangles. The reference category of the variables is always given after "vs." HDM = human decision-making, ADM = algorithmic decision-making.

3.3 Methodology

3.3.1 Pre-Study: Validation of ADM Stereotypes

3.3.1.1 ADM Stereotypes in Newspaper Articles

To analyze ADM stereotypes perceived by the public, we gathered articles from newspapers in Germany. We selected several news outlets and scraped articles that focused on AI or ADM from their websites[10]. The chosen outlets varied in size and range (i.e., regional or local newspapers), as well as in their target group. After obtaining consent from the respective publishers, we scraped articles from seven German news outlets: Frankfurter Allgemeine Zeitung, Frankfurter Rundschau, taz, Rheinische Post, Kölner Stadt-Anzeiger, Tagesspiegel, and PERSONALquarterly.

We filtered newspaper articles from 2019 to 2024, assuming that articles before 2019 did not influence opinions on ADM. We included several search terms in German for data

[10] We argue that the general public does not strongly differentiate between AI and ADM; hence, we treated these terms as synonyms for this part of our analysis.

scraping: AI, ADM, machine learning, and algorithm(s). The scraping was conducted in R with the *rvest* package. We removed duplicate articles and those where AI was only mentioned at the end of the text as a writing support, indicating that the article itself did not refer to AI. We then cleaned the text by removing numbers and special characters, and we retrieved 5,947,814 words in total. Articles dating to 2019 accounted for 107,519 (1.81%) of all words, compared with 1,783,226 words (29.98%) in 2023, reflecting the increasing relevance of AI and ADM over time.

We conducted various analyses on the scraped data to determine the predominant sentiment toward AI and translate the results into the most prevalent stereotypes (see Table 3-1). To achieve this, we employed sentiment analysis using the *tidytext* and *dplyr* packages in R, which yielded an overall sentiment score. Our primary analysis utilized the *AFINN* lexicon, which assigns scores to words, ranging from +5 for strongly positive sentiment to –5 for strongly negative sentiment, with 0 indicating neutral sentiment. Each sentence was categorized as positive, negative, or neutral based on its overall word score (Menaha & Ananthi, 2024). Additionally, we performed sentiment analysis using the *BING* lexicon from the *text* and *sentiment* packages to ensure the robustness and comparability of our findings. To further validate our analysis, we used the *NRC* lexicon, which categorizes words into eight distinct emotions (i.e., disgust, fear, anger sadness, anticipation, joy, surprise, trust), in addition to identifying positive or negative sentiment (Khoo & Johnkhan, 2017). The results revealed a strong emphasis on emotions such as joy and trust, further reinforcing the positive framing of AI in media outlets. Conversely, while emotions such as fear and anger were less prevalent, they surfaced in discussions about privacy concerns and potential biases in ADM systems. Across all three lexicons (i.e., *AFINN*, *BING*, and *NRC*), our findings show that positive framings of AI are more frequent than neutral or negative ones.

Table 3-1. Results of the Sentiment Analysis

Sentiment	Phrase/word count (Absolute)	Phrase/word count (Relative)
AFINN lexicon		
Positive	168,982	50.93%
Negative	83,210	25.08%
Neutral	79,592	23.99%
Total	**331,784**	**100.00%**
BING lexicon		
Positive	103,662	55.26%
Negative	62,707	33.43%
Neutral	21,225	11.31%
Total	**187,594**	**100.00%**
NRC lexicon		
Negative	116,544	12.10%
Fear	80,098	8.32%
Anger	50,384	5.23%
Sadness	48,864	5.07%
Disgust	26,895	2.79%
Positive	269,119	27.95%
Trust	160,273	16.64%
Anticipation	102,823	10.68%
Joy	72,160	7.49%
Surprise	35,832	3.72%
Total	**962,992**	**100.00%**

Note. For the *AFINN* and *BING* lexicon, whole sentences were used for the analysis. A positive sentiment when sentiment > 1; A negative sentiment when sentiment < 1; A neutral sentiment when sentiment = 0. For the *NRC* lexicon, single words were used for the analysis instead of sentences.

Based on these patterns, we infer ADM stereotypes by transferring emotions to broader cognitive shortcuts. Specifically, following previous research suggesting that affective cues are central to stereotype formation (Fiske et al., 2002), we suggest that positive emotions, such as trust and joy, can be subsumed under positive stereotypes, with negative emotions, such as fear and anger, subsumed under negative stereotypes. Overall, the sentiment analysis was important to demonstrate that positive ADM stereotypes exist and that several positive (but also negative) emotions are involved when ADM is introduced.

3.3.1.2 Conducting Interviews

In addition to analyzing the existing literature, we conducted interviews (n = 10, four male, six female) to identify stereotypes that previous research might have overlooked. Using the Gioia method (Gioia et al., 2013), we developed a questionnaire with open-ended questions. Participants received a short version of our vignette scenarios. We asked them about their initial thoughts, associations, and emotions upon learning that ADM was used in the application process, as well as the perceived advantages and disadvantages of ADM. After transcribing the interviews, we highlighted first-order codes in the text that captured potential positive or negative thoughts, associations, and emotions. Similar to our sentiment analysis, we translated these emotions into stereotypes, which we labeled as second-order themes. Finally, we combined these second-order themes to retrieve the direction of stereotypes and define aggregate dimensions.

Figure 3-2 depicts the results of our interview analysis. The mean age of the interviewees was 29 years. They had an average of 4.5 years of work experience. The results indicated that respondents had both positive and negative feelings about ADM. Notably, we found that the stereotypes exist at the same time within one person, meaning that the individuals held positive and negative stereotypes simultaneously. Moreover, participants revealed many positive ADM stereotypes that the literature has not explored in detail such as faster decision-making.

Figure 3-2. First-Order Codes, Second-Order Themes, and Aggregate Dimensions

Overall, through both validation steps, we found that both positive and negative stereotypes are prevalent. Accordingly, we derived innovativeness, performance, and speed as positive stereotypes, based on the frequency of interview phrases together with previous findings (Da Motta Veiga et al., 2023; Jöhnk et al., 2021; Mikalef et al., 2023). Similarly, we derived three negative stereotypes: distrust, unfairness, and creepiness. Most interviewees initially commented that introducing ADM would make them feel weird or strange, indicating a sense of creepiness. The constructs of distrust, unfairness, and creepiness are also prevalent in previous research (Glikson & Woolley, 2020; Köchling et al., 2023; Langer & König, 2018; Ochmann et al., 2024).

3.3.2 Two Experimental Studies: Overview of Study 1 and Study 2

After the pre-study, we conducted two experimental studies to validate the positive and negative stereotypes of ADM. Study 1 explored whether the decision entity (ADM vs. HDM) leads to significant differences in stereotypes in recruitment. In addition, we examined whether the company type (established vs. new ventures) as an inter-organizational boundary condition moderates the relationships. Study 2 investigated the effect of psychological distance (low vs. high) on ADM stereotypes. Additionally, we introduced managerial context (i.e., bonus payments, recruitment, layoffs) as an intra-organizational boundary condition. For brevity, we jointly present descriptive statistics, correlations, and factor loadings within the same tables for Studies 1 and 2.

3.3.3 Study 1

3.3.3.1 Sample

We conducted a G*Power analysis (Faul et al., 2007) with a MANOVA statistical test (repeated measures, between factors), where we set α = .05, power ($1-\beta$) = .95, and the number of groups to four, revealing that at least 388 participants were necessary to achieve statistical power. We used Prolific, an ISO 9001:2008-certified online sample provider, to obtain a quota-based sample. Before conducting the study, we performed a pre-test with the sample provider and 30 participants to ensure that the questionnaire was understood. We slightly oversampled and recruited 436 participants, from which we excluded 31 participants who did not answer the implementation or attention checks correctly. Therefore, our final sample consisted of 405 respondents, of whom 50.12% were female and 49.88% male. The mean age was 32.22 years (*SD* = 8.66). Participants were required to be currently employed and over 18 years old. Table 3-2 gives a comprehensive overview of the sample's characteristics (Studies 1 and 2).

3.3.3.2 Scenarios

The scenarios in this vignette study followed a 2 × 2 design (two decision entities, two company types) to allow realistic manipulation while controlling for potential third variables (Aguinis & Bradley, 2014). For each vignette, we first provided a brief definition of AI based on Prikshat et al. (2023) and Tambe et al. (2019) to ensure that participants shared a common understanding. We defined AI rather than ADM to ensure that our scenarios were easily understood, as the term ADM is not yet in widespread public use. We introduced the scenario by explaining that the participant is currently looking for a new job and they find a suitable job description from a company. After introducing the company, we provided more information about the company, which was displayed on their website, including whether it is a new venture (founded in 2019, currently with 12 employees) or an established company (founded in 1972, currently with 112,000 employees), following the procedure in the previous literature (Seong & Parker, 2024). More information was then provided about the application process, such as whether ADM or HDM was employed (see Appendix B1 for more details). We conducted a balance check to confirm the effectiveness of the random assignment after completing the survey (see Appendix B2).

Table 3-2. Detailed Sample Characteristics

Characteristics	**Study 1**	**Study 2**
Mean age	32.22 years (*SD* = 8.66)	31.01 years (*SD* = 8.37)
Gender distribution		
Female	203 (50.12%)	139 (43.85%)
Male	202 (49.88%)	176 (55.52%)
Diverse	0 (0.00%)	2 (0.63%)
Highest educational background		
Secondary school leaving certificate	3 (0.74%)	0 (0.00%)
Intermediate school leaving certificate	15 (3.70%)	14 (4.42%)
Grammar school	78 (19.26%)	63 (19.87%)
Completed vocational training	50 (12.35%)	38 (11.99%)
Bachelor’s degree	139 (34.32%)	104 (31.81%)
Master’s degree	111 (27.41%)	92 (29.02%)
Doctorate	9 (2.22%)	6 (1.89%)
Form of employment		
Full time	269 (66.42%)	206 (64.98%9
Part time	136 (33.58%)	110 (34.70%)
Job experience	8.83 years (*SD* = 8.02)	7.75 years (*SD* = 7.34)
Currently looking for a job		
Yes	105 (25.93%)	–
No	300 (74.07%)	–
Previous experience with AI in recruitment		
Yes	79 (19.51%)	–
No	326 (80.49%)	–
Current usage of AI at the workplace		
Yes	–	154 (48.58%)
No	–	163 (51.42%)

Note. Relative values are given in parentheses. Study 1: n = 405; Study 2: n = 317; *SD* = standard deviation.

3.3.3.3 Implementation Checks and Pre-Test of Scenarios

Implementation Checks. We asked the participants whether ADM was used in their scenario, as well as which company type was introduced. Participants who answered incorrectly were removed from the sample. In addition, we asked them to rate how realistic they perceived the scenario using two questions, which they rated as 5.66 on average on a 1–7 scale.

Pre-Test. Since our scenarios included a company name (i.e., AUREONA), we conducted a pre-test to ensure that it did not resemble well-known brands or evoke associations with them. Participants were presented with AUREONA alongside three widely recognized software companies (i.e., Microsoft, SAP, Oracle) and were asked to evaluate each in terms of familiarity, perceived innovativeness, reputation, and overall attractiveness. Additionally, we collected open-ended responses to assess associations with the name. The pre-test was conducted with the same service provider as the main study and included 105 participants (42.4% female; M = 41.35 years). T-tests confirmed that AUREONA was rated significantly differently from the known brand names across all measures. Moreover, the open-ended responses revealed no consistent or concrete associations with the name. These results support the suitability of AUREONA as a neutral and fictitious company name for the main study.

3.3.3.4 Measures

All items in the questionnaire were measured on a seven-point Likert scale (1 = strongly disagree to 7 = strongly agree). To reduce common method bias, the items of each scale were randomly rotated (Podsakoff et al., 2003). This approach minimizes certain response patterns and enhances data quality by preventing biases related to item sequencing (Podsakoff et al., 2012). An overview of all measurements for Studies 1 and 2, along with the factor loadings, is presented in Appendix B3.

Treatment Variables. We dichotomized the decision entity (0 = HDM, 1 = ADM) and the company type, so that 0 = new venture and 1 = established company.

Positive Stereotypes. Innovativeness was measured with three items (sample item: “This company takes novel approaches to making decisions”). Cronbach’s α was .96.

Performance was measured with three items based on Yalcin et al. (2023), a sample item being: "The decision-making process improves the company's performance." Cronbach's α was .87. Speed was measured with three items, one of them being: "The decision-making processes in this company happen quickly." Cronbach's α was .94.

Negative Stereotypes. We measured distrust with three reverse-coded items from Höddinghaus et al. (2021). One sample item was: "I would not at all rely on the company's decisions." Cronbach's α was .92. Unfairness was introduced with three reverse-coded items from Höddinghaus et al. (2021), one sample item being: "I think the company makes unfair decisions". Cronbach's α was .97. For creepiness, we employed Langer and König's (2018) scale, divided into emotional creepiness and creepy ambiguity (Sample item: "This situation somehow felt threatening"). Cronbach's α was .89 for emotional creepiness and .97 for creepy ambiguity.

Dependent Variable. 14 items from Highhouse et al. (2003) were used to measure organizational attractiveness. A sample item was: "This company is attractive to me as a place for employment". Cronbach's α was .97.

3.3.3.5 Analytical Procedures

We adopted a three-stage approach to examine our structural equation model (SEM) for the proposed research model, as an SEM allows moderation and mediation to be investigated beyond the restrictions of an analysis of variance (ANOVA; Breitsohl, 2019). We conducted all analyses in R software with the *lavaan* package (Rosseel, 2012).

First, we carried out a confirmatory factor analysis (CFA) of the items for the latent variables at the first-order level, meaning that we included all stereotypes as separate single variables and measured our model. In the next step, we conducted a second-order factor CFA, which acknowledges the unique contributions of each first-order construct and preserves their individual characteristics, considering them as facets of the overarching second-order construct (Koufteros et al., 2009). Therefore, we built one latent second-order variable for positive stereotypes, comprising innovativeness, performance, and speed, and a second latent second-order variable for negative stereotypes, comprising unfairness, distrust, and creepiness.

We then compared the fits of both models (i.e., Model 1 = only first-order factors; Model 2 = two second-order factors reflecting the first-order stereotypes) to assess whether the second-order factor model was meaningful (Schwarz, 1978). In our case, the second-order factor CFA showed a slightly worse fit than the first-order model, although the difference was not significant (Model 1: $\chi^2 = 982.27$, $df = 499$, $p < .001$; RMSEA = .05; CFI = .96; Model 2: $\chi^2 = 1{,}283.75$, $df = 515$, $p < .001$; RMSEA = .06; CFI = .94). Given this and the theoretical importance of testing second-order factors (Koufteros et al., 2009; Krause & Hayward, 2014), we proceeded with the analysis, as both models showed acceptable fit. Items with factor loadings below .70 were excluded to ensure robustness (see Appendix B3). See Appendix B4 for an overview of the model fits.

Next, we conducted an overall SEM to test the mediating effects. Both first-order and second-order SEMs demonstrated acceptable fit, with a better fit for the second-order factor model (Model 1: $\chi^2 = 2{,}011.16$, $df = 546$, $p < .001$; RMSEA = .08; CFI = .89; Model 2: $\chi^2 = 1{,}386.88$, $df = 548$, $p < .001$; RMSEA = .06; CFI = .94). We then examined company type as a moderator, again achieving satisfactory fit indices (Model 1: $\chi^2 = 1{,}454.89$, $df = 587$, $p < .001$; RMSEA = .06; CFI = .94; Model 2: $\chi^2 = 1{,}698.64$, $df = 615$, $p < .001$; RMSEA = .07; CFI = .92).

To assess the potential influence of common method bias, we conducted Harman's single-factor test using exploratory factor analysis on all observed items included in our measurement model. The analysis revealed that a single factor accounted for 37.96% of the total variance, which is below the commonly accepted threshold of 50% (Podsakoff et al., 2003). This suggests that common method bias is unlikely to pose a threat to the validity of our findings.

To ensure robustness, we tested additional SEMs incorporating control variables (age, gender, and education), which did not significantly alter the models' effects or outcomes. Consequently, these controls were excluded from the final analysis, as they worsened the model fits. Furthermore, we examined the impact of the moderator on the *B*-path (from stereotypes to organizational attractiveness) but found no significant effects, leading us to proceed with our original SEMs.

3.3.3.6 Results

Descriptive Statistics. All means, standard deviations, and correlations of the variables used in the study are presented in Table 3-3. The correlations ranged from weak to strong. In particular, we found the strongest correlation between variables that represent the same first-order factor, such as creepy ambiguity and emotional creepiness (r = .81). However, the variance inflation factors (VIFs) ranged from 1.55 to 3.41, which does not indicate instances of multicollinearity. Nonetheless, when employing a second-order factor model, it is necessary to introduce variables that are linked closely together; otherwise, the model is not meaningful (Koufteros et al., 2009). Consequently, we acknowledge and accept the presence of sometimes strong correlations.

Table 3-3. Means, Standard Deviations, and Correlations

Variable	***M***	***SD***	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	
Study 1													
1. Decision-entity	0.51	0.50											
2. Company type	0.51	0.50	.01										
3. Innovativeness	4.65	1.70	.68*	.01	*(.96)*								
4. Performance	4.64	1.27	.03	.02	.34*	*(.87)*							
5. Speed	4.51	1.15	.31*	.03	.34*	.36*	*(.94)*						
6. Distrust	3.56	1.43	.49*	.04	.19*	−.38*	−.05	*(.92)*					
7. Unfairness	3.22	1.43	.36*	.09	.20*	−.29*	.05	.59*	*(.97)*				
8. Emotional creepiness	3.19	1.40	.38*	.10*	.21*	−.21*	.01	.56*	.62*	*(.91)*			
9. Creepy ambiguity	3.46	1.28	.35*	.11*	.23*	−.15*	.01	.51*	.53*	.81*	*(.89)*		
10. Organizational attractiveness	4.49	1.16	−.36*	.10	−.08	.42*	.09	−.72*	−.60*	−.51*	−.43*	*(.97)*	
Study 2			***(1)***	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***	***(7)***	***(8)***	***(9)***	***(10)***	***(11)***
(1) Recruiting	0.33	0.47											
(2) Employee layoff	0.33	0.47	−.49*										
(3) Psychological distance	0.51	0.50	.00	.01									
(4) Innovativeness	5.41	1.07	.04	−.16*	−.16*	*(.87)*							
(5) Performance	4.63	1.31	.04	−.03	−.11*	.45*	*(.88)*						
(6) Speed	4.87	0.99	−.05	−.10	−.15*	.48*	.29*	*(.91)*					
(7) Unfairness	3.72	1.30	−.17*	.01	.14*	−.32*	−.49*	−.26*	*(.96)*				
(8) Distrust	4.09	1.33	−.21*	.05	.09	−.34*	−.50*	−.29*	.79*	*(.90)*			
(9) Emotional creepiness	3.78	1.56	−.19*	.18*	.19*	−.20*	−.29*	−.15*	.51*	.47*	*(.91)*		
(10) Creepy ambiguity	3.70	1.49	.10	.15*	.21*	−.10	−.15*	−.10	.31*	.28*	.73*	*(.66)*	
(11) Organizational attractiveness	3.67	1.38	.15*	−.10	.00	.31*	.52*	.26*	−.67*	−.72*	−.24*	−.44*	*(.96)*

Note. *M* = mean, *SD* = standard deviation; Decision-entity: 0 = human decision-making, 1 = algorithmic decision-making. Company type: 0 = new venture, 1 = established company. Psychological distance: 0 = high distance, 1 = low distance. For recruiting, the reference scenarios are bonus payments and employee layoff, and for employee layoff, the reference scenarios are bonus payments and recruiting. * indicates $p < .05$. Cronbach's α (after eliminating items based on their factor loadings) is reported on the diagonal in parentheses. Study 1: $n = 405$; Study 2: $n = 317$.

Structural Equation Modeling Results. Table 3-4 presents our second-order SEM results (see Appendix B5 for the results of the first-order factor SEM). We found evidence that positive and negative stereotypes were influenced by whether HDM or ADM was employed. At the first-order level, our results showed significant effects for all of our included stereotypes, except for performance (β = .07, p = .354). Thus, we found positive relationships between ADM and innovativeness (β = .70, p < .001) and speed (β = .33, p < .001), as well as between ADM and distrust (β = .51, p < .001), unfairness (β = .37, p < .001), and creepiness (emotional creepiness: β = .39, p < .001; creepy ambiguity: β = .37, p < .001). At the second-order level, we found significant effects for positive (β = .67, p < .001) and negative stereotypes (β = .50, p < .001) in regard to ADM, leading us to confirm hypotheses 1a and 1b. In terms of our moderator, we found no significant effects for company type at both the first-order and second-order levels, leading us to reject hypotheses 3a and 3b. However, we observed some direct effects of company type on negative stereotypes (second-order factor model: β = .17, p = .012).

At the second-order level, we found significant effects of both positive (β = .17, p < .001) and negative (β = −.70, p < .001) stereotypes on organizational attractiveness, thereby confirming hypothesis 6. Only partial moderating effects were observed for our stereotypes, as we found a direct relationship between ADM and organizational attractiveness at both the first-order (β = −.22, p = .003) and second-order (β = −.22, p < .001) levels. This allowed us to only partially confirm hypothesis 7.

Table 3-4. Results of the Second-Order Factor Structural Equation Modeling (Study 1)

Variables		***B***	***SE***	***β***	***p*-value**
Treatment effects (Path A)					
Decision-entity	→ Positive stereotypes	2.37**	.12	.67**	< .001
Company type	→ Positive stereotypes	0.15	.17	.08	.360
Decision-entity	→ Negative stereotypes	1.05***	.11	.50***	< .001
Company type	→ Negative stereotypes	0.32*	.13	.17*	.012
Two-way interactions for moderator					
Positive stereotypes: Decision-entity	→ Company type	−0.23	.23	−.06	.318
Negative stereotypes: Decision-entity	→ Company type	−0.22	.18	−.10	.214
Effects of the mediators (Path B)					
Positive stereotypes	→ Org. attractiveness	0.11***	.04	.17***	< .001
Negative stereotypes	→ Org. attractiveness	−0.81***	.07	−.70***	< .001
Indirect effects of the mediators (Path A*B)					
Positive stereotypes	→ Org. attractiveness	0.27***	.08	.11***	< .001
Negative stereotypes	→ Org. attractiveness	−0.84***	.10	−.37***	< .001
Direct effects (Path C)					
Decision-entity	→ Org. attractiveness	−0.33*	.14	−.13*	.020

Note. *B* = unstandardized effect, *SE* = standard error, *β* = standardized effect, org. = organizational, *n* = 405, decision-entity: human decision-making = 0, algorithmic decision-making = 1, company type: established company = 1, new venture = 0. * *p* < .05; ** *p* < .01; *** *p* < .001.

3.3.3.7 Brief Discussion of Study 1

Our results revealed that individuals perceived ADM both more positively and more negatively than HDM for our introduced stereotypes (i.e., innovativeness, performance, speed, distrust, unfairness, creepiness). Contrary to our expectations, company type (established vs. new ventures) did not significantly moderate these effects. In addition, both positive and negative stereotypes significantly impacted organizational attractiveness. Overall, we found that the stereotypes partially mediated the relationship between ADM and organizational attractiveness.

Taken together, these findings suggest that individuals simultaneously hold both positive and negative stereotypes of ADM, highlighting the presence of attitudinal ambivalence. This shifts the predominantly negative framing of ADM in the literature (i.e., algorithm aversion; Dietvorst et al., 2015) in a more positive direction.

However, it remains unclear how psychological distance shapes ADM stereotypes and whether our findings extend to other settings. Thus, we proceeded with Study 2, which manipulated the psychological distance of ADM decisions (high vs. low). This also allowed us to test the robustness of our validated stereotypes and to examine an additional potential factor that may influence ADM stereotypes: psychological distance.

3.3.4 Study 2

3.3.4.1 Sample

Again, we used Prolific to obtain a quota-based sample. We performed a pre-test with 15 participants to enhance the clarity of the scenario and instruments, yielding satisfactory results. A G*Power analysis for MANOVA global effects indicated that a minimum of 224 participants was required to achieve sufficient statistical power (Faul et al., 2007). Based on this analysis, we slightly oversampled and recruited 355 participants, all over 18 years old and currently employed. 38 participants who failed to answer two attention checks correctly or an implementation check about the allocated context were excluded, resulting in a final sample of n = 317 participants (see Table 3-2 for more information).

3.3.4.2 Scenarios

In Study 2, we used a between-subjects design with six hypothetical scenarios based on a 2 × 3 structure (psychological distance: low vs. high; bonus payments, recruitment, layoffs). Participants were randomly assigned to one of these scenarios and answered identical questions about it.

The scenarios started with a description of AI, similar to Study 1. In the high-psychological-distance scenarios, participants read a newspaper article about a company that used ADM. In the low-distance scenarios, participants either applied for or worked at a company that used ADM and the decision was framed to affect them personally. To manipulate the managerial context, we use bonus payment allocation, recruitment, and employee layoffs to examine how context impacts the relationship between psychological distance and stereotypes. In all contexts, ADM did not make the final decision; rather, it provided decision support. In the recruitment scenarios, we used a similar description to Köchling and Wehner (2023), explaining that a company used ADM to screen CVs and cover letters, as well as an asynchronous interview. In the bonus payment scenarios, we followed Höddinghaus et al. (2021) and Newman et al. (2020), depicting a company using ADM to allocate bonus payments for its employees. In the employee layoff scenarios, we adopted the description of Newman et al. (2020), where a company used ADM to determine which positions should be cut. See Appendix B1 for complete scenario descriptions and Appendix B2 for the balance check of random participant assignment.

3.3.4.3 Implementation Checks

First, we asked participants which context their scenario took place in (i.e., recruitment, bonus payments, employee layoff), with those who answered incorrectly removed from the sample. Second, we asked participants how much the scenario concerned a company in general compared with a company where they worked at or had applied to. Third, we asked how much they were personally affected by the decision, to check their understanding of psychological distance. We conducted an ANOVA to determine whether participants had understood the implementation checks. Results showed that participants assigned to the high-psychological-distance scenarios understood that a company in general was being described, as the means significantly differed from those in the low-distance scenarios (high-distance mean = 5.84, low-distance mean = 4.48, F-value = 46.32, $p < .001$). The same result emerged for the second implementation check. Participants in the low-distance scenarios understood they were personally affected by the decision (high-distance mean = 2.54, low-distance mean = 5.58, F-value = 232.20, $p < .001$). In addition, we asked participants two questions to rate how realistic they perceived the scenario, which they rated as 5.45 on average.

3.3.4.4 Measures

Unless indicated otherwise, all questionnaire items were measured on a seven-point Likert scale (1 = strongly disagree to 7 = strongly agree). Once again, the items of each scale were randomly rotated (Podsakoff et al., 2003) to reduce common method bias. An overview of all measurements for Study 2, along with the factor loadings, is presented in Appendix B3.

Treatment Variables. We created one dichotomous variable for the level of psychological distance (0 = high distance, 1 = low distance). We dichotomized the context treatments, using bonus payments as the reference variable. Accordingly, we created two dummy variables: one for recruitment (1 = recruitment, 0 = bonus payments) and one for employee layoff (1 = employee layoff, 0 = bonus payments).

Positive Stereotypes. Our measurements for innovativeness, performance, and speed were identical to those in Study 1 (see Appendix B3). Cronbach's α was .87 for innovativeness, .88 for performance, and .91 for speed.

Negative Stereotypes. We used the same measurements as in Study 1 for negative stereotypes (see Appendix B3). However, distrust and unfairness were adopted from Höddinghaus et al.'s (2021) scales; they were reverse-coded after data collection, rather than beforehand. Cronbach's α was .90 for distrust, .96 for unfairness, .91 for emotional creepiness, and .66 for creepy ambiguity.

Organizational Attractiveness. We adopted five items from Aiman-Smith et al. (2001) to measure organizational attractiveness. One sample item was "This would be a good company to work for." Cronbach's α was .96.

3.3.4.5 Analytical Procedures

We employed the same three-stage approach as in Study 1 for the SEM. We conducted both first- and second-order factor CFA, where both models demonstrated acceptable fit indices (Model 1: $\chi^2 = 491.36$, $df = 296$, $p < .001$; RMSEA = .05; CFI = .98; Model 2: $\chi^2 = 767.22$, $df = 314$, $p < .001$; RMSEA = .07; CFI = .94). Although the second-order factor model showed slightly worse fit indices, the differences were minor, so we continued with our analysis. Again, items with factor loadings below .70 were excluded.

Next, we conducted an overall SEM to test the mediating effects. Both first- and second-order SEMs demonstrated acceptable fit (Model 1: $\chi^2 = 1{,}473.53$, $df = 336$, $p < .001$; RMSEA = .10; CFI = .86; Model 2: $\chi^2 = 88.64$, $df = 338$, $p < .001$; RMSEA = .07; CFI = .94). We then examined moderating effects by introducing managerial context as a moderator, again achieving satisfactory fit indices (Model 1: $\chi^2 = 432.34$, $df = 264$, $p < .001$; RMSEA = .05; CFI = .97; Model 2: $\chi^2 = 741.65$, $df = 301$, $p < .001$; RMSEA = .07; CFI = .92).

To assess potential common method bias, we conducted Harman’s single-factor test again. The analysis yielded a single-factor solution that accounted for 40.17% of the total variance, suggesting that common method bias is unlikely to pose a significant threat to the validity of our findings.

We also tested additional SEM models including control variables (age, gender, and education). However, these controls did not significantly impact the model’s effects or outcomes and were ultimately excluded, as their inclusion reduced the model fit. Finally, we assessed the moderator’s effect on the *B*-path (stereotypes → organizational attractiveness) but found no significant impact. We therefore proceeded with our original SEM models.

3.3.4.6 Results

Descriptive Statistics. See Table 3-3 for the means and correlations of the variables used in the study. We found the strongest correlation between the first-order factors of the negative stereotypes (r = .79), indicating that these variables formed a latent second-order factor. VIFs ranged from 1.07 to 3.11, indicating no threat of multicollinearity.

Structural Equation Modeling Results. Table 3-5 presents the results of the second-order SEM (see Appendix B6 for the results of the first-order SEM).

Table 3-5. Results of the Second-Order Factor Structural Equation Modeling (Study 2)

Variables		***B***	***SE***	***β***	***p*-value**
Treatment effects (Path A)					
Psychological distance	→ Positive stereotypes	−.25**	.09	−.21**	.003
Recruiting	→ Positive stereotypes	−.13	.24	−.10	.587
Employee layoff	→ Positive stereotypes	−.12	.26	−.11	.648
Psychological distance	→ Negative stereotypes	.34**	.13	.16**	.008
Recruiting	→ Negative stereotypes	.61**	.20	.27**	.003
Employee layoff	→ Negative stereotypes	−.13	.20	−.06	.507
Two-way interactions for moderators					
Positive stereotypes					
Psychological distance	× Recruiting	.40	.33	.14	.231
Psychological distance	× Employee layoff	−.38	.35	−.14	.284
Negative stereotypes					
Psychological distance	× Recruiting	−.05	.31	−.02	.868
Psychological distance	× Employee layoff	−.10	.32	−.04	.753
Effects of the mediators (Path B)					
Positive stereotypes	→ Org. attractiveness	.50**	.17	.23**	.004
Negative stereotypes	→ Org. attractiveness	−.81***	.09	−.65***	< .001
Indirect effects of mediators (Path A*B)					
Positive stereotypes	→ Org. attractiveness	−.13*	.06	−.05*	.031
Negative stereotypes	→ Org. attractiveness	−.27*	.11	−.10*	.011
Direct effects (Path C)					
Psychological distance	→ Org. attractiveness	.40***	.10	.15***	< .001

Note. B = unstandardized effect, SE = standard error, β = standardized effect, n = 317, org. = organizational, psychological distance: high distance = 0, low distance = 1. For the moderators, recruiting and employee layoff, the bonus payment scenario is taken as the reference (= 0). * p < .05; ** p < .01; *** p < .001.

Concerning our treatment effects, we found evidence that the level of psychological distance affected both positive and negative stereotypes. At the first-order level, we found significant effects for all proposed stereotypes, except for perceived distrust (perceived innovativeness: $\beta = -0.33$, $p = .006$; perceived performance: $\beta = -0.27$, $p = .024$; perceived speed: $\beta = -0.35$, $p = .003$; perceived unfairness: $\beta = 0.28$, $p = .012$; perceived distrust: $\beta = 0.22$, $p = .060$; perceived creepiness: $\beta = 0.41$, $p < .001$). At the second-order level, we found a negative effect on positive stereotypes ($\beta = -0.41$, $p = .003$) and a positive effect on negative stereotypes ($\beta = 0.29$, $p = .014$), supporting hypothesis 2. We cannot support hypotheses 4 and 5, as no moderating effects were found for recruitment or layoff. However, we observed a direct impact of recruitment on positive stereotypes ($\beta = .61$, $p = .003$). Moreover, we found significant effects between stereotypes and organizational attractiveness at both the first- and second-order levels (positive stereotypes: $\beta = 0.24$, $p = .003$; negative stereotypes: $\beta = -0.64$, $p < .001$), confirming hypothesis 6. Finally, we can confirm hypothesis 8, because partial mediation effects were found for both positive and negative stereotypes at the second-order level, as the indirect effects between stereotypes and organizational attractiveness were significant (positive stereotypes: $\beta = -0.10$, $p = .040$; negative stereotypes: $\beta = -0.19$, $p = .018$).

3.3.4.7 Brief Discussion of Study 2

Our results revealed that our validated ADM stereotypes could be extended to another setting, as we again found partial mediation effects for both positive and negative stereotypes. In addition, psychological distance impacted how ADM is perceived: When individuals felt further away from the decision (i.e., high psychological distance), they viewed ADM more positively and less negatively than individuals who were directly affected (i.e., low psychological distance). We found no moderating effects for our proposed types of tasks (i.e., bonus payments, recruitment, layoffs).

3.4 Overall Discussion

This study aimed to answer the following research questions: (1) Does ADM also lead to positive stereotypes? (2) If so, do these stereotypes coexist with negative ones? (3) What role does psychological distance play in shaping these stereotypes? Through a pre-study and two experimental studies, we showed that individuals indeed hold positive stereotypes of ADM and that they coexist with negative ones. Table 3-6 depicts which hypotheses were supported and which were rejected based on the results of both studies. Building on categorization theory (Oakes & Turner, 1990), we found that ADM triggers perceptions of innovativeness, performance, and speed (positive stereotypes), as well as distrust, unfairness, and creepiness (negative stereotypes). Drawing on construal level theory (Trope & Liberman, 2010), we found that psychological distance significantly shapes ADM stereotypes. Direct confrontation with ADM decisions resulted in fewer positive and more negative evaluations. Inter-organizational (i.e., company type) and intra-organizational (i.e., managerial context) boundary conditions did not significantly moderate these relationships.

Table 3-6. Overview of Supported Hypotheses

Hypotheses	Results
H1a: ADM → positive stereotypes	Supported
H1b: ADM → negative stereotypes	Supported
H2a: Psychological distance → positive stereotypes	Supported
H2b: Psychological distance → negative stereotypes	Supported
H3a: Moderating effects of company type on positive stereotypes	Rejected
H3b: Moderating effects of company type on negative stereotypes	Rejected
H4: Moderating effects of recruiting and employee layoff on positive stereotypes	Rejected
H5: Moderating effects of recruiting and employee layoff on negative stereotypes	Rejected
H6a: Positive stereotypes → org. attractiveness	Supported
H6b: Negative stereotypes → org. attractiveness	Supported
H7: Mediation effects of ADM → positive and negative stereotypes	Supported (partial mediation)
H8: Mediation effects of psychological distance → positive and negative stereotypes	Supported (partial mediation)

Note. ADM = algorithmic decision-making.

3.4.1 *Theoretical Implications*

Drawing on categorization theory (Oakes & Turner, 1990), we extend prior work by examining both positive and negative stereotypes associated with ADM. While much of the existing literature has focused on either algorithm aversion or algorithm appreciation in isolation, our study demonstrates that both positive and negative stereotypes can be activated *simultaneously*. This coexistence distinguishes our work from previous studies, allowing us to derive our newly introduced concept of *algorithm ambivalence*. Building on this idea, closely linked to attitudinal ambivalence (Thompson et al., 1995), we aim to bridge the concepts of algorithm aversion and appreciation, as we found evidence that they can occur concurrently within individuals. We define algorithm ambivalence as the simultaneous experience of both positive and negative stereotypes of ADM within the same individual. For example, individuals may perceive ADM as innovative while also distrusting it. Therefore, we showed that ADM can lead to internal conflict, where individuals may feel torn between opposing evaluations. Prior research may have overlooked this tension by treating algorithm aversion and appreciation separately.

These findings have important implications for future research. First, the consequences of this internal conflict remain largely unexplored. While our findings show that algorithm ambivalence can have both positive and negative effects on organizational attractiveness, it remains unclear how such ambivalence affects individuals at a psychological level or influences team dynamics and organizations over time. Second, it is not yet understood whether and how this internal tension can be managed or even resolved. Third, this conflict may not manifest uniformly across all stakeholder groups. For example, first parties using ADM—who were not included in this study—may experience different forms or intensities of ambivalence than second or third parties. We therefore encourage future research to include the concept of algorithm ambivalence to generate more nuanced theoretical insights and to develop practical guidance for implementing ADM systems in organizations.

Furthermore, we explicitly differentiate distrust and unfairness as distinct constructs, rather than treating them as mere opposites of trust and fairness (Lewicki et al., 1998). Previous studies predominantly measured fairness or trust and showed that ADM led to lower reactions of fairness and trust than HDM. However, some studies have argued that unfairness or injustice is evident, something that cannot simply be derived from this analysis, as justice and injustice, or trust and distrust, do not appear as direct opposites on the spectrum (Kramer, 1999). We integrated the measurement of distrust and unfairness directly, thus offering a more refined conceptualization of negative ADM stereotypes.

By applying construal level theory (Trope & Liberman, 2010), we showed that psychological distance, specifically whether individuals are directly or indirectly affected by ADM decisions, significantly impacts how ADM is evaluated. When individuals are directly impacted (i.e., low psychological distance, second parties), they report fewer positive and more negative perceptions, likely due to increased scrutiny, emotional involvement, and reduced perceived control. Conversely, third parties (i.e., high psychological distance) tend to rely on abstract, generalized cues and, thus, express more favorable stereotypes of ADM. This insight addresses a gap in ADM research, which has so far overlooked the role of psychological distance in shaping ADM stereotypes.

Finally, we investigated inter- and intra-organizational boundary conditions that may shape how ADM is perceived. Although company type (i.e., established vs. new ventures) did not moderate the effects of ADM, we observed direct effects: Established companies were more strongly associated with negative stereotypes such as creepiness and unfairness, regardless of ADM usage. This suggests that organizational characteristics may shape general perceptions, reinforcing certain associations even before ADM is introduced.

Regarding managerial context, we found that high-stakes decisions (e.g., recruitment and layoffs) intensified negative perceptions under low psychological distance, consistent with prior findings on sensitivity to power asymmetries in decision-making contexts (Höddinghaus et al., 2021; Lee, 2018). These findings highlight the importance of recognizing the contextual sensitivity of ADM use within organizations.

3.4.2 Practical Implications

Our findings challenge the predominantly negative discussion surrounding ADM by introducing the concept of algorithm ambivalence. Thus, we urge organizations to focus on the positive stereotypes and try to mitigate the negative ones. To leverage the benefits, organizations should not only integrate ADM strategically but also actively communicate its advantages. For example, emphasizing how ADM enhances consistency or decision-making speed may also improve individuals' perceptions of the organization. Specifically, for applicants, organizations could outline their use of ADM on their websites, clearly explaining the advantages it has for them (e.g., faster replies, innovative working environment). Organizations could also do the same for employees once ADM systems are introduced.

To mitigate the negative stereotypes, organizations could engage in transparent communication about the role and scope of ADM, such as when it is used, how it works, and what human oversight is in place (Langer et al., 2025; Tarafdar et al., 2023). However, the level of transparency should be considered carefully, as prior work found that too much transparency can lead to information overload (Hu et al., 2024). Thus, it is important for organizations to consult the affected individuals to determine their preferred communication approach.

Additionally, our findings on psychological distance underscore the importance of tailoring ADM communication and implementation strategies to the audience's proximity to the decision. Individuals directly affected by ADM tend to react more critically, reporting fewer positive and more negative perceptions than those who only observe it from a distance. This suggests that proximity heightens scrutiny, likely due to perceived loss of control and direct consequences. To mitigate this, organizations should provide clear information to those directly impacted by ADM, helping them understand both the process and its implications. In addition, discussing ADM introduction in the media may be a suitable employer branding technique, as individuals perceive the introduction more positively. However, it is important for organizations to be prepared once these individuals shift from being third to second parties (i.e., encounter ADM directly).

3.4.3 Limitations and Future Research

Several limitations of this study should be noted. First, although the experimental vignette design enabled us to manipulate both ADM vs. HDM and low vs. high psychological distance (Aguinis & Bradley, 2014), hypothetical scenarios cannot fully capture the complexity of real-life ADM exposure. Future research should complement these findings with field studies involving applicants and employees directly confronted with ADM decisions. In particular, such studies could explore the effects of ADM over time and investigate actual behavior, such as application or employee retention.

Second, we employed a second-order factor SEM to capture broader patterns of ADM-related perceptions while reducing correlations between first-order constructs (e.g., unfairness, distrust, emotional creepiness, and creepy ambiguity). While this approach supports theoretical parsimony, it simplifies the unique contributions of each first-order construct. Moreover, our model fit comparison showed that the second-order model performed slightly worse than the first-order model, suggesting that aggregation might come at the cost of slightly reduced precision (Schwarz, 1978). Future research should consider testing first- and second-order models with additional variables and intra- and inter-organization contexts to refine theoretical understanding.

Third, our sentiment analysis of media discourse helped validate commonly held public stereotypes of ADM, but such techniques are inherently limited. Lexicons, such as *NRC*, may misclassify words due to limited contextual understanding—for example, mistaking “distrust” for trust (Cero et al., 2024). To improve robustness, we used the *AFINN* lexicon, which analyzes full sentences. Nevertheless, aggregating sentiment into categories such as positive or negative oversimplifies emotional complexity (Yue et al., 2019). Future research could apply natural language processing methods to capture the nuances of public discourse on ADM.

Fourth, although we examined relevant boundary conditions, further refinements are possible. For example, while we compared new ventures and established companies, other organizational types—such as non-profits, public institutions, or multinational corporations—may elicit different ADM perceptions. Future research could also examine variables such as industry type (e.g., tech vs. manufacturing) or digital maturity.

Finally, our study focused on three managerial contexts: bonus payments, recruitment, and layoffs. Although these differ in their stakes, they may all involve high power asymmetries, limiting variance in perceived control. The absence of stronger context effects may be explained by this limited range. Future studies should explore lower-stakes or short-term ADM use cases (e.g., task allocation, feedback suggestions) or compare roles of first parties (i.e., users of ADM), second parties (i.e., affected individuals), and third parties (i.e., observers; Langer & Landers, 2021; Lee, 2018) to better understand how power dynamics and proximity impact ADM evaluations.

4 Essay III: Too Much Information? The Role of Algorithm Transparency and Type of Task in Employee Reactions to Algorithmic Management[11]

Abstract

The use of algorithmic management (AM) expands continuously in organizations, whereas knowledge about the impact of boundary conditions, such as algorithm transparency and managerial task, on employee reactions to AM is still underdeveloped. To fill these voids, this study draws on the affective response model (Zhang, 2013) and examines the role of algorithm transparency (i.e., high vs. low) and different managerial tasks (i.e., work allocation, training allocation, performance evaluation) for the relationship between AM and employee reactions (i.e., perceived data security, emotional creepiness, opportunity to perform). Using a vignette study with German employees (*n* = 354), we showed that AM diminished perceived data security and opportunity to perform and increased emotional creepiness compared to human management. In turn, all reactions mediated the relationship between AM and turnover intention. We found that in training allocation and performance evaluation, high algorithm transparency was perceived more negatively than low transparency, with performance evaluation under high transparency eliciting the most negative reactions. Our findings clarify how employee reactions to ADM vary by algorithm transparency and type of managerial task, offering guidance for tailoring AM implementation and communication.

Keywords: algorithmic management, algorithmic decision-making, employee reactions, algorithm transparency

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- *83rd Annual Meeting of the Academy of Management (AOM)*, Boston, USA, 2023.
- *23rd European Academy of Management Conference (EURAM)*, Dublin, Ireland, 2023.
- *AI in Business and Economics – The Economics Perspective on Artificial Intelligence (EPEAI)*, Mülheim, Germany, 2023.

4.1 Introduction

Algorithmic management (AM) refers to the use of data-driven algorithms, often enhanced by machine learning, to perform core managerial functions such as coordinating, monitoring, evaluating, and controlling workers' tasks and behaviors (Benlian et al., 2022; Möhlmann et al., 2021). While much of the existing research on AM has focused on non-standard, platform-mediated gig work with minimal human oversight (e.g., Duggan et al., 2020; Huo et al., 2025; Wood et al., 2018), AM progressively permeates standard work environments. In these work contexts, algorithmic systems are embedded within existing hierarchies, often operating in hybrid, less visible ways alongside human managers and tending to augment rather than replace human decision-making (Raisch & Krakowski, 2021; Stark & Vanden Broeck, 2024). Consequently, it becomes more difficult to isolate and assess the actual impact of AM, as its influence is entangled with established managerial roles and organizational practices. Yet, for AM to be successfully implemented and to unfold its full potential, it is important to understand how employees react to AM integration, as their responses may also have detrimental impact for the whole organization, such as reduced turnover intention (Köchling et al., 2023). Therefore, it is surprising that despite its growing prevalence, AM is an underexplored and undertheorized topic of interest in standard-work settings within the broader literature (Cropanzano et al., 2022; Duggan et al., 2020).

So far, previous literature described employee reactions to AM to largely depend on the degree of transparency and the nature of the substituted task. First, transparency (e.g., clarifying the algorithm's role within the decision-making process) can enhance individuals' trust and acceptance of AM (Benlian et al., 2022; Köchling & Wehner, 2023; Park et al., 2021). However, too much transparency may evoke information overload or confusion, particularly when individuals lack the necessary expertise (Ananny & Crawford, 2018). This reflects a transparency paradox where efforts to enhance understanding can inadvertently generate skepticism or distrust (Hu et al., 2024; Lehmann et al., 2022). However, the conditions under which transparency shifts from being beneficial to detrimental remain insufficiently explored.

Second, previous studies showed that AM tends to be less accepted for tasks involving human intuition or emotional intelligence and more accepted for mechanical or data-driven tasks (Höddinghaus et al., 2021; Köchling et al., 2023; Lee, 2018). In particular, employees may resist AM when it is applied to managerial tasks where employees feel that empathy, human intuition, and sensitivity are needed, such as training allocation or performance evaluation (Langer et al., 2019). By contrast, AM is typically more accepted in technical or administrative tasks, such as work allocation or scheduling, which are perceived as objective and rule-based (Lee, 2018).

Based on previous findings on AM in different transparency and task settings separately, we argue that the effect of transparency varies across different types of tasks. For one, high levels of transparency may evoke more positive employee reactions to AM in mechanical tasks (e.g., work allocation), where it reinforces perceptions of objectivity and efficiency. Thus, employees may perceive transparency in these types of tasks more congruent with their expectations (i.e., introducing AM in these tasks is perceived as meaningful). However, in tasks where human skills are needed (e.g., performance evaluation), increased transparency may be perceived as intrusive or inappropriate. This may heighten concerns about fairness, privacy, or dehumanization, due to the incongruence of employees' expectations toward the situation (i.e., AM use not perceived as meaningful). Thus, we propose that the impact of the transparency paradox is not universal but contingent on the nature of the managerial task involved.

Consequently, our study proposes the following research question: ***How do employee reactions to AM vary across levels of algorithm transparency (i.e., high vs. low) and managerial tasks (i.e., work allocation, training allocation, performance evaluation)?***

To answer this research question, we conduct a vignette experiment (*n* = 354) and make two contributions to the literature. First, we shed light on the complexities of the transparency paradox by examining whether algorithm transparency may have unintended negative effects on employee reactions. Contrary to the assumption that transparency mitigates negative responses (Köchling & Wehner, 2023; Wang & Qiu, 2024), our results indicate that increased algorithm transparency can have detrimental effects. We argue that due to the high complexity of algorithms, employees may lack the technical expertise to fully comprehend AM-related information in attempts to create transparency. Providing detailed explanations of the underpinnings of AM may lead to confusion and information overload. In doing so, we challenge prior research that predominantly highlights the positive implications of transparency by showing that transparency might not be a panacea for negative employee reactions.

Second, we provide first empirical evidence that the transparency paradox unfolds differently across types of managerial tasks. Building on Lee's (2018) work that task characteristics shape employees' affective responses to AM, we extend the theoretical understanding of how increased transparency may be particularly detrimental in tasks requiring human skills (e.g., performance evaluation), while having less impact in more mechanical tasks (e.g., work allocation). In our study, participants perceived training allocation and performance evaluation more negatively under high transparency than under low transparency. In contrast, transparency did not significantly change AM reactions in work allocation. Interestingly, training allocation, especially under low transparency, was evaluated more positively than work allocation, which diverges from our initial expectations.

These results suggest that the binary classification of managerial tasks as either “human” or “mechanical” may be overly reductive. Instead, perceptions of AM likely depend on additional contextual factors, such as the level of transparency provided.

In doing so, we provide more substantiating evidence for the importance of taking a relational perspective when investigating advanced technologies (Bailey et al., 2022). Whereas previous studies introduced, for example, a differentiation of the type of tasks (e.g., Lee, 2018; Newman et al., 2020) or the countries where AM is introduced (Kleinlogel et al., 2023), we exemplify that the reactions to these boundary conditions are (inter-)dependent. Consequently, we urge future researchers to account for the simultaneous effect of varying boundary conditions on AM reactions

4.2 Theoretical Background and Hypotheses Development

4.2.1 AM and Employee Reactions

AM is conceptualized as the use of systems and processes that employ algorithms to oversee, evaluate, and guide employee performance (Benlian et al., 2022; Parent-Rocheleau & Parker, 2022). Algorithms refer to step-by-step computational procedures designed to process information and produce outputs (Kellogg et al., 2020). AM systems automate tasks traditionally performed by human managers, such as task assignment, performance monitoring, and feedback provision, by processing large volumes of data to optimize work processes and guide employee behavior (Jarrahi et al., 2021; Kellogg et al., 2020). AM systems often incorporate artificial intelligence (AI), which refers to the ability of machines to analyze large datasets, recognize patterns, and make predictions or decisions in complex environments (Prikshat et al., 2023). AM can range from relatively simple rule-based algorithms, which follow predefined settings, to complex applications using machine learning, which enables systems to learn from data and adapt their outputs (Meijerink & Bondarouk, 2023).

Employee reactions to AM in supervisory and decision-making roles encompass a range of cognitive and emotional responses (Chang et al., 2024; Köchling et al., 2025; Zhang, 2013). These reactions reflect how employees interpret the purpose, fairness, and consequences of AM introduction. Such reactions can range from positive responses—such as increased trust, perceived usefulness, or confidence in the decision (Lee, 2018; Suen & Hung, 2023)—commonly referred to as *algorithm appreciation* (Logg et al., 2019), to negative responses—such as heightened skepticism, resistance, or psychological discomfort (Langer & König, 2018)—often described as *algorithm aversion* (Dietvorst et al., 2015). Key employee reactions that have been introduced in the context of AM include perceived data security risks (Shin et al., 2022), the degree of autonomy and control retained in performance (Köchling et al., 2023), and the emotional discomfort (i.e., creepiness), evoked by the feeling of constant digital surveillance (Langer et al., 2018). The majority of previous work on AM indicates that employees are more averse to AM (i.e., algorithm aversion is more prevalent; Carter & Wynne, 2024; Mahmud et al., 2022), as AM leads to perceptions of reduced justice (Ochmann et al., 2024) or fairness (Höddinghaus et al., 2021) compared to HM.

Understanding employee reactions is essential for the effective implementation of algorithmic systems in the workplace (Langer, König, & Hemsing, 2020). Negative employee reactions to AM (i.e., algorithm aversion) can have significant long-term consequences for organizations, including reduced performance, lower compliance, and increased turnover intentions (Köchling et al., 2023; Prikshat et al., 2023). In contrast, positive employee reactions (i.e., algorithm appreciation) can foster increased trust in the system and improved efficiency of decision-making processes (Glikson & Woolley, 2020; Mahmud et al., 2024).

4.2.2 Affective Response Model

Affective reactions to the introduction of AM can take the form of both discrete emotions and broader affective evaluations (Zhang, 2013). For instance, concerns about data security, limited opportunity to perform, and feelings of emotional creepiness represent employees' reactions both on an emotional and evaluative basis. Each of these factors can trigger discomfort, anxiety, or unease—emotional responses that directly influence broader organization outcomes, such as turnover intention (Köchling et al., 2023). We use the affective response model (ARM) as our theoretical lens, as it recognizes the duality of emotional and evaluative states and emphasizes the role of affect in shaping individuals' attitudes toward new technologies (Zhang, 2013). The ARM posits that individuals have attitudes based not only on evaluative assessments but also on emotional responses triggered by external stimuli. These affective reactions result from largely unconscious processes that help individuals orient themselves in a given situation (Russell, 2003).

Prior research has applied the ARM in communication and information technology contexts and, more recently, in human–algorithm studies (Agogo & Hess, 2018; Cui & Kankanhalli, 2023; Köchling et al., 2023). Building on this work, we propose that perceived data security, opportunity to perform, and feelings of emotional creepiness act as key employee reactions to AM. In our study, we chose these three affective reactions, because previous studies indicated them to be main factors impacting AM introduction in organizations (Köchling et al., 2025; Köchling et al., 2023; Langer & König, 2018). *Perceived data security* becomes a concern when employees believe that AM systems collect and analyze sensitive data, such as performance ratings and assessments (Abraha, 2023; Köchling et al., 2025). This may lead to an information asymmetry: The employer now has a lot more knowledge about the employee than vice-versa. These asymmetries can erode trust and foster fears of surveillance or misuse (Van Berkel et al., 2020; Zhou et al., 2023).

Opportunity to perform refers to whether employees feel able to demonstrate their competencies or respond to decisions (Köchling et al., 2023; Noble et al., 2021). AM often limits such opportunities through standardized rules and metrics (Lindebaum et al., 2019), reducing personalization, clarification, and feedback (Liu et al., 2025; Rosenblat & Stark, 2016). This can lead to frustration, powerlessness, and diminished engagement. *Emotional creepiness* captures discomfort when AM systems behave unpredictably or impersonally (Langer & König, 2018). The lack of empathy and contextual sensitivity may cause uncertainty about decision processes and accountability, making AM feel mechanistic (Köchling et al., 2023; Nordström, 2022). In line with the ARM, we argue that these employee reactions (i.e., perceived data security, opportunity to perform, emotional creepiness) play an important role in shaping whether employees are averse or appreciative to AM systems. Therefore, we hypothesize:

Hypothesis 1: Compared to HM, AM decreases (a) perceived data security and (b) opportunity to perform and c) increases emotional creepiness.

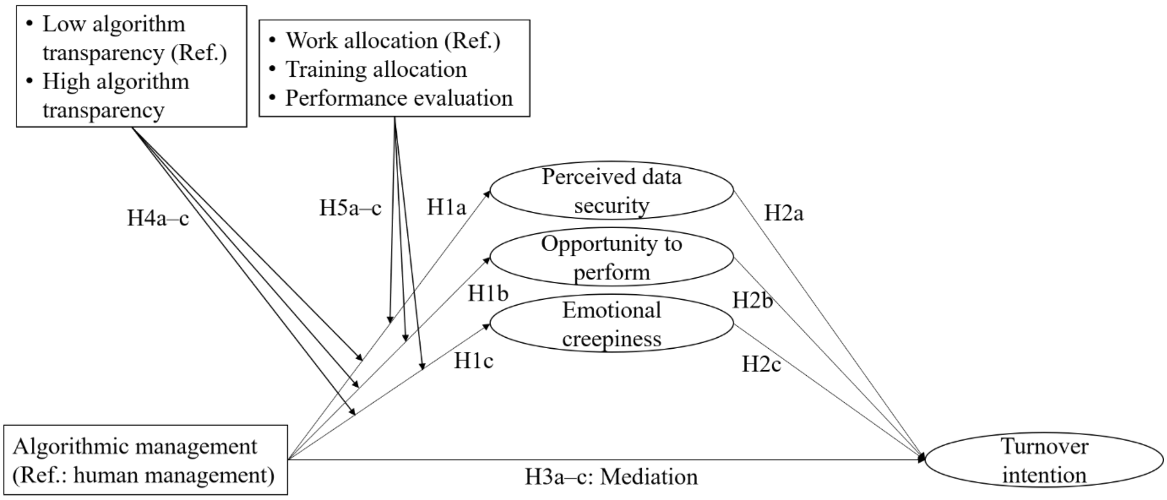
Perceived data security, opportunity to perform, and emotional creepiness impact how employees experience AM and, in turn, shape their intention to stay in the company (Aşkun et al., 2018; Köchling et al., 2023). Low perceived data security can create privacy concerns, diminishing employees' trust in their employer and leading them to seek work environments with greater protection (Zhou et al., 2023). Similarly, a lack of opportunity to perform can undermine perceptions of fairness and career growth, which can make employees feel undervalued and more likely to consider alternative employment (Köchling et al., 2023). Lastly, emotional creepiness may lead to psychological discomfort and detachment, reinforcing the desire to leave (Langer & König, 2018). Thus, we hypothesize:

Hypothesis 2: (a) Perceived data security and (b) opportunity to perform are negatively associated with turnover intention, whereas (c) emotional creepiness is positively associated with turnover intention.

Hypothesis 3: (a) Perceived data security, (b) opportunity to perform, and (c) emotional creepiness mediate the relationship between AM and turnover intention.

Our hypothetical research model is depicted in Figure 4-1.

Figure 4-1. Hypothetical Research Model



Note. Ref. = reference; Latent constructs are depicted as ellipses, while the observed variables (i.e., treatments) are depicted as rectangles.

4.2.3 Transparency Paradox in AM

The literature distinguishes between two primary forms of transparency: process transparency and algorithm transparency (Park et al., 2021). Process transparency refers to clarifying the algorithm's role in decision-making, specifically, when and how the algorithm contributes to or impacts outcomes (Candrian & Scherer, 2022). This type of transparency provides employees with a clearer understanding of the system's function without requiring technical expertise. As such, employees generally react positively to process transparency, because it reduces uncertainty (Friedrich et al., 2022). In contrast, algorithm transparency involves disclosing more technical details, such as the algorithm's mathematical principles, decision criteria, and the nature of the data used in decision-making (Bitzer et al., 2023; Park et al., 2021). Despite the beneficial effects of process transparency being widely understood and evidenced for a range of work-related settings, organizations often times focus on algorithmic transparency as required by regulatory demands (e.g., New York Algorithmic Pricing Disclosure Act, General Data Protection Regulation [GDPR], California Consumer Privacy Act [CCPA]/California Privacy Rights Act [CPRA]; California State Legislature, 2020; European Commission, 2016; New York State Senate, 2025). Consequently, our study focuses on the impact of algorithm transparency to provide insights on how employees perceive it and whether the effects are also solely positive as previously mentioned regarding process transparency.

In addition, we focus specifically on algorithm transparency rather than process transparency, as we expect the differences in the type of task to be relevant majorly for algorithm transparency. Process transparency emphasizes how the algorithm is embedded within the broader decision-making process, which may divert attention away from the algorithm itself. For example, explaining that a human oversees or validates the final decision can downplay the algorithm's role. In contrast, providing information about the algorithm (i.e., high algorithm transparency) directly reinforces its importance in the decision process. Therefore, we expect the differences for the type of task to apply particularly to algorithm transparency.

While increased algorithm transparency may foster trust by revealing aspects of the "black box" (Von Eschenbach, 2021), it can also create information overload and confusion, particularly for employees who lack the technical expertise (Ananny & Crawford, 2018). This phenomenon, known as the *transparency paradox* (Hu et al., 2024; Lehmann et al., 2022; Park et al., 2021), suggests that while some level of transparency is beneficial, excessive disclosure can increase skepticism (Schmitt et al., 2021).

Both forms of transparency aim to reduce uncertainty and build trust, but they differ in cognitive demand. Process transparency communicates the logic and scope of the algorithm's involvement in accessible terms (Park et al., 2021). In contrast, algorithm transparency often demands significant technical understanding, which may not only fail to improve comprehension but can also trigger negative employee responses (i.e., algorithm aversion). For instance, organizations' efforts to disclose what types of personal data are used to train algorithms may raise concerns among employees regarding the perceived data security and may heighten fears of surveillance or misuse (Zhou et al., 2023). Moreover, complex explanations (i.e., algorithm transparency) may also reduce employees' sense of opportunity to perform, as employees may feel unable to challenge or meaningfully engage with algorithmic decisions. Finally, overly technical or impersonal information may increase emotional creepiness, reinforcing discomfort between employees and AM systems. In line with the ARM, we argue that these employee reactions are critical mediators of how transparency shapes employee responses to AM. Therefore, we hypothesize:

Hypothesis 4: Compared to AM with low algorithm transparency, AM with high algorithm transparency is negatively associated with (a) perceived data security and (b) opportunity to perform, and positively associated with (c) emotional creepiness.

4.2.4 The Impact of Managerial Tasks on Algorithm Transparency

We further argue that algorithm transparency may not elicit negative employee reactions in all tasks equally. Here, we draw on previous findings that employees are generally more accepting of AM when it supports objective, rule-based tasks such as *work allocation*, and more critical when it is used for tasks requiring subjective judgment, such as *training allocation* or *performance evaluation* (Höddinghaus et al., 2021; Köchling et al., 2023; Newman et al., 2020). In more objective tasks, employees tend to view machines as well-suited decision-makers, because the criteria involved are transparent and largely devoid of social complexity (Lee, 2018). By contrast, subjective tasks are typically associated with social meaning, contextual understanding, and developmental implications (Oltedal Thorp et al., 2024). Employees may expect individualized judgment and human reasoning, especially in areas such as performance evaluation, hence, AM is viewed negatively (Votto et al., 2021).

These task-specific expectations are critical for understanding how employees respond to algorithm transparency. In work allocation, transparency may be tolerated or even appreciated, as the logic underpinning algorithmic decisions is perceived to be rational, rule-based, and aligned with expectations for impartiality (Lee, 2018). However, in more socially sensitive tasks such as training allocation and performance evaluation, algorithm transparency may have unintended consequences. In these contexts, revealing the algorithm's logic can expose its lack of nuance (Kaufmann et al., 2023). For example, decisions about training allocation involve judgments about long-term growth potential, while performance evaluations affect recognition and career progression (Zhang & Amos, 2024). When employees are confronted with rigid criteria or opaque weighting systems in such areas, algorithm transparency may not mitigate concerns, but rather intensify them by highlighting the inadequacy of algorithmic logic for these complex, socially embedded tasks.

We therefore examine employee reactions to AM across three distinct managerial tasks (i.e., work allocation, training allocation, performance evaluation) with varying algorithm transparency. Work allocation involves assigning tasks based on relatively explicit, measurable factors, such as workload balance or availability, making algorithmic decisions in this domain appear efficient and justifiable (Lee, 2018). In contrast, training allocation requires nuanced assessments of development needs and potential, and performance evaluation is even more complex, incorporating behavioral assessments, interpersonal history, and cultural context (Cha, 2025; Votto et al., 2021). These tasks rely heavily on human intuition and social judgment (Höddinghaus et al., 2021), which algorithms may fail to replicate. Hence, we propose that AM decisions in training and performance evaluation may elicit more negative reactions—especially under high algorithm transparency—than those in work allocation. Therefore, we hypothesize:

Hypothesis 5: Compared to AM in work allocation, AM in training allocation and performance evaluation under high algorithm transparency is negatively associated with (a) perceived data security and (b) opportunity to perform, and positively associated with c) emotional creepiness compared to low algorithm transparency.

4.3 Methodology

4.3.1 Sample

We recruited a quota-based sample through an ISO 20252:19 certified online panel provider. To determine the required sample size, we conducted a G*Power analysis for MANOVA global effects, which indicated a minimum of 324 participants was needed to achieve sufficient statistical power (Faul et al., 2007). We slightly oversampled, resulting in 393 participants. After removing 39 participants who failed the implementation checks, the final sample consisted of 354 participants, with 49.40% identifying as female and 50.60% as male. The average age was 45.33 years (*SD* = 12.14; see Table 4-1 for more information). The participants were required to be at least 18 years old and currently employed.

Table 4-1. Detailed Sample Characteristics

Characteristics	Absolute Value	Relative Value
Mean age	45.33 years (*SD* = 12.14)	
Gender distribution	175 female 178 male 1 diverse	43.85% female 55.52% male 0.63% diverse
Highest educational background	10 Lower school leaving certificate 72 Intermediate school leaving certificate 93 High school diploma 55 Bachelor's degree 112 Master's degree 10 Doctorate 2 No data	2.80% Lower school leaving certificate 20.30% Intermediate school leaving certificate 26.30% High school diploma 15.50% Bachelor's degree 31.60% Master's degree 2.80% Doctorate .60% No data

Note. The final sample consists of 354 participants. *SD* = standard deviation.

4.3.2 Scenarios

We conceptualized this experimental vignette study as a between-subjects design with twelve hypothetical scenarios according to a 3 × 2 × 2 structure (3 tasks, 2 levels of algorithm transparency, 2 decision entities). This approach allows a realistic manipulation, while controlling for the independent and potential third variables (Aguinis & Bradley, 2014). Participants were randomly assigned to one of the twelve scenarios to which they all were required to answer the same questions about their perceptions about the decision.

We adapted three managerial tasks (i.e., work allocation, training allocation, performance evaluation) for our study. The work allocation and performance evaluation decisions were adapted from Lee (2018). The self-developed training allocation scenario was designed to reflect AI-driven employee development programs, where algorithms assess employees' past performance and skill levels to assign tailored training based on previous research in this field (e.g., Rožman et al., 2023; Votto et al., 2021). In the scenario, the algorithm or the manager evaluates an employee's past presentations using speech analysis and gesture tracking to determine areas for improvement.

Each task was presented in both low transparency and high transparency conditions, where algorithm transparency was manipulated by varying the level of explanation provided for how the algorithm or manager made the decision. To establish high algorithm transparency in these scenarios, we introduced detailed explanations of how the algorithms processes data and makes decisions. This included specifying the type of data analyzed (e.g., speech characteristics, performance metrics, or component wear rates), the methodologies used (e.g., Fourier analysis, tensor-based evaluations, or benchmarking against established criteria), and the iterative nature of the decision-making process (Körner, 2022; Schmitz et al., 2004). Appendix C1 depicts the scenarios in more detail.

4.3.3 Measures

All questionnaire items were measured on a 5-point Likert scale, where 1 indicated strongly disagree and 5 strongly agree. To reduce common method bias, the items were randomly rotated (Podsakoff et al., 2003). We performed a pre-test with 35 participants to enhance scenario and instrument clarity. Participants in the experiment who failed to answer two attention checks correctly or three comprehension questions about the independent variable (AM vs. HM) were excluded to ensure attentiveness. We provided a brief definition of AI in the AM scenarios to ensure participants shared a common understanding of AI.

For our multigroup structural equation modeling (multigroup SEM; see 3.3 Analytical Procedures), we created six distinct groups representing the different experimental conditions. These groups were based on combinations of the managerial task (i.e., work allocation, training allocation, and performance evaluation) and the level of algorithm transparency (i.e., low vs. high). For AM, we created a dichotomous variable (0 = HM, 1 = AM; see Appendix C2 for a balance check of the groups).

Perceived data security was measured with two items from the organizational justice scale by Roch and Shanock (2006), being “I could trust that my data would be treated confidentially in this matter" and "In this situation, no private information about me would be disclosed". Cronbach's α was .63.

Opportunity to perform was measured with two items from Bauer et al. (2001): "In this situation, I could really show my skills and abilities" and "I would be able to show what I can". Cronbach's α of this measure was .89.

Emotional creepiness was measured with two items from Langer and König (2018): "During this situation, I would have a queasy feeling" and "This situation would feel threatening to me". Cronbach's α for these items was .90.

Turnover intention was measured with two items: "In this scenario, I would consider changing my job" and "If I could choose, I would not work for this organization" (Mobley et al., 1978). Cronbach's α of this scale was .85.

4.3.4 Analytical Procedures

We employed a four-stage process to examine the structural relationships for the mediation as well as for the analysis of moderating effects across different experimental groups. In the first stage, we performed a confirmatory factor analysis (CFA) using the *lavaan* package in R (Rosseel, 2012) to assess the model fit. For model estimation, we employed maximum likelihood estimation. The model fit was evaluated using several commonly accepted indices: a non-significant χ^2 statistic, a comparative fit index (CFI) greater than 0.95, a root mean square error of approximation (RMSEA) below 0.06, and a standardized root mean square residual (SRMR) below 0.08 (Bollen, 1989; Browne & Cudeck, 1992; Hu & Bentler, 1998). These conditions were consistently met in this study's CFA model (model fit: χ^2 = 18.36, df = 14, p = .19; RMSEA = .03; SRMR = .02; CFI = .99).

Second, we employed an SEM to analyze the direct and mediation relationships between AM, reactions, and turnover intention in an overall model (i.e., our H1−H5). The model fit was acceptable and allowed us to continue with our analysis (χ^2 = 43.17, df = 30,

p = .06; RMSEA = .03; SRMR = .02; CFI = .99). We introduced the experimental manipulations (i.e., training allocation, performance evaluation, algorithm transparency) as control variables by dichotomizing them. The reference category for the managerial tasks was work allocation and for algorithm transparency the low transparency scenarios.

Third, we test for metric invariance, as this is an important pre-requisite to conduct the multigroup SEM. Metric invariance tests whether the factor loadings are equivalent across groups (Steinmetz et al., 2009). Establishing metric invariance is crucial, because it ensures that the constructs are measured in the same way for all groups, allowing for meaningful comparisons of structural relationships (Vandenberg & Lance, 2000). To evaluate metric invariance, we compared the metric invariance model to the configural invariance model. The comparison was based on the χ^2-difference test, along with changes in model fit indices such as Akaike information criterion (AIC) and Bayesian information criterion (BIC). The results showed a χ^2 difference of 17.97 with 15 degrees of freedom (configural model: χ^2 = 55.85, df = 54, AIC = 5,431.5, BIC = 5,419.4; metric model: χ^2 = 73.82, df = 69, AIC = 5,988.7, BIC = 5,918.6), yielding non-significant differences (p = .264), which indicates that constraining the factor loadings to be equal across our groups did not lead to a worse model fit.

Lastly, we conducted the multigroup SEM, in which AM directly affected our employee reactions (i.e., perceived data security, emotional creepiness, opportunity to perform). This analysis reveals the regression coefficients for each group, respectively. The model fit for the multigroup SEM was acceptable in all indices; hence, we can continue with our analysis (χ^2 = 55.85, df = 54, p = .41; RMSEA = .02; SRMR = .05; CFI = .99). To examine whether there were significant differences between the groups, we conducted a χ^2-difference test by comparing the unconstrained model, where parameters were freely estimated, with the constrained model, where parameters were restricted to be equal across groups.

We conducted Harman's single-factor test to assess the risk of common method bias. The analysis showed that a single factor accounted for 40.80% of the total variance, below the commonly used threshold of 50%. Moreover, the poor model fit ($\chi^2(20) = 407.89$, $p < .001$) suggests that the items do not load onto a single factor, indicating that common method variance is unlikely to be a major concern in our data (Podsakoff et al., 2003).

As a robustness check, we calculated alternative multigroup SEM models to ensure that our version had the best model fit. We checked alternative SEM models with our control variables age, gender, and education. These controls neither had significant direct effects nor changed our proposed effects of our mediation model. Therefore, we excluded them in our final multigroup SEM.

4.4 Results

4.4.1 Descriptive Statistics

All means, standard deviations and correlations are depicted in Table 4-2. The correlations ranged from small to moderate and the variance inflation factors (VIF) ranged from 1 to 4.32, indicating that multicollinearity was not a threat in our study. The highest correlations were between emotional creepiness and turnover intention ($r = .64$) as well as perceived data security and turnover intention ($r = -.42$).

Table 4-2. Means, Standard Deviations, and Correlations

Variable	*M*	*SD*	1	2	3	4
1. Perceived data security	3.47	0.86	(.63)			
2. Emotional creepiness	2.92	1.10	−.36*	(.90)		
3. Opportunity to perform	3.35	0.96	.17*	−.36*	(.89)	
4. Turnover intention	2.93	1.12	−.42*	.64*	−.40*	(.85)
5. Algorithmic management	0.49	0.50	−.10	.18*	−.31*	.22*

Note. *M* = mean, *SD* = standard deviation. Algorithmic management: 0 = human management, 1 = algorithmic management. Cronbach's α is reported on the diagonal in parentheses. * $p < .05$; $n = 354$.

4.4.2 *Results of the Overall SEM*

The results of our overall SEM can be seen in Table 4-3. We found a significant direct relationship between AM and perceived data security ($\beta = -.12$, $p = .039$), between AM and opportunity to perform ($\beta = -.33$, $p < .001$) as well as AM and emotional creepiness ($\beta = .19$, $p < .001$). Therefore, we can support our hypothesis 1.

Table 4-3. Results of the Overall Structural Equation Modeling

Variables		***B***	***SE***	***β***	***p*-value**
Treatment effects (Path A)					
AM	→ perceived data security	−0.21*	.10	−.12*	.039
Training allocation	→ perceived data security	−0.36**	.12	−.20**	.004
Performance evaluation	→ perceived data security	−0.50***	.13	−.28***	< .001
Transparency	→ perceived data security	−0.09	.10	−.06	.352
AM	→ opportunity to perform	−0.57***	.10	−.33***	< .001
Training allocation	→ opportunity to perform	−0.03	.11	−.02	.782
Performance evaluation	→ opportunity to perform	−0.23	.12	−.12	.954
Transparency	→ opportunity to perform	−0.25**	.10	−.15**	.009
AM	→ emotional creepiness	0.39***	.09	.19***	< .001
Training allocation	→ emotional creepiness	1.13***	.12	.52***	< .001
Performance evaluation	→ emotional creepiness	1.50***	.13	.68***	< .001
Transparency	→ emotional creepiness	0.18	.09	.09	.059
Effects of the mediators (Path B)					
Perceived data security	→ turnover intention	−0.31***	.09	−.25***	< .001
Opportunity to perform	→ turnover intention	−0.19**	.07	−.16**	.006
Emotional creepiness	→ turnover intention	0.54***	.09	.52***	< .001
Direct effects (Path C)					
AM	→ turnover intention	0.12	.10	.06	.196
Training allocation	→ turnover intention	−0.04	.14	−.02	.762
Performance evaluation	→ turnover intention	0.12	.15	.05	.438
Transparency	→ turnover intention	−0.02	.09	−.01	.821

Notes. B = unstandardized coefficients, SE = standard error, β = standardized coefficients, $n = 354$, Algorithmic management (AM): 0 = human management, 1 = algorithmic management. * $p < .05$; ** $p < .01$; *** $p < .001$.

The results further showed that all three employee reactions were connected to turnover intention (perceived data security: $\beta = -.25$, $p < .001$; opportunity to perform: $\beta = -.16$, $p = .006$; emotional creepiness: $\beta = .52$, $p < .001$), thus, supporting our hypotheses

2a–c. The direct relationship between AM and turnover intention was not significant (β = .12, p = .196), suggesting that this relationship is mediated by our employee reactions. Thus, we can support our hypothesis 3a–c.

4.4.3 Results of the Multigroup SEM

The results of our multigroup SEM are depicted in Table 4-4. For our first group (i.e., work allocation, low algorithm transparency), we found a relationship between AM and opportunity to perform (β = −.29, p = .031), but not between AM and emotional creepiness (β = .30, p = .061) as well as AM and perceived data security (β = −.25, p = .355). In the second group (i.e., work allocation, high algorithm transparency), the relationships between AM and perceived data security (β = −.19, p = .036), AM and opportunity to perform (β = −.39, p = .004) as well as AM and emotional creepiness (β = .33, p = .025) were all significant. In the third group (i.e., training allocation, low algorithm transparency), perceived data security (β = −.13, p = .409), opportunity to perform (β = .20, p = .151), and emotional creepiness (β = .19, p = .202) were not connected to AM. The results showed similar relationships in our fourth group (i.e., training allocation, high algorithm transparency). AM was not connected to perceived data security (β = −.23, p = .083), opportunity to perform (β = −.24, p = .070), and emotional creepiness (β = .12, p = .355). In our fifth group (performance evaluation, low algorithm transparency), results indicated a significant relationship between AM and opportunity to perform (β = −.52, p < .001), but not for AM and perceived data security (β = .11, p = .627) nor emotional creepiness (β = .04, p = .792). In our last group (i.e., performance evaluation, high algorithm transparency), we found that opportunity to perform and emotional creepiness were both connected to AM (opportunity to perform: β = −.65, p < .001; emotional creepiness: β = .45, p < .001).

Table 4-4. Results of the Multigroup Structural Equation Modeling

Variables	***B***	***SE***	***β***	***p*-value**
Group 1: Work allocation – low algorithm transparency				
AM → perceived data security	−0.18	.19	−.25	.355
AM → opportunity to perform	−0.56*	.26	−.29*	.031
AM → emotional creepiness	0.46	.25	.30	.061
Group 2: Work allocation – high algorithm transparency				
AM → perceived data security	−0.49*	.24	−.19*	.036
AM → opportunity to perform	−0.70**	.25	−.39**	.004
AM → emotional creepiness	0.36*	.16	.33*	.025
Group 3: Training allocation – low algorithm transparency				
AM → perceived data security	−0.21	.26	−.13	.409
AM → opportunity to perform	0.24	.17	.20	.151
AM → emotional creepiness	0.24	.19	.19	.202
Group 4: Training allocation – high algorithm transparency				
AM → perceived data security	−0.42	.24	−.23	.083
AM → opportunity to perform	−0.37	.20	−.24	.070
AM → emotional creepiness	0.19	.21	.12	.355
Group 5: Performance evaluation – low algorithm transparency				
AM → perceived data security	0.10	.16	.11	.627
AM → opportunity to perform	−0.86***	.23	−.52***	< .001
AM → emotional creepiness	0.07	.28	.04	.792
Group 6: Performance evaluation – high algorithm transparency				
AM → perceived data security	0.06	.25	.03	.827
AM → opportunity to perform	−1.20***	.22	−.65***	< .001
AM → emotional creepiness	0.69***	.21	.45***	< .001

Notes. B = unstandardized effect, SE = standard error, β = standardized effect, n = 354, Algorithmic management (AM): 0 = human management, 1 = algorithmic management. * $p < .05$; ** $p < .01$; *** $p < .001$.

For the group differences, we calculated the χ^2-difference test for the unconstrained and constrained model separately (see Table 4-5). The results indicated a significant χ^2-difference between the two models ($\Delta\chi^2(15) = 34.06$, $p = .003$), suggesting that constraining the regression coefficients to be equal across all groups worsened the model fit. This means that the structural paths differed among our six groups.

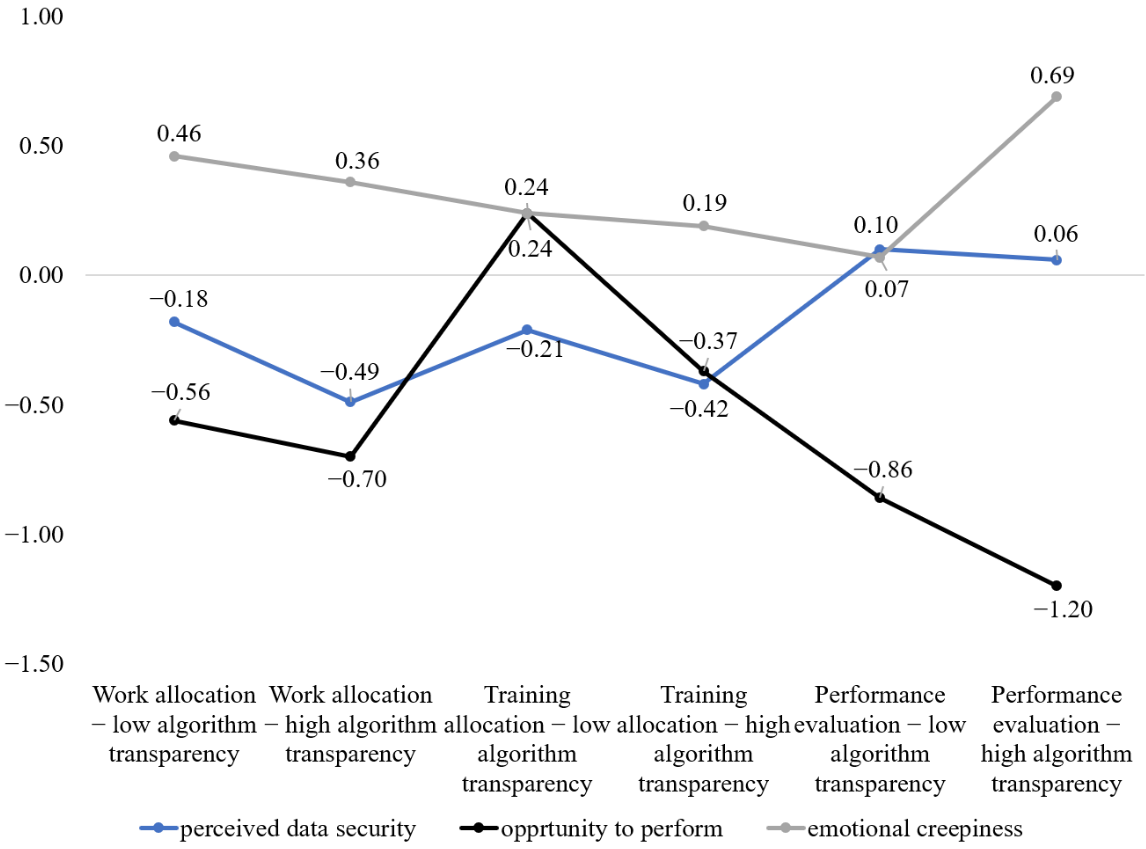
Table 4-5. χ^2 Difference Test for Group Differences

	Df	**Δ*Df***	**AIC**	**BIC**	χ^2	**ΔCFI**	**ΔRMSEA**	***p*-value**
Unconstrained model	54	–	5,431.5	5,988.7	55.85	–	–	–
Constrained model	69	15	5,435.4	5,934.6	89.81	0.03	0.15	.003**

Note. *Df* = degrees of freedom, AIC = Akaike information criterion, BIC = Bayesian information criterion, CFI = comparative fit index, RMSEA = root mean square error of approximation. $n = 354$. * $p < .05$; ** $p < .01$; *** $p < .001$.

Figure 4-2 visualizes the relationships between AM and employee reactions in the different groups. In work allocation, perceived data security and opportunity to perform were lower in the high algorithm transparency scenarios, while emotional creepiness was also lower. Compared to work allocation, emotional creepiness was lower and opportunity to perform higher in training allocation, suggesting that employees were more comfortable with algorithms allocating training rather than work tasks. Furthermore, in training allocation and performance evaluation, we found that employee reactions were more negative in the high algorithm transparency scenarios. The strongest negative effects of algorithm transparency emerged in performance evaluation. Compared to both work allocation and training allocation, opportunity to perform was lowest, and emotional creepiness was highest when transparency was high. This suggests that employees were particularly uncomfortable with detailed information on AM in performance evaluation.

Figure 4-2. Visualization of Group Differences



Notes. The unstandardized regression coefficients for AM (human management is the reference category) on the three mediators (i.e., perceived data security, opportunity to perform, emotional creepiness) are depicted.

Regarding our algorithm transparency hypotheses, hypothesis 4a was not supported, as we found no substantial differences in perceived data security between low and high algorithm transparency. However, hypotheses 4b and 4c were supported in training allocation and performance evaluation, but not in work allocation. Similarly, regarding the differentiation into different managerial tasks, hypothesis 5a was not supported, as no significant differences in perceived data security were found across tasks. Hypotheses 5b and 5c were supported for performance evaluation, but not for work or training allocation because the coefficients were in the opposite direction of our expectations.

4.5 Discussion

The aim of this study was to investigate employee reactions to AM in varying levels of algorithm transparency (i.e., low vs. high) and different managerial tasks (i.e., work allocation, training allocation, performance evaluation). Our findings indicate that, compared to HM, AM was associated with lower perceived data security and opportunity to perform as well as higher emotional creepiness. Additionally, all reactions mediated the relationship between AM and turnover intention. A multigroup SEM revealed significant variations across tasks and transparency levels. Notably, scenarios with high algorithm transparency tended to be perceived more negatively than those with low transparency, suggesting potential unintended consequences of algorithm transparency in AM. Contrary to expectations, employee reactions to training allocation were more favorable than those for work allocation, challenging our initial assumptions. Among all conditions, performance evaluation under high algorithm transparency was perceived most negatively, highlighting concerns about AM implementation in high-stakes evaluative processes.

Consequently, our studies makes three relevant contributions. First, our findings suggest that high algorithm transparency leads to more negative employee reactions. In all three tasks, AM was perceived more negatively under high transparency conditions, suggesting that greater transparency may create uncertainty in employees. The most pronounced effects emerged in performance evaluation, where high algorithm transparency led to the highest increase in emotional creepiness and the lowest level of opportunity to perform. These findings highlight the potential negative implications of opening the “black box” of algorithms (Nordström, 2020; Von Eschenbach, 2021), as greater transparency does not always yield to positive effects. While increasing transparency is often assumed to enhance trust and fairness (Köchling & Wehner, 2023), our results suggest that for certain tasks, algorithm transparency can amplify skepticism and discomfort, which ultimately affects the intended behavior of employees. This aligns with the transparency paradox, where more information does not necessarily improve perceptions but may instead introduce unintended negative consequences (Park et al., 2021). A possible explanation is grounded in the concept of algorithmic reductionism (Newman et al., 2020). By revealing the internal logic of algorithmic decisions, transparency may expose the mechanistic, decontextualized, and impersonal nature of such systems. In doing so, transparency risks making employees feel reduced to data points or stripped of their individuality (Choung et al., 2024), particularly in high-stakes contexts. Thus, algorithm transparency may actively trigger concerns about dehumanization and unfair simplification. Future research should focus on identifying the tipping point at which transparency shifts from being beneficial to harmful. Pinpointing this threshold would provide more actionable insights for organizations, helping them determine the optimal level of transparency that balances trust and acceptance without triggering adverse reactions.

Second, this study found that AM in training allocation was perceived with a higher opportunity to perform and lower emotional creepiness compared to work allocation, especially in the low algorithm transparency scenarios. These results are surprising, as we designed the scenarios for training allocation with higher needed human skills compared to work allocation, based on the findings of Lee (2018). Therefore, we expected employee reactions to be less positive in the training allocation scenarios. One reason might be that this study used a German sample, while the sample of Lee (2018) consisted of employees of the U.S.; hence, the results might be subject to the German culture. Eitle and Buxmann (2020) state that the level of individualism−collectivism in a country could lead to different acceptance patterns of AM. As the U.S. scores higher in individualism than Germany (Hofstede, 2011), U.S. employees may prioritize efficiency and individual benefits, whereas German employees might place greater emphasis on fairness and collective well-being.

In addition, we argue that it may not be the task itself that is the differentiating factor, but other mechanisms that lie behind it. Here, a combination of the psychological distance to the decision (i.e., how close does the decision feel to me personally?; Li & Sung, 2021) and the stakes of the decision (i.e., how much does this decision affect my life?; Langer et al., 2019) might be at play here. We intended to design the scenarios so that they differ in the stakes and that training allocation has higher stakes than work allocation. However, AI is increasingly used in e-learning settings; hence, employees might have become more familiar with AM in training allocation (Kashive et al., 2020), which may have reduced their psychological distance to the decision.

4.5.1 Theoretical Implications

This study advances current theoretical debates on employee reactions to AM by investigating the role of algorithm transparency. While process transparency is commonly assumed to increase trust and acceptance of AM systems (Friedrich et al., 2022), our findings challenge this assumption for algorithm transparency by revealing that its effects are highly task-contingent. Specifically, algorithm transparency evoked negative emotional reactions (i.e., reduced perceived data security and opportunity to perform, increased emotional creepiness) in certain managerial tasks. These findings align with the transparency paradox (Ananny & Crawford, 2018), which suggests that more transparency does not necessarily translate into more positive reactions. By showing that transparency can have detrimental impact depending on the task, our study adds important nuance to theoretical discussions on human–algorithm interaction. We also contribute to the ARM (Zhang, 2013) by positioning algorithm transparency as a key factor that shapes employee reactions in AM introduction.

In addition, by examining two boundary conditions simultaneously (i.e., the type of managerial task and the level of algorithm transparency) and their interaction, this study offers valuable theoretical insights. Previous research has often focused on only one moderating factor at a time (e.g., task type or country), which limits the generalizability of findings and overlooks the complex interplay between contextual variables. Our results demonstrate that considering both boundary conditions together enables more nuanced interpretations. For example, had we only investigated algorithm transparency within the context of performance evaluation, our conclusion might have been that algorithm transparency should generally be avoided. However, by comparing this with reactions to work allocation and training allocation, we show that the effects of algorithm transparency are task-dependent, and that transparency in work allocation does not elicit similarly negative reactions. This highlights the importance of investigating AM under different conditions, and we encourage future researchers to adopt our approach to better capture the complex dynamics of AM implementation in real-world organizational settings.

Furthermore, this study offers new insights into specificities of task-dependent employee reactions. Contrary to our initial hypotheses, the implementation of AM for training allocation is perceived more favorably than its use for work task assignment or performance evaluation. This finding challenges earlier research suggesting more favorable perceptions of AM in task allocation (e.g., Lee, 2018) and underscores the importance of considering the specific managerial function in which AM is deployed.

Finally, this study contributes to the emerging body of literature on AM in traditional work settings, which remain underexplored compared to gig-economy settings. In contrast to gig-work (i.e., where AM is typically involved in algorithmic matching and control), AM in traditional organizations is often applied more selectively, potentially managing only a single task or decision process. As such, the previously established dichotomy of algorithmic control vs. algorithmic matching (Möhlmann et al., 2021) may be less applicable in these settings, necessitating a reconceptualization of AM in traditional work environments. Nonetheless, our findings also showed that algorithm aversion is prevalent. Prior studies in gig-work highlight different forms of algorithmic resistance or "algoactivism" (Cobonpue et al., 2024). In line with previous findings, our study revealed that AM can provoke strong negative reactions, most notably an increase in turnover intention. This suggests that even when AM systems are limited in scope, their impact can still be substantial. We therefore call for more theorizing that bridges AM introduction in gig-work and traditional employment settings, recognizing both the differences in AM and the potential psychological mechanisms which are at play.

4.5.2 Practical Implications

The findings of this study carry significant practical implications for organizations and managers. While AM presents many advantages, organizations must weigh potential negative employee reactions when implementing AM. Our findings on algorithm transparency offer critical insights for practitioners. While transparency is often viewed as a means to increase trust and acceptance, our results suggest that excessive transparency can backfire, particularly in high-stakes decisions such as in performance evaluation. Organizations should carefully calibrate the level of transparency provided to employees, ensuring that it enhances understanding without overwhelming or unsettling them. A one-size-fits-all approach to transparency is unlikely to be effective, and instead, managers should tailor transparency levels based on the specific AM application and employee concerns. In addition, our results indicate that AM elicits fewer adverse employee reactions when used to allocate trainings compared to work tasks or performance evaluation. Thus, our findings suggest that training allocation may serve as a more suitable task to introduce AM compared to work allocation or performance evaluation.

Additionally, it is also worth noting that employee reactions toward AM may evolve over time. On one hand, increased exposure to AM in the workplace may lead to greater familiarity and acceptance, aligning AM with innovation and technological proficiency

(Mahmud et al., 2022). On the other hand, growing public discourse and scrutiny surrounding AI may intensify negative reactions, particularly if concerns about fairness, surveillance, or job displacement become more pronounced. Consequently, companies should take a proactive approach by regularly assessing employee reactions and adapting their AM strategies.

4.5.3 Limitations and Future Research

Despite the insights offered by this study, several limitations must be acknowledged, each of which presents promising avenues for future research. Our study only investigates employee reactions to AM at one point in time. However, these reactions may evolve over time. Thus, a longitudinal study would be valuable for understanding the potential development of employee reactions over time. Horowitz et al. (2024) found that using AI over time improves the feelings individuals have toward these systems; hence, a longitudinal approach could uncover these nuances. However, future research should pay close attention to whether differences over time relate to procedural transparency (as employees get a better [procedural] understanding of AM the longer they interact with it) or improved algorithmic transparency.

Furthermore, it may be difficult to derive turnover intentions from one single scenario, as normally employees have experiences and interactions throughout their work day, which all shape their turnover intentions. Moreover, future research could extend our findings, so that actual turnover is investigated, as it is hard to predict whether the intentions that we found translate to actual behavior.

Besides our three depicted tasks, we are aware that other contextual or individual factors, for example, organizational culture, job insecurity, or trust in technology, could also contribute to differences in employee reactions. Hence, research concerning additional boundary conditions on employee reactions to AM is needed to increase our understanding of how and why employees react to the implementation of AM.

Previous research emphasized the importance of transparency in affecting employee reactions positively (Köchling & Wehner, 2023). We offer new insights about how algorithm transparency influences affective reactions by dividing transparency into high and low levels. Despite these insights, we did not address all possible nuances of transparency, for example, whether the level of explainability or auditability might matter for employees. Langer et al. (2019) highlighted that the level of justification of the transparent process may have positive effects in employee reactions. Thus, researchers could examine algorithm transparency in more detail in future studies. In addition, we did not address process transparency further in our study; hence, future studies could elaborate on the interplay between process and algorithm transparency in more detail.

Finally, our study relied on a vignette-based experimental design, which, while useful for isolating causal effects, may not fully capture realistic complexities of AM implementation (Augunis & Bradley, 2014). Employees' actual responses may differ in at work where interpersonal dynamics, company policies, and long-term exposure to AM systems play a role. Future research could complement experimental findings with field studies or qualitative research to provide a more holistic perspective on employee reactions to AM.

4.6 Conclusion

This study aimed at deriving how employees react to AM introduction, particularly when differentiating into two levels of algorithm transparency (i.e., low vs. high) and three managerial tasks (i.e., work allocation, training allocation, performance evaluation). Our findings contribute to the growing research on algorithm aversion by demonstrating that AM can lead to lower perceived data security and opportunity to perform, and higher emotional creepiness, particularly when algorithm transparency is high in decisions where human skills are expected (i.e., training allocation, performance evaluation). Thus, our study highlighted the intricacies of the transparency paradox, indicating that increased transparency may not always lead to positive reactions. In addition, training allocation emerged as a more favorable application of AM compared to work allocation. Overall, these findings challenge the assumption that shedding light into the “black box” of AM always fosters acceptance, emphasizing the need for a context-sensitive approach to transparency in AM systems.

5 Essay IV: Navigating Institutional Pressures in the Age of Artificial Intelligence: A Typology of Entrepreneurial Responses[12]

Abstract

This study explores how entrepreneurs in Germany and Japan perceive and respond to institutional pressures as artificial intelligence (AI) transforms entrepreneurship. Following 32 semi-structured interviews, we identify regulative, normative, and cultural–cognitive institutional enablers and barriers of AI usage, isomorphic pressures, and how entrepreneurs respond to these pressures. We build a framework linking institutional pressures, strategic responses, and identity transformation, from which we derive four entrepreneurial profiles with differing levels of institutional compliance and identity reconstruction. This study shows how entrepreneurs interpret and respond to AI-related institutional demands, advancing research on institutional theory and digital entrepreneurship.

Keywords: artificial intelligence, generative artificial intelligence, institutional theory, isomorphism, cross-cultural comparison

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- *85th Annual Meeting of the Academy of Management (AOM)*, Copenhagen, Denmark, 2025.

5.1 Introduction

Artificial intelligence (AI)—the performance of cognitive tasks, such as reasoning, learning, and problem-solving, by machines (Rai et al., 2019)—is reshaping entrepreneurship, reducing information asymmetries, and enabling ventures to adapt more quickly and navigate uncertainty with greater precision (Chalmers et al., 2021; Giuggioli & Pellegrini, 2022; Townsend & Hunt, 2019). One particularly prominent development in AI is generative AI (GenAI), which can autonomously produce novel content, such as text, images, or computer code (Dwivedi et al., 2023). The capabilities of GenAI extend beyond predictive analytics and automation, offering the potential to reshape creative work and decision-making in entrepreneurship (Liu & Wang, 2024).

While previous research has highlighted the transformative potential of AI in entrepreneurship, particularly in terms of business model innovation (Breidbach & Maglio, 2020; Jorzik et al., 2024) or opportunity recognition (Duong & Nguyen, 2024), far less is known about how entrepreneurs actually integrate AI into their everyday practices and decision-making. Unlike managers of established firms, entrepreneurs often operate with fewer structural constraints and limited organizational routines, giving them greater autonomy in experimenting with and appropriating emerging technologies (Townsend & Hunt, 2019). However, they also face distinct pressures—such as scarce resources (Reypens et al., 2021), time constraints (McMullen & Shepherd, 2006), and concerns about gaining legitimacy (Lounsbury & Glynn, 2001)—that may shape the scope, purpose, and manner of their AI use. Given the rapid development of AI tools and their growing role in entrepreneurial ecosystems, a systematic understanding of how AI is experienced and enacted at the individual level is of increasing importance. Limiting the research focus to high-tech or digital-native ventures that readily adopt AI may inadvertently overexaggerate its overall impact on entrepreneurship. It is critical to understand how entrepreneurs across diverse industries and business models, regardless of digital maturity, engage with AI in practice.

While much of the literature on AI and entrepreneurship has focused on how AI disrupts business models at the firm or ecosystem level (e.g., Jorzik et al., 2024; Shepherd & Majchrzak, 2022), how the institutional environment shapes and is reshaped by AI integration remains underexplored. Institutional theory offers a valuable lens for examining this phenomenon, as it emphasizes that entrepreneurs are embedded in social structures that are comprised of *regulative* (e.g., laws, policies), *normative* (e.g., values, expectations), and *cultural–cognitive* (e.g., shared beliefs, taken-for-granted assumptions) institutional pillars (Scott, 2014). These pillars exert institutional pressure on entrepreneurs, often in the form of isomorphic forces: *coercive pressures* stemming from legal guidelines and regulations, *normative pressures* arising from industry norms and professional communities, and *mimetic pressures* that prompt imitation of perceived successful peers or models (DiMaggio & Powell, 1983). Entrepreneurs often conform to these pressures in order to attain legitimacy—the generalized perception that their actions are desirable, proper, or appropriate within a socially constructed system of norms, values, and beliefs (Suchman, 1995).

Institutional theory helps explain how ventures navigate uncertainty, signal their credibility, and align with the expectations of key stakeholders (Bruton et al., 2010). Little is known, however, about how entrepreneurs perceive the development of AI as transforming institutional structures or how AI reshapes the pressures that entrepreneurs face. The development of AI may alter the institutional landscape by challenging regulatory frameworks (e.g., due to a lack of legal clarity; Mökander et al., 2022), introducing new norms (e.g., data-driven decision-making; Berente et al., 2021), or destabilizing practices that are taken for granted (e.g., human-centered intuition in decision-making; Berente & Seidel, 2022; Kim & Lee, 2024). Understanding how entrepreneurs perceive and strategically respond to these shifting pressures is critical, as it reveals not only how institutional conformity evolves under technological disruption but also indicates where institutional change or resistance may emerge. Without such insight, we will fail to understand how AI may reconfigure both entrepreneurial practices and the very structures within which they are embedded.

This study addresses these gaps by examining the following research questions:

How do entrepreneurs integrate AI into their practices on an individual level? How do they perceive and respond to institutional pressures and changes brought about by AI?

Given the exploratory nature of this topic and the need to capture context-dependent meaning (Bluhm et al., 2011), we employed a qualitative approach, conducting 32 semi-structured interviews with entrepreneurs from Germany and Japan—countries with contrasting institutions (e.g., AI Guidelines for Business Version 1.0, EU AI Act, General Data Protection Regulation [GDPR]; European Commission, 2016; European Commission, 2021; Ministry of Economy, Trade, and Industry, 2024).

Our study makes three key contributions. First, we advance institutional theory (Scott, 2014) by showing how entrepreneurs perceive AI to be a catalyst of institutional change across regulative, normative, and cultural–cognitive pillars. Entrepreneurs not only mention changes to laws, stakeholder expectations, and societal norms, but also feel pressured to adapt their behavior to align with these shifts. These pressures take the form of coercive demands (e.g., EU AI Act), normative expectations (e.g., from investors), and mimetic tendencies (e.g., copying peers or competitors). We directly address Obschonka and Audretsch's (2020) call for an investigation of how institutions impact the development of AI.

Second, we shed light on how entrepreneurs respond to the identified institutional pressures through a range of strategic actions and by adapting their professional identity.

Entrepreneurs selectively interpret institutional demands and respond with strategies that either (partially) comply with the demands, resist them, or avoid them. For some, these responses entail deep identity transformation, reframing their role, values, and/or tasks as entrepreneurs.

Third, we develop an integrative framework that links institutional pressures, strategic responses, and identity shifts. From this framework, we derive a typology of four entrepreneurial response profiles: the visionary, the conformer, the rebel, and the skeptic. These profiles capture how entrepreneurs vary in their degree of compliance with institutional demands and the transformation of their identity, building upon and extending institutional theory.

5.2 Literature Review

5.2.1 AI Integration in Entrepreneurship

While much of the literature on AI in entrepreneurship has centered on firm-level innovation and strategic transformation (e.g., business model development or market positioning; Jorzik et al., 2024), an emerging strand of research has explored how entrepreneurs individually engage with AI tools in their daily work. At the individual level, AI can support routine tasks, augment decision-making, and extend creative capabilities (Shepherd & Majchrzak, 2022). Entrepreneurs use AI to automate administrative processes (e.g., scheduling, document management), simulate stakeholder communication (e.g., with investors or customers), support strategic decision-making (e.g., opportunity analysis, scenario forecasting), and experiment with novel ideas (e.g., product naming, branding concepts) in real time (Liu & Wang, 2024). GenAI allows entrepreneurs to iteratively and interactively test, refine, and communicate their ideas (Dwivedi et al., 2023). For resource-constrained founders in particular, GenAI can offer access to otherwise unaffordable capabilities and services, including copywriting, design, data analysis, and code generation (Banh & Strobel, 2023; Thanasi-Boçe & Hoxha, 2024).

Entrepreneurs typically operate with fewer bureaucratic constraints than employees or managers in larger firms, which enables them to experiment more freely with new tools (Townsend & Hunt, 2019). However, they also face acute limitations (e.g., scarce resources, legitimacy concerns) and liabilities of newness (Stinchcombe, 1965), that influence both whether and how they integrate AI (McMullen & Shepherd, 2006; Reypens et al., 2021). Not all entrepreneurs experience or utilize AI in the same way; differences in technological familiarity, industry, venture stage, or personal values shape the depth and manner of AI adoption (Duong, 2024; Tursunbayeva & Chalutz-Ben Gal, 2024).

5.2.2 Institutional Theory

Institutional theory offers a foundational lens for understanding how organizations, including entrepreneurial ventures, are embedded in and shaped by broader social, cultural, and regulatory environments (Scott, 2014; Wijen & Ansari, 2007). Rather than acting solely in accordance with economic rationality or internal efficiency, organizations are understood to be social and cultural entities, embedded in a socially constructed and historically situated institutional order (Avgerou & Li, 2013; Meyer & Rowan, 1977). Institutions provide meaning and stability to stakeholders by shaping how actors interpret and respond to their environment (Zilber, 2002). Consequently, institutional theory has become a prominent framework for explaining how legitimacy, structure, and agency interact in complex organizational settings (Bruton et al., 2010).

At the core of institutional theory lies the idea that organizational behavior is guided by three interrelated pillars (i.e., regulative, normative, and cultural–cognitive), which together serve as the “vital ingredients” of institutions (Scott, 2014, p. 59). These pillars offer distinct but complementary mechanisms through which institutions exert influence over organizational and individual action. The regulative pillar includes the formal rules, laws, and sanctions that influence behavior through monitoring and enforcement. Regulatory systems define what is legally (im)permissible and may include licensing, inspection, and sanctioning procedures, which control organizational behavior (Scott, 2014). Compliance with regulatory frameworks often reflects calculations of expedience, such as pursuing incentives or avoiding penalties. Regulatory actors (i.e., the state or oversight bodies) may empower or constrain organizational action by granting privileges or imposing constraints (Bruton et al., 2010).

The normative pillar captures social obligations, values, and expectations about what constitutes morally appropriate behavior. These normative elements often manifest through practical rules, professional standards, and the expectations of influential communities, such as industry associations or accrediting bodies (Scott, 2014). Organizations conform to normative institutions out of a sense of moral legitimacy, rooted in the guilt or shame they may feel if norms are violated (Deephouse & Suchman, 2017). Indicators of normative influence include certifications, occupational standards, and professional ethics that are not mandated by governmental bodies (Scott, 2014).

The cultural–cognitive pillar reflects deeply ingrained, shared understandings, belief systems, and taken-for-granted assumptions that define what is meaningful, recognizable, and appropriate for actor within institutions. This pillar affects symbolic systems, languages, routines, and mental models that actors use to make sense of their environment (Scott, 2014). Compliance with cultural–cognitive institutions is based on orthodoxy and the idea of taken-for-grantedness; that is, organizations follow prevailing scripts not because they must or should, but because they cannot imagine doing otherwise (Deephouse & Suchman, 2017).

A key dynamic that often emerges from institutional pressures is *isomorphism*—the process by which organizations within a field become similar over time (DiMaggio &

Powell, 1983). As a mechanism for securing legitimacy and reducing uncertainty in institutional environments, isomorphism typically takes three forms: coercive, normative, and mimetic isomorphism (Suchman, 1995). *Coercive isomorphism* results from the formal and informal pressures imposed by institutions in positions of authority, such as governments or funding agencies. Organizations may choose to adopt certain practices or structures (e.g., recruiting legal experts) to comply with legal mandates or obtain necessary resources (Greenwood et al., 2002). *Normative isomorphism* arises from professionalization and the diffusion of occupational standards through educational systems, certification bodies, and occupational networks. Shared professional training or affiliation with standard-setting institutions can lead organizations to adopt similar behaviors (Delmas & Toffel, 2008). *Mimetic isomorphism* occurs in situations of uncertainty, when organizations emulate the structures, strategies, and practices of perceived leaders or peers in their field. This form of isomorphism stems from a need to reduce ambiguity and align with behaviors which appear to be successful or legitimate (DiMaggio & Powell, 1983).

5.2.3 AI as an Institutional Force

Technological development influences and reshapes institutions and the pressures that they face (Ahlstrom & Bruton, 2002; Orlikowski & Barley, 2001; Seidel et al., 2025). Saldanha et al. (2015), for example, highlighted how technological shifts can increase the institutional importance of digital expertise, creating expectations for actors to acquire and apply new technological knowledge. Orlikowski and Barley (2001) emphasized that technology is both shaped by institutions and actively shapes institutional fields through recursive interactions with organizational routines, structures, and meanings. As technologies diffuse, they often gradually become institutionalized, shifting from novel tools to taken-for-granted components of legitimate organizational conduct. Digital technologies can give rise to competing institutional logics, such as efficiency versus personalization, thereby generating tensions in how actors respond and adapt (Hinings et al., 2018). These tensions may lead to institutional complexity, where actors are forced to navigate and reconcile contradictory expectations.

We argue, however, that the rise of AI, particularly GenAI, introduces institutional dynamics that may not be analogous to those observed in previous waves of technological innovation. Unlike earlier technologies that primarily enhanced efficiency or enabled automation, AI actively intervenes in core cognitive, creative, and decision-making tasks that have previously been understood as uniquely human (Berente et al., 2021). This raises new questions about agency, responsibility, and legitimacy in entrepreneurial contexts. The integration of AI may not simply require entrepreneurs to adopt new tools, but may also cause them to renegotiate their roles, values, and identities in relation to increasingly autonomous systems.

Furthermore, AI has triggered an evolving regulatory landscape (e.g., the EU AI Act; European Commission, 2021) and heightened normative pressures for its responsible and transparent use (Usman et al., 2024). In this sense, AI may constitute a qualitatively different institutional force, rather than a continuation of past technological trends. Understanding how entrepreneurs perceive and respond to the specific institutional pressures introduced by AI is essential for developing a more accurate and forward-looking theory of technological change in entrepreneurship.

5.2.4 Germany and Japan as Distinct Institutional Contexts

To better understand how entrepreneurs navigate institutional influences when adopting AI, we examined the institutional environments within Germany and Japan. These two countries represent contrasting cases in terms of regulative, normative, and cultural–cognitive institutions (see Table 5-1).

Table 5-1. Institutional Differences Between Germany and Japan

Institutional Factor	Germany	Japan
Cultural–Cognitive Institutions		
Cultural differences according to Hofstede (2011) and Hofstede Insights (2025)	Cultural values for Germany: • Power distance: 35 • Individualism: 79 • Motivation towards achievement and success: 66 • Uncertainty avoidance: 65 • Long-term orientation: 57 • Indulgence: 40	Cultural values for Japan: • Power distance: 54 • Individualism: 62 • Motivation towards achievement and success: 95 • Uncertainty avoidance: 92 • Long-term orientation: 100 • Indulgence: 42
Normative Institutions		
Global Entrepreneurship Monitor (Global Entrepreneurship Monitor, 2022a, 2022b)	• Perceived opportunities rate: 40% • Perceived capabilities rate: 38% • Female/male TEA ratio: 0.65 • Entrepreneurship seen as a good career choice: 60%	• Perceived opportunities rate: 11% • Perceived capabilities rate: 12% • Female/male TEA ratio: 0.40 • Entrepreneurship seen as a good career choice: 23%
Global Competitiveness (Institute for Management Development, 2024)	• Technology readiness: 22nd place in global ranking • Future readiness: 26th place in global ranking	• Technology readiness: 26th place in global ranking • Future readiness: 38th place in global ranking
Innovation Ecosystem	• Home to strong small and medium sized companies (SMEs; “Mittelstand”)	• Strong in robotics and hardware innovation
Risk tolerance & failure stigma	• Moderate aversion to entrepreneurial failure • Insolvency laws allow for recovery, but social stigma persists	• High stigma of failure • Failure often perceived as personal dishonor
Regulatory Institutions		
Regulatory Environment	• General data protection regulation (European Commission, 2016) • EU AI Act (European Commission, 2021)	• Act on the Protection of Personal Information (APPI; Personal Information Protection Commission Japan, 2023) • AI Guidelines for Business Version 1.0 (tentative; Ministry of Economy, Trade, and Industry, 2024)
International Trade Agreements	• *Single market framework:* Ensures free movement of goods, services, capital, and labor within the EU (European Commission, 2025) • *Customs Union Agreement:* Agreements between EU member states to eliminate internal tariffs and adopt a common external tariff for goods entering the EU	• *Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP):* A multilateral agreement among 11 Pacific Rim countries, promoting trade liberalization across Asia-Pacific • *Regional Comprehensive Economic Partnership (RCEP):* Covering 15 Asia-Pacific nations, strengthening Japan’s economic ties with China, South Korea, and ASEAN members (Association of Southeast Asian Nations Secretariat, 2024)

Note. TEA = total early-stage entrepreneurial activity; EU = European Union; ASEAN = Association of Southeast Asian Nations. Cultural values are taken from Hofstede Insights (2025) and can range from 0 to 100.

5.2.4.1 Regulative Institutions

Data protection and AI governance have become central concerns in both Germany and Japan, but the regulatory systems of the two countries diverge in structure and scope. Germany operates under the EU's GDPR (European Commission, 2016) and will be subject to the forthcoming EU AI Act taking effect on August 2, 2026 (European Commission, 2021, 2025), which introduces legally binding classifications and risk-based obligations for using and introducing AI systems. Japan, by contrast, has developed non-binding AI guidelines for businesses, with a more consultative and industry-led approach, and regulates AI under the Act on the Protection of Personal Information (APPI), rather than a specialized law (Ministry of Economy, Trade, and Industry, 2024). We therefore expect German entrepreneurs to face more comprehensive and rigid regulative frameworks, which may either positively (e.g., due to legal clarity and transparency on how AI should be used; Shah et al., 2024) or negatively (.g., due increased feelings of being controlled or reduced flexibility; Ebers, 2019) affect their usage of AI, depending on how regulations are viewed and how practically feasible they are.

5.2.4.2 Normative Institutions

Normative institutions shape how entrepreneurs approach emerging technologies such as AI (Scott, 2014). Data from the Global Entrepreneurship Monitor (GEM; 2022a, 2022b) reveals significantly different perceptions of opportunity, capability, and societal approval of entrepreneurship between Germany and Japan. In Germany, entrepreneurial careers are relatively well-regarded, and individuals report higher perceived self-efficacy and recognition of opportunities (Global Entrepreneurship Monitor, 2022a). Japan, however, exhibits low perceptions of capabilities and opportunities, and entrepreneurship remains less socially endorsed (Global Entrepreneurship Monitor, 2022b). Strong societal support for entrepreneurship in Germany may encourage AI adoption as a signal of innovation and digital competence. In Japan, where entrepreneurship lacks similar normative legitimacy, entrepreneurs may seek to avoid reputational risk by being more cautious about AI adoption, taking care to closely align with stakeholder expectations and professional norms (Fukuda, 2020; Global Entrepreneurship Monitor, 2022b).

5.2.4.3 Cultural–Cognitive Institutions

Germany and Japan differ notably in their orientation toward Hofstede's (2011) cultural dimensions of uncertainty avoidance, power distance, collectivism, and long-term orientation. Germany scores lower than Japan on power distance and higher on individualism (Hofstede Insights, 2025), suggesting the German cultural context values autonomy, self-initiative, and decentralized decision-making. In contrast, Japan scores higher than Germany on uncertainty avoidance and long-term orientation, reflecting a preference for stability, discipline, and gradual, risk-averse progress. Previous research has found that individualism and power distance may impact AI adoption by individuals (Eitle & Buxmann, 2020; Fessenko & Jasperse, 2024; Mahmud et al., 2022), which may affect whether entrepreneurs decide to adopt AI and how they do so.

5.3 Research Methodology

5.3.1 Study Design

We adopted a qualitative research methodology to gain an in-depth understanding into how entrepreneurs perceive and respond to institutional pressures surrounding AI adoption. Qualitative research is particularly well-suited to capturing nuanced, context-dependent interpretations of phenomena, especially between distinct environments such as Germany and Japan (Bluhm et al., 2011). It allows for the exploration of lived experiences, sensemaking processes, and institutional logics that are difficult to quantify. To facilitate the investigation of differing and shared experiences of the institutional pressures that arise with the development of AI, we conducted semi-structured interviews following Gioia et al.

(2013), which provided a flexible yet systematic means of data collection (Kvale & Brinkmann, 2009).

Prior to conducting our interviews, we developed research questions according to our study objectives. We next developed an interview guide comprising all components of our research questions (i.e., the general adoption of AI by entrepreneurs, the institutional enablers and barriers that are visible to entrepreneurs, and the pressures they perceive and how they respond). This flexible guide allowed the interviews to be adapted to the situation and the participant (Gioia et al., 2013). Appendix D1 displays the final interview guide, after several adaptions following the initial interviews.

To identify entrepreneurs that regularly use some of form of (Gen)AI in their work life, we employed a non-probability sampling technique by adopting a purposive sampling approach, followed by a snowballing technique. We identified eligible participants through LinkedIn together with attending networking events at a German university that invited (nascent) entrepreneurs. To be eligible to participate, individuals were required to have founded a new venture, to plan on founding a new venture, or to be self-employed in either Germany or Japan. All interviews were conducted via common online meeting platforms (i.e., WebEx, Zoom, Microsoft Teams). To make sure that questions during the interview process could be answered appropriately, one of the authors conducted all interviews. Interviews were held in German for German entrepreneurs and in English for Japanese entrepreneurs. The interview audio was recorded with the interviewees' consent and later transcribed. For the transcription, the authors used a GenAI tool to create an initial draft of the transcripts, manually reviewed this draft by listening to the interviews again, and made changes when necessary. Interviews conducted in German were translated into English by one author, who is a German native speaker, so that both authors could engage in the coding.

5.3.2 Overview of Participants

Our final sample consisted of 32 interviews, 16 from Germany and 16 from Japan. The mean age of the participants was 35.70 years; 31.25% of the sample was female and 68.75% male. Respondent demographics are presented in more detail in Table 5-2. Throughout the rest of the text, interview responses are labeled with either G or J, for Germany and Japan, respectively, and the interviewee number. The length of the interviews ranged from roughly 19 to 64 minutes, with a mean time of 32.50 minutes. To help ensure consistency between populations, we tried to maintain similar distributions of gender, age, and industry background.

Appendix D2 presents the tools interviewees reported using in more detail. The most commonly used AI tools amongst respondents were GenAI tools such as ChatGPT or Microsoft Copilot. The interviewees also reported adopting AI tools to meet their specific needs and task requirements. For example, some reported using a tool that summarized meeting minutes and allowed to search the transcripts, which was a relevant use case in their daily work life.

5.3.3 Coding Procedure

Following Gioia et al. (2013), we coded interviews after interview transcription, using MAXQDA software in its most recent version (24.6.00). Both authors engaged in transcript coding using an abductive coding process (Golden-Biddle, 2020). We created first-order codes and second-order themes inductively, and then tried to group them as aggregate dimensions under regulative, normative, and cultural–cognitive institutions. Any second-order themes that did not fit under the three institutional pillars were combined into additional aggregate dimensions (i.e., solely inductive coding).

Table 5-2. Overview of Interviewees

No.	Country	Age	Gender	Education	Industry	Founding Year	Number of Employees	Entrepreneurial Status	AI in Product/ Service	Profile
G1	Germany	32	Female	Bachelor's Degree	Medicine	Not yet founded	–	Nascent entrepreneur	–	Skeptic
G2	Germany	35	Male	High School Diploma	Consulting	2014, 2017, 2021	1	Founder	No	Skeptic
G3	Germany	21	Male	Intermediate Secondary School Certificate	Medicine/ Neuroscience	Not yet founded	–	Nascent entrepreneur	–	Skeptic
G4	Germany	31	Male	Master's Degree	Consulting/ SaaS	2022	5	Founder	Yes	Visionary
G5	Germany	39	Male	Master's equivalent	Software	several	from 3 to 80	Founder, co-founder	Yes	Skeptic
G6	Germany	23	Male	Bachelor's Degree	Smart architecture	2023	11	Founder	No	Skeptic
G7	Germany	30	Male	Master's Degree	Sanitary products	2023	3	Co-founder	Yes	Rebel
G8	Germany	44	Female	MBA	Electronics	2012, 2023	65, none	Founder	Yes	Visionary
G9	Germany	50	Male	Ph.D.	Consulting	2007	5	Founder	No	Visionary
G10	Germany	35	Male	Master's Degree	Camping	2020	4	Founder	No	Visionary
G11	Germany	45	Male	Ph.D.	Marketing	2012	3	Co-founder	Yes	Visionary
G12	Germany	38	Male	Bachelor's Degree	Media, real-estate, photovoltaic	2008, 2017, 2023	17, 80, none	Founder, CEO	No	Skeptic
G13	Germany	45	Female	Ph.D.	Hunting, org. development	2021, 2024	1, 1	Founder, self-employed	No	Skeptic
G14	Germany	24	Male	Bachelor's Degree	Health & Wellness	2019	2	Co-founder	No	Skeptic
G15	Germany	29	Female	Bachelor's Degree	Health	2024	2	Co-founder	Not yet, but planned	Rebel
G16	Germany	38	Female	Ph.D.	Smart city	2023	4	Co-founder	Yes	Rebel
J1	Japan	29	Male	Master's Degree	AI solutions	2018	5	Co-founder	Yes	Visionary
J2	Japan	45	Male	MBA	SaaS	2017	23	Co-founder	Yes	Visionary
J3	Japan	34	Male	Master's Degree	Engineering design	2020	13	CEO	No	Skeptic
J4	Japan	28	Male	Master's Degree	Relocation Services	2024	3	CEO	No	Conformer
J5	Japan	26	Male	Bachelor's Degree	Coworking space	2023	11	Co-founder	No	Skeptic
J6	Japan	41	Female	Bachelor's Degree	Cybersecurity	2023	3–4	Founder, self-employed	Yes	Conformer

No.	Country	Age	Gender	Education	Industry	Founding Year	Number of Employees	Entrepreneurial Status	AI in Product/ Service	Profile
J7	Japan	46	Female	MBA	Consulting	2022	1	Self-employed	No	Skeptic
J8	Japan	45	Female	Master’s Degree	Health	2019	10 part-time	Founder	No	Skeptic
J9	Japan	65	Male	Master’s Degree	Information technology	2024, 2007	25	CMO, CSO	Yes	Skeptic
J10	Japan	42	Male	Master’s Degree	AI	2019	16	CEO	Yes	Conformer
J11	Japan	25	Female	Bachelor’s Degree	Customer relationship management	2024	3	Co-founder	Yes	Visionary
J12	Japan	25	Male	Bachelor’s Degree	Consulting	2024	1	Self-employed	Yes	Visionary
J13	Japan	32	Male	Bachelor’s Degree	Robotics	2023	4.5	Founder	No	Visionary
J14	Japan	27	Male	No degree	Recruiting, Skill Matching	2022	1	Founder	Yes	Visionary
J15	Japan	38	Male	Ph.D.	Media/ Entertainment	2023	None	Founder	Yes	visionary
J16	Japan	60	Female	Master’s Degree	Voluntary work, recruitment	2011	6, 2	Founder	No	Conformer

Note. Abbreviation *G* stands for interviewees from Germany. Abbreviation *J* stands for interviewees from Japan. AI = artificial intelligence; MBA = Master of Business Administration, Ph.D. = Doctor of Philosophy, Org. = organizational, SaaS = Software as a Service, CEO = Chief Executive Officer; CMO = Chief Marketing Officer; CSO = Chief Sales Officer. Entrepreneurs were noted with all of their entrepreneurial endeavors, if there were several.

This approach enabled us to identify the overarching strategic approaches entrepreneurs adopted to navigate institutional pressures, as well as their perceptions of any shift in entrepreneurial identity (EI) resulting from AI advancements. We discussed potential changes to the coding system among the author team twice; once after creating the first-order codes and once after grouping the first-order codes and second-order themes into aggregate dimensions. In total, we identified 845 codes, with an intercoder agreement between both coders of 97.07% (O'Connor & Joffe, 2020).

5.4 Results

5.4.1 Regulative Institutions

Figure 5-1 shows our coding system, including first-order codes, second-order themes, and aggregate dimensions. We derived enablers and barriers of AI use as perceived by the entrepreneurs for each institutional pillar (i.e., regulative, normative, cultural–cognitive). Our findings suggest that entrepreneurs from Japan generally perceive the current legislative environment surrounding AI as relatively permissive, enabling the straightforward integration of AI tools into their ventures (J2, J4, J6, J14). Several interviewees also acknowledged the proactive role the Japanese government plays in promoting AI adoption through national initiatives such as the Digital Transformation strategy (J2) and broader ambitions to position Japan as the "next Silicon Valley" (J13). Despite an apparently supportive environment, entrepreneurs from Japan expressed uncertainty about future regulatory developments. Some anticipated that the current lenient regulatory stance might become more restrictive (J3, J16), which created a hesitation to go "all in" (J6) on AI integration.

Figure 5-1. First-Order Codes, Second-Order Themes, and Aggregate Dimensions

First-Order Codes	Second-Order Themes	Aggregate Dimensions
• Loose AI legislations regarding AI usage & integration (J) • DX (digital transformation); Japanese government wants to create second *Silicon Valley* (J) • Many AI-related governmental funds and support available	Enablers	Regulative institutions
• Uncertainty about current regulations regarding AI (J) • Development of EU AI Act (G) • GDPR seen as hindrance to using and integrating AI (G)	Barriers	
• Compliance to strict AI-related regulations (G) • Obtaining necessary licenses to integrate AI is mandatory (G) • Keeping up with advancements from government (J)	Coercive isomorphism	
• AI is accepted as a tool used by entrepreneurs in pitches • The integration of AI is believed to be inevitable in the future (e.g., to tackle societal issues)	Enablers	Normative institutions
• Clients and investors increasingly expect high-quality outputs • Skepticism to introduce AI for decision-making • Gender norms as barriers for women to use and integrate AI (J)	Barriers	
• Entrepreneurs may assimilate due to de-skilling when using AI • Pressure from stakeholders to integrate AI responsibly • Fear of long-term assimilation of companies using the same AI providers	Normative isomorphism	
• AI use by entrepreneurs is taken-for-granted • Japanese grow up with AI as something positive (J)	Enablers	Cultural-cognitive institutions
• Cultural hindrance to include AI in decision-making (J) • Rather critical description of AI in Germany (G) • LLMs based on Western believe system, which does not always fit to Japanese culture (J)	Barriers	
• Influence of AI adoption through attitudes of peer group • Pressure to integrate AI due to other entrepreneurs heavily using it already	Mimetic isomorphism	
• Either comply (J) or resist (G) demands from peer group • Adopt GenAI more heavily than other AI tools • Type of tools depend on what peer group is using	Dealing with pressures from peer group	Entrepreneurial strategies
• Reduce AI use in order to not experience de-skilling • Focus on creating a unique USP • Communicating AI introduction to investors	Dealing with strategic positioning	
• Adjust AI use to comply with regulations • Reduce the level of AI integration (G) • Leaving the country to avoid strict regulations (G) • Trust in government and ready to comply with regulations (J)	Dealing with regulations	
• AI as an an additional co-founder/colleague • Advice of AI tools highly valued	AI as identity-relevant actor	Reconstructing entrepreneurial identity
• AI can give a comprehensive first draft of content • Entrepreneurial creativity is re-defined • Cognitive reframing to see identity change as a chance	Shifting from *creating* to *judging* output	

Note. LLMs = Large Language Models, GDPR = general data protection regulation. If one first-order code appeared in one country only, the country is indicated in parentheses (J = Japan, G = Germany).

Although governmental support for AI use in Germany was also noted in the form of visible resources and infrastructure, including workshops, online materials aimed at enhancing AI literacy (G13), and targeted funding programs designed to encourage AI integration (G4, G6, G10, G11), entrepreneurs from Germany experienced the regulatory landscape as considerably more restrictive (G1, G4, G9). The GDPR was mentioned as a significant constraint limiting the extent to which AI systems can be employed, particularly due to restrictions on the types of data that can be put in (G9). While the EU AI Act was generally appreciated for promoting ethical and responsible AI use (G1, G4, G15), it was also viewed as introducing technical limitations that could hinder the full realization of AI's potential in entrepreneurial contexts.

> *And I think [the EU AI Act] is written from a societal perspective that doesn't understand the technical aspects of AI. And I understand where the desire comes from, to make everything safer, but that's not how the strong models work. (G15)*

G15 noted that under the EU AI Act, it is necessary to provide transparency regarding how algorithmic decisions are made. This poses a challenge, as high-performing AI models often rely on self-learning mechanisms, making it difficult to articulate the specific criteria or processes that lead to any given decision.

Interviewees from both countries identified multiple pressures stemming from the regulatory environment. In Japan, entrepreneurs expressed concerns about their ability to keep pace with the ambitious AI integration agenda set forth by the government, which includes substantial efforts to accelerate digital transformation (J13). In Germany, entrepreneurs operating in high-risk domains, as defined by the EU AI Act, reported feeling significant pressure to obtain required certifications and licenses, as the process demanded considerable time and financial resources. Interviewee G15 explicitly stated that they are refraining from further integrating AI into their business due to these regulatory constraints:

> *Then we fall into the medical product guideline, where we need a TÜV [Technical Supervisory Association] certificate.*[13] *That's a lot of money, half a million [euros] or so, for a plan to go through the whole certification process. So, we'd rather not do that now. (G15)*

Additionally, compliance with the stringent GDPR was frequently mentioned by German entrepreneurs as a further burden, particularly in relation to data input limitations and privacy obligations (G4, G9).

5.4.2 Normative Institutions

According to interviewees, stakeholders, such as clients and consumers, generally accept and even expect entrepreneurs to use AI tools (J10, J16). AI integration was often positioned as a solution to broader societal challenges, including demographic decline and labor shortages (G12, J2, J13, J16). However, several interviewees reported growing normative pressures from clients and investors regarding the quality of AI-supported outputs (G6, J7, J15). This pressure was especially pronounced among entrepreneurs in the consulting and service sectors, where clients are increasingly capable of independently accessing industry-relevant information. As a result, entrepreneurs feel compelled to deliver distinct added value beyond what AI alone can offer:

> *For me, as a sole trader […], I have to show the added value to my client, and my clients are mostly large companies. So, they can choose a consultant from […] any big consultancy company, right? They can also*

[13] The Technical Supervisory Association (Technischer Überwachungsverein [TÜV]) comprises independent service organizations based in Germany and Austria. They specialize in testing, inspecting, and certifying technical systems, facilities, and various objects to minimize risks and prevent potential damage.

use ChatGPT themselves. So, my service needs to be better than everything they can do on their own. (J7)

Respondents also expressed ethical concerns about introducing AI into decision-making processes, stressing that final decisions should ultimately remain with the human to ensure accountability and moral responsibility (G4, G8, G15). This human-in-the-loop perspective reflects a strong normative boundary around the role of AI in decision-making. Several entrepreneurs from Japan also highlighted gender-based barriers to AI use and integration, noting that prevailing gender norms may limit women's access to or confidence in engaging with such technologies (J7, J10, J14). J3 explained:

Japan is very peculiar, because most women kind of stop working or start working part-time after marriage as a relatively common phenomenon. […]. So, they may not have as many use cases to use AI and may be less proficient in the long run. (J3)

In terms of normative isomorphism, entrepreneurs explained that they fear becoming dependent on AI, because they might lose their skills over the long term (e.g., creativity, critical thinking skills; G13, G4, J3).

Before AI was there, I needed to write and translate English by myself. So, I learned new words and sentence structures. But now I can ask ChatGPT, which provides better English than me. I don't use my brain anymore to improve my English. So, I fear that [my language skills] are not a strength for me in the future. (J8)

This represents a fear that all entrepreneurs assimilate in their skills and strengths in the long run, as GenAI systems are publicly available, which allow all entrepreneurs to use the same tools and potentially receive similar advice. Interviewees expressed concerns that this could lead to a loss of individuality and make their ventures indistinguishable from others (G15). G2 stated, “Regarding individuality, it’s a topic [of concern] whether websites become generic. Does the personal touch get lost? Or the identity of the company?”

Interviewees also mentioned that stakeholders expect ethical and responsible AI use (J7). J9 elaborated, “So, whenever I talk with customers, their number one concern is always security. Because when I use AI, I use their confidential internal data. So, security is priority number one always.”

5.4.3 Cultural–Cognitive Institutions

The interviews revealed that entrepreneurs in Japan grow up with AI or AI-like technologies portrayed as positive and friendly in popular anime and TV shows (J6, J10). This positive portrayal generally impacts their attitude toward AI, as J6 explained, “Since we are very small children, every day we watch anime, for example, Doraemon or Tetsuwan Atom. They’re kind of cute, friendly robots with AI, so as Japanese, we feel that AI is very friendly to human beings.” In contrast, entrepreneurs from Germany associated AI with negative connotations, such as with the movie *Terminator* (G3), which influenced their general attitude toward the technology.

Entrepreneurs from Japan also emphasized that their decision-making typically involved multiple hierarchical layers, making it unlikely that full decision authority would ever be delegated to an AI system. Instead, they viewed AI as an additional layer within the broader decision-making structure (J10). Furthermore, several interviewees noted that AI-generated texts often lacked the formality required for professional communication in Japan (J13, J14). One entrepreneur (J11) observed that U.S.-developed GenAI tools do not effectively meet the expectations and communication styles of local stakeholders, stating, “Obviously, the tools have a Western bias, so when I tried to understand how Japanese or other Asian people would think, it tends not to be correct.”

During the interviews, several pressures emerged within the cultural–cognitive pillar that align with mimetic isomorphism. Entrepreneurs reported being influenced by their peers in deciding which AI tools to adopt, reflecting a tendency to emulate the practices of others (G12, J13). This dynamic was particularly evident in the interviews with Japanese entrepreneurs, who emphasized the role of peer opinion in both the selection of specific tools and in shaping broader decisions about whether to adopt AI at all (J11, J15). Many respondents expressed a perceived need to adopt AI simply because other entrepreneurs were doing so, often driven by a fear of falling behind in technological advancement (G6, G15). G1 mentioned, "Either you follow the wave [of AI development] and you stay up-to-date, or you don't follow it as a company […] and unfortunately stay behind."

5.4.4 Entrepreneurial Strategies

The interviews revealed several strategies that entrepreneurs employ to mitigate the isomorphic pressures associated with AI adoption. First, entrepreneurs developed strategies to manage pressures associated with adopting AI technologies arising from their peer groups. In Japan, interviewees tended to comply with peer expectations by aligning their AI usage with the opinions of their peer group (J14, J15). In contrast, German entrepreneurs maintained individual autonomy, often striving to form independent opinions and deliberately distancing themselves from peer influence, as G2 explained, "I'm very strong in my opinion. I listen to [my peer group], but I don't need them to accept what I am doing or adopt what they are doing."

Despite these cultural differences, a shared pattern of AI adoption emerged; entrepreneurs tended to adopt GenAI tools but not broader AI systems. Peer group discussions were centered around GenAI, which influenced the adoption of AI tools (G3, G6, J1, J7).

Second, interviewees reported engaging in strategies aimed at preserving their core skills and reinforcing their distinct market positioning. Entrepreneurs often placed deliberate constraints on their use of AI to safeguard their core competencies. For instance, J8 reported intentionally minimizing the use of GenAI for English translation tasks in order to maintain and develop their own communication skills. J9 added the following:

> *Before ChatGPT, we were creating the new idea, the title, the name, ourselves. It functions as training for the brain. But if we utilize ChatGPT too much, maybe some of our brain capacity gets lost. That's why I still try to talk to my friends to keep brainstorming without ChatGPT.*

Other entrepreneurs emphasized that the increasing pressure to adopt AI heightened their commitment to crafting a unique selling proposition, one that could not be easily replicated by AI (G13). Several entrepreneurs noted the strategic importance of actively communicating their AI use to investors, as they perceived a funding bias in favor of ventures that integrate AI in some way (J7, J16, G13, G15).

Third, most entrepreneurs adjusted their AI practices to ensure compliance with regulatory pressures. This included avoiding inputting personal client data into AI systems (G9, J6, J15). In Germany specifically, interviewees reported limiting AI use in areas requiring formal licensing to circumvent regulatory constraints (G15). G5 explained the following about their peer group and their strategy to deal with regulatory demands:

> *We have a really big tech scene in Berlin, but I can say that many of my friends have left for other countries. To South Korea, Dubai, or Switzerland. […]. Because of the data protection guidelines.*

In contrast, entrepreneurs from Japan expressed a high degree of trust in governmental institutions and confidence that authorities would guide their AI use appropriately. J16 stated, that “The government in Japan is a very trustworthy government. I think a lot of us, we leave it to the government to say what to do next.”

5.4.5 Reconstructing Entrepreneurial Identity

The interviewed entrepreneurs perceived both the broader development of AI and their own AI use as contributing to a transformation of their EI. Many interviewees described GenAI as an identity-relevant actor, often characterizing it as a co-founder (J11, J14, J15), colleague (G11, J3), or assistant (G4, J10), playing an integral role in their daily work. They reported attributing significant value to the input provided by GenAI, allowing it to influence their strategic thinking and decision-making processes (G9, J13).

Respondents also reflected on a fundamental shift in their entrepreneurial role; moving from creators of original content or ideas to evaluators of AI-generated outputs. This shift was perceived as important, as many entrepreneurs had previously associated their core identity with the act of creation. J15 elaborated, “Now, I am a judge of content, instead of being a creator [as I was] before. At first, this was strange to me, but I have gotten used to it.” While interviewees still considered themselves capable of generating novel ideas, they increasingly relied on AI tools for initial idea generation, redefining what entrepreneurial creativity looks like (G4, G16, J14).

Importantly, most interviewees embraced this evolving role. They engaged in cognitive reframing, interpreting the shift not as a loss of creativity or agency, but rather as an opportunity to enhance their efficiency and focus on higher-level tasks. Many expressed a sense of optimism about the future and viewed these changes as part of a broader transformation that could ultimately strengthen both themselves and their businesses (G5, G7, J1).

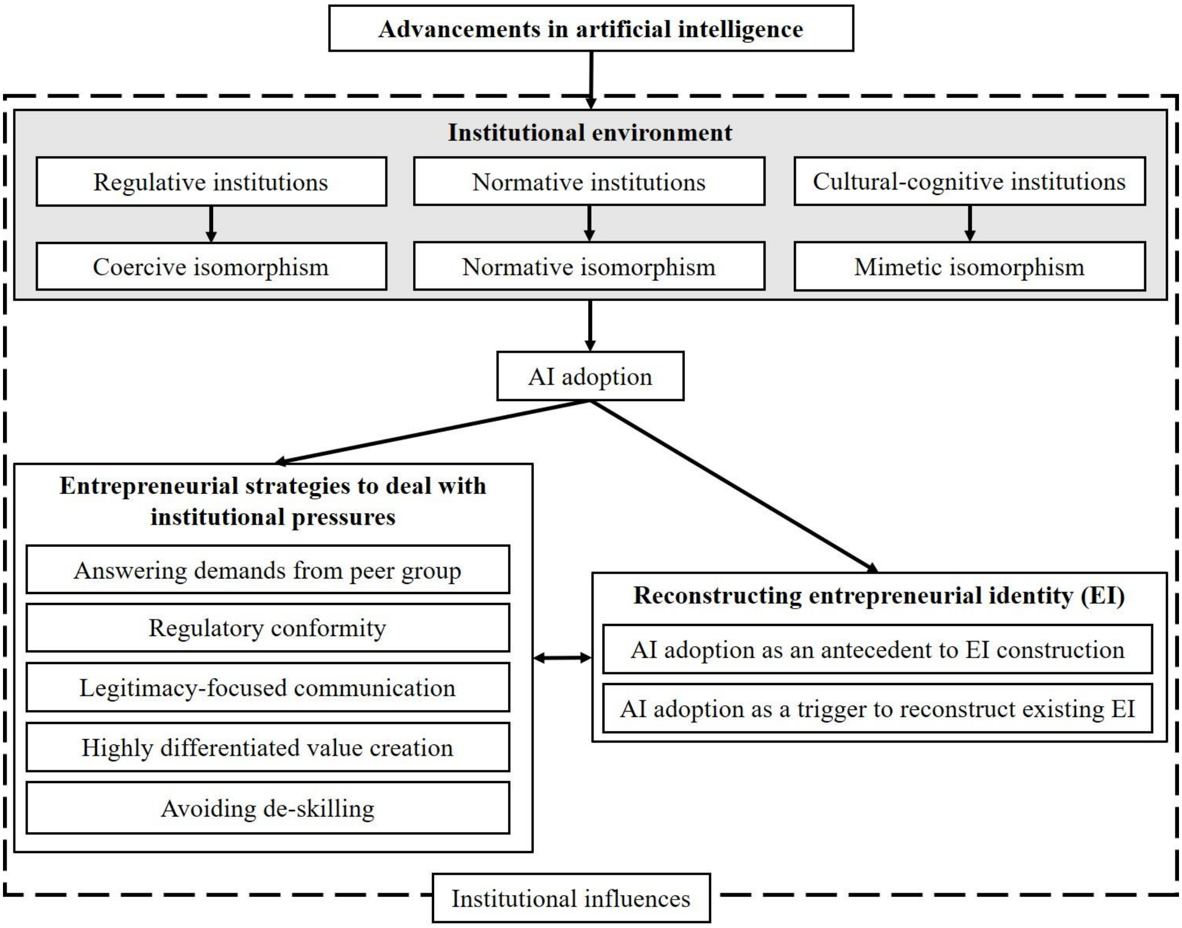
5.4.6 Overarching Framework

Based on our coding of the interviews, we developed an integrative framework that illustrates how the emergence of AI is not only embedded within institutional structures but is actively reshaping them. Our framework, shown in Figure 5-2, demonstrates how AI-induced changes are reflected across all three institutional pillars (i.e., regulative, normative, cultural–cognitive). These institutional changes then give rise to isomorphic pressures (i.e., coercive, normative, mimetic) that shape how entrepreneurs engage with AI. It is important to note, however, that our framework only reflects the institutional forces and isomorphic pressures that are visible to entrepreneurs, and other pressures may occur in reality.

Entrepreneurs do not respond to institutional pressures in a uniform way. Instead, they adopt a variety of strategies to navigate their environment. Some choose to conform to institutional expectations by aligning with peer-group norms or complying with regulatory requirements. Others pursue more independent approaches, differentiating their value proposition, trying to gain legitimacy through communication, or deliberately limiting their reliance on AI in order to maintain control over their core skills. These strategic responses contribute to a broader change in how entrepreneurs understand and perform their identity. This includes altering core tasks, reframing AI as a co-founder or colleague, and other fundamental changes in entrepreneurial cognition and self-perception. However, shifting EI can have consequences for the strategies that entrepreneurs use to respond to isomorphic pressures, as new goals, values, and approaches to engaging with institutional demands are required. Importantly, identity shifts may also occur as a direct response to institutional pressures themselves, particularly when these pressures challenge existing expectations, norms, or taken-for-granted assumptions about the role of the entrepreneur. Thus, both isomorphic pressures and entrepreneurial strategies shape how EI evolves in the context of AI adoption.

Importantly, these institutional dynamics and strategic responses are shaped by regional influences. Cultural and structural differences between Japanese and German entrepreneurial contexts impact how institutional pressures are experienced and how identity shifts unfold. Our framework, therefore, not only captures the institutionalization of AI in entrepreneurship but also highlights the embeddedness of entrepreneurial agency within regionally specific institutional logics.

Figure 5-2. Overarching Framework

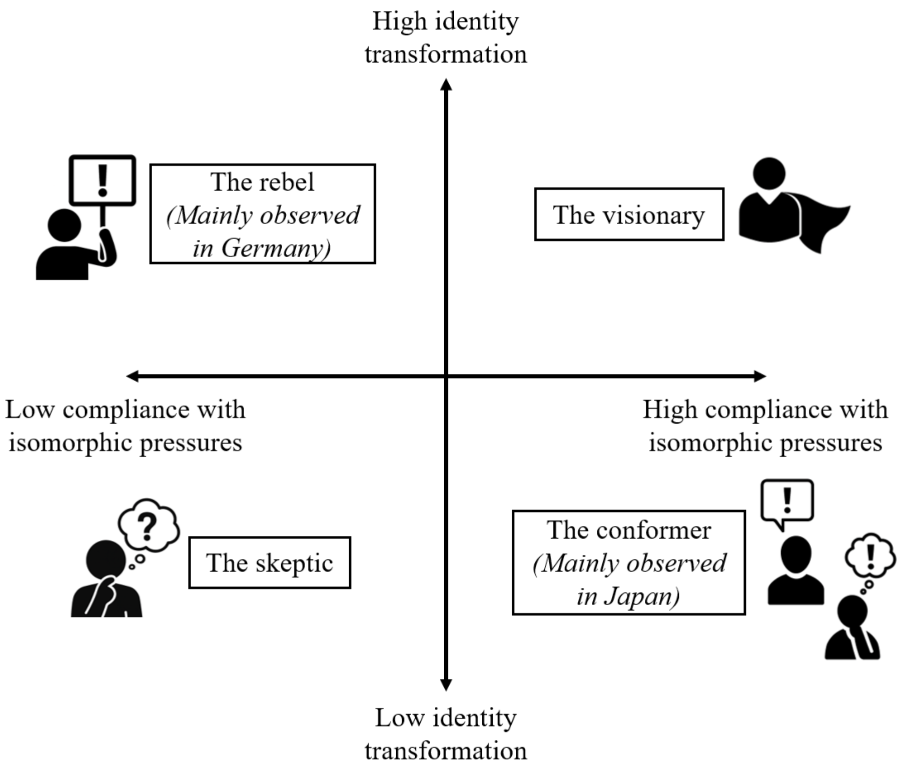


5.4.7 *Typology of Entrepreneurial Profiles*

To deepen our understanding of how entrepreneurs respond to AI-related institutional pressures, we developed a typology of four entrepreneurial profiles. A typology is a systematic classification of empirically observed patterns into ideal types that helps reduce complexity and reveals underlying logics of action (Doty & Glick, 1994). In our case, typology building allows us to capture and interpret the heterogeneity of entrepreneurial responses to AI within and across different institutional settings. The profiles within our typology emerged inductively through a two-step process. First, we systematically coded the interview data along two dimensions: (1) the degree of compliance with isomorphic pressures (i.e., coercive, normative, mimetic), and (2) the extent of the transformation of EI. These two dimensions emerged from our data as important entrepreneurial responses to AI-related institutional changes and directly build upon institutional theory (Scott, 2014). The first dimension, compliance to institutional pressures, captured whether entrepreneurs conformed to institutional expectations, such as emulating peer practices, responding to stakeholder demands, or adhering to regulations, while the second dimension, identity transformation, assessed whether and the extent to which entrepreneurs redefined their roles, values, or core tasks in light of AI integration.

Second, we conducted a comparative pattern analysis of the interviews, clustering entrepreneurs into distinct response types. Building on our framework that we derived from our interviews, we constructed a cross-case matrix that allowed us to compare patterns of perceptions of strategic responses and identity shifts. To identify shared logics of action and response, we looked for convergence and divergence across cases, guided by the principle of analytical abstraction (Kluge, 2000), which entails reducing the complexity of empirical data by abstracting from individual cases to identify generalizable dimensions, types, or patterns. Through iterative team discussions, we refined the clusters through an assessment of internal coherence (i.e., the consistency of reasoning and behavior within each profile) and between-case contrast (i.e., the distinctiveness across profiles). We then engaged in axial coding to develop meaningful distinctions. The resulting four ideal types—*the visionary, the conformer, the skeptic*, and *the rebel*—are displayed in Figure 5-3 and further detailed in Table 5-3. Each profile identified in our typology is grounded in the interview data, although the frequency of profiles varied. Although we examined whether entrepreneurs might fit multiple profiles, the two-dimensional structure we employed provided sufficient differentiation, and all interviewees could be classified into a single profile.

Figure 5-3. Typology of Entrepreneurial Profiles



The *visionary* is characterized by high compliance and strong identity transformation. These entrepreneurs deeply integrate AI into operations, sometimes extending its integration into their business models. While the *conformer* also complies with institutional expectations, they undergo limited identity change. Conformers adopt AI to meet external demands (e.g., investors, markets), not because of any intrinsic motivation or strategic vision. This profile was especially common among entrepreneurs in Japan. The *skeptic* exhibits low compliance and minimal identity transformation. Often wary of AI due to risk aversion or low technological literacy, they perceive minimal pressure to adapt and view AI as of limited relevance to their business. Finally, the *rebel* resists institutional pressures while actively redefining their identity through AI. They tend to reject regulative norms and use AI to assert their autonomy and innovate on their own terms. This profile was found more frequently among interviewees from Germany.

Table 5-3. Information on Entrepreneurial Profiles

Entrepreneurial Profile		Compliance with Pressures	Identity Transformation	Representative Context	Key Characteristics	Frequency
	The visionary	High	High	Not country-specific	• Strong personal interest in AI • High AI-related knowledge • Integrates AI into both processes and offerings	37.50%
	The conformer	High	Low	Mainly observed in Japan	• Responds to stakeholder pressures • Adopts AI to meet external expectations • Low intrinsic motivation	12.50%
	The skeptic	Low	Low	Not country-specific	• Risk- and/or technology-averse • Limited AI use due to perceived irrelevance • Low AI literacy • Low external influence	40.63%
	The rebel	Low	High	Mainly observed in Germany	• High autonomy orientation • Critical of regulation, norms, and peers • Uses AI creatively to break norms • High AI-related knowledge and interest	9.38%

Note. The key characteristics describe the typical overserved traits per profile. Not every entrepreneur falling into the profiles displayed all characteristics.

5.5 Discussion

This study explored how entrepreneurs in two different institutional environments—Germany and Japan—perceive and respond to institutional pressures related to AI adoption. Drawing on 32 semi-structured interviews, we identified the isomorphic pressures that are salient to entrepreneurs across regulative, normative, and cultural–cognitive institutional pillars. Our analysis revealed that entrepreneurs develop differing strategies in response to these pressures, such as complying with regulatory demands or aligning with peer expectations. Moreover, we found that the development of AI prompts a reconstruction of EI, as participants describe a shift from being a creator to a judge of AI outputs. Based on the themes emerging from the interviews, we developed a framework that captures the interplay between institutional pressures, entrepreneurial strategies, and identity shifts. We derived four entrepreneurial profiles (i.e., *visionary, conformer, skeptic*, and *rebel*) that reflect the different ways in which entrepreneurs interpret institutional demands and the extent to which they experience and embrace identity transformation.

5.5.1 Theoretical Implications

Our study makes several important contributions to institutional theory. First, we demonstrate how AI can catalyze institutional change. While institutions are often conceptualized as relatively stable systems of rules, norms, and beliefs (Scott, 2014), they can undergo alteration in response to major societal or technological disruptions such as the development of AI (Greenwood et al., 2002). Our findings show that entrepreneurs perceive the institutional changes linked to AI to be both enabling and constraining across regulative, normative, and cultural–cognitive pillars. These changes include new regulations (e.g., EU AI Act; European Commission, 2021), shifting peer expectations, and evolving norms around the role of technology in entrepreneurship (e.g., using AI is increasingly accepted). Our interviews revealed that these institutional shifts give rise to isomorphic pressures, aligning with previous findings (Han & Ito, 2024; Muda et al., 2024). Importantly, our results suggest that entrepreneurs do not experience these institutional pressures uniformly; they may interpret the pressures as either enablers or barriers depending on their strategic orientation and professional identity. Our findings advance an understanding of institutions as socially constructed forces that can be differentially interpreted by entrepreneurial actors, depending on the country in which they operate, rather than as neutral entities.

Second, we identify a novel and empirically grounded set of entrepreneurial strategies for responding to isomorphic pressures in the context of AI development. Our strategies can be directly connected to the institutional pillars identified by Scott (2014). For instance, strategies that deal with complying or resisting regulations directly refer to pressures arising from regulative institutions. In addition, we can connect our identified strategies to previous work from Oliver (1991), who categorized responses to institutional pressures as acquiescence, compromise, avoidance, defiance, and manipulation. The entrepreneurs in our sample primarily made use of acquiescence (e.g., complying with demands from peer group), compromise (e.g., listening to peer group, but deciding for oneself if they want to conform to its demands), avoidance (e.g., leaving the country to better make use of AI), and defiance (e.g., being openly against the EU AI Act). Notably, we did not observe the use of manipulation as a strategic response. Our findings offer nuanced insights into how entrepreneurial strategies evolve in response to AI-driven institutional change, highlighting important differences from patterns identified in previous studies (Boxenbaum & Arora-Jonsson, 2017; Hinings et al., 2018).

Our study also revealed that many interviewees began to rethink and reconstruct their EI in response to AI adoption, pointing to a potential intersection between the literatures on EI and institutional theory. Our findings suggested that AI could either be interpreted as a trigger of EI construction (i.e., *before* entrepreneurs build their EI) or as a trigger to reconstruct their EI (i.e., *after* entrepreneurs already established an EI). Radu-Lefebvre et al. (2021) further distinguished EI as a process and EI as a property. EI as a process refers to dynamic identity work through which entrepreneurs define and re-define themselves over time; and EI as a property refers to more stable self-conceptions and enduring role-related traits. Our results give first insights that AI adoption may impact both levels: altering how entrepreneurs narrate their roles and relationships (i.e., EI as a process), as well as prompting them to reconsider core aspects of who they are and what they stand for as entrepreneurs (i.e., EI as a property). While exploring identity transformation was not the primary objective of our study, this theme emerged as a noteworthy aspect of how entrepreneurs responded to the institutional changes of AI integration. Thus, we call future research to embed EI in investigations on AI and institutions and further extend on our first insights.

Third, we offer a new typology of entrepreneurial response profiles that captures how identity transformation and strategic compliance intersect in the context of AI development and adoption. Whereas prior institutional research has primarily focused on organizations or fields, our typology reflects how individual entrepreneurs experience and respond to institutional pressures in divergent ways (Friedland & Alford, 1991; Powell & Rerup, 2017). Patterns within our sample reveal four ideal entrepreneur types that differ in their degree of compliance with institutional expectations and the extent to which they reinterpret or transform their EI. This represents a distinct theoretical contribution. While prior work has conceptualized responses to institutional complexity (Greenwood et al., 2011) or hybrid logics (Battilana & Lee, 2014), it has rarely developed typologies that connect entrepreneurial responses, specifically as relates to AI. Our typology reveals that entrepreneurs are not only institutional actors responding to external demands, but are also trying to redefine what it means to be an entrepreneur today. This typology helps explain the heterogeneity of entrepreneurial behavior under institutional strain and opens new avenues for understanding agency in digital entrepreneurship.

5.5.2 Practical Implications

Our findings also have several practical implications for entrepreneurs and policymakers. First, our findings offer guidance for entrepreneurs by highlighting how institutional environments shape the opportunities and constraints of AI adoption. The four distinct response profiles identified in our study help entrepreneurs reflect on their own positioning and recognize alternative strategies for engaging with AI under institutional pressure. Our typology allows entrepreneurs to understand how others navigate similar challenges and to develop more informed, context-sensitive approaches in AI adoption. More specifically, we urge entrepreneurs who see themselves as conformers to critically assess whether their compliance is strategically beneficial or driven by a fear of non-conformity. Such entrepreneurs should consider more proactive uses of AI that align with long-term innovation goals. Skeptics may benefit from targeted exposure to low-risk AI use cases (e.g., using AI to create meeting minutes) and peer learning to reduce uncertainty and build AI literacy (Thanasi-Boçe & Hoxha, 2024). For rebels, we recommend maintaining a critical (but objective) stance toward AI while also selectively engaging with institutional actors to ensure legitimacy and avoid marginalization. Recognizing the strengths and risks of each approach allows entrepreneurs to navigate AI adoption with greater strategic awareness and institutional sensitivity.

Second, we encourage entrepreneurs to become more attuned to the institutional landscapes in which they operate. Regulations, peer norms, and societal expectations fundamentally influence how AI can be meaningfully and sustainably integrated into entrepreneurial activity. Awareness of these forces is particularly critical in environments with rapid technological and regulatory change. Understanding the implications of the EU

AI Act or shifting societal narratives about responsible AI use, for example, can help entrepreneurs avoid compliance pitfalls and identify strategies that enhance legitimacy.

Third, from a policy perspective, our findings suggest that AI regulation and support mechanisms should account for the diverse ways in which entrepreneurs engage with institutional pressures. Rebels and skeptics, for instance, may need more assistance in understanding the details and reasons behind AI regulations. Policy institutions may offer such guidance by actively engaging in discussions with entrepreneurs at events or by creating mentoring programs.

5.5.3 Limitations

While our qualitative, exploratory design was well-suited for inductive theory building (Gioia et al., 2013), it resulted in several limitations. First, our sample was limited to 32 entrepreneurs in Germany and Japan. This limited scope naturally constrains the generalizability of our findings. Broader comparative studies are needed to test the prevalence and relevance of the four entrepreneurial profiles in other contexts. Future research could use larger, more diverse samples and employ mixed-method approaches to assess the robustness of our typology. Fuzzy-set qualitative comparative analysis (Pappas & Woodside, 2021) or latent profile analysis (Spurk et al., 2020), for example, could be used to validate the presence and variation of entrepreneurial profiles across different institutional environments.

Second, the typology we present should not be interpreted as static or exhaustive. While we identified four distinct profiles, these were derived inductively from our specific sample and may not capture the full range of possible entrepreneurial responses to AI-related institutional pressures. Entrepreneurs may transition between these profiles over time as the institutional field evolves, as new affordances of AI emerge, or as their own identities and competencies shift. Future research should examine whether additional types exist in other contexts not explored in this research and adopt a longitudinal design to trace how entrepreneurial responses unfold and change over time.

Third, it is important to emphasize that our study captured how entrepreneurs perceived institutional changes, rather than quantifying institutional change itself. While these perceptions are crucial for understanding entrepreneurial behavior, they do not necessarily reflect comprehensive transformations occurring at the field, organizational, or policy levels. Future research could complement our study with multi-level institutional analyses that assess how changes in formal structures, discourse, and practice are unfolding in response to AI adoption across time and contexts.

5.5.4 Avenues for Future Research

5.5.4.1 Institutional Pillars and Isomorphism

While our study sheds light on how entrepreneurs in Germany and Japan experience and respond to AI-related institutional pressures, important questions remain about the broader applicability and evolution of these dynamics. Institutional environments differ widely between countries, especially when comparing mature, highly regulated economies with emerging or less formalized ones. These differences may result in distinct forms of isomorphic pressures, variations in institutional interpretation, and entirely different strategic responses. Crucially, institutional conditions are not static. As AI technologies mature and public discourse, regulations, and peer norms evolve, so too will the strategies entrepreneurs adopt, necessitating additional longitudinal and cross-contextual work. Future research could examine the following questions:

- How do entrepreneurial responses to AI-related institutional pressures differ in other institutional contexts, such as in emerging economies or highly deregulated markets?
- How do isomorphic pressures evolve over time, and how do entrepreneurs adapt their strategies in response to these shifts?

5.5.4.2 Entrepreneurial Strategies and Gaining Legitimacy

Our study revealed several distinct strategies that entrepreneurs employ to navigate institutional pressures emerging from the development and integration of AI. However, our qualitative research design does not allow us to assess the relative effectiveness of these strategies in securing legitimacy from key stakeholders such as investors, customers, or regulators. Nor can we determine whether specific entrepreneurial profiles are associated with different performance outcomes or improved long-term viability. It remains unclear whether these profiles remain stable over time or whether entrepreneurs may shift between profiles in response to changing institutional conditions or personal learning processes. We therefore encourage future research to address the following questions:

- Which entrepreneurial responses and profiles are most effective in securing pragmatic, moral, and cognitive legitimacy? What can they learn from each other?
- Can entrepreneurs shift from one entrepreneurial profile to another (e.g., from skeptic to visionary) and, if so, under which conditions do such shifts occur?

5.5.4.3 Reconstructing Entrepreneurial Identity

A key insight from our study is that AI adoption catalyzed a redefinition of what it means to be an entrepreneur. For some, AI adoption enabled entrepreneurs to align with a future-oriented, data-driven identity; for others, it posed a threat to their autonomy or professional self-concept. We found that the level of identity transformation was partially depended on the institution where entrepreneurs operated. However, we know little about how EI is reshaped in other institutional contexts, such as, in Northern or Southern America, Africa, or other parts of Europe or Asia. In addition, this study gives only initial insights on how EI is reconstructed in terms of AI introduction. Future research could draw on identity theory (Burke & Stets, 2009; Stryker & Burke, 2000) and prior work on EI (Radu-Lefebvre et al., 2021) to analyze how AI disrupts EI as a process or property or as a potential antecedent to the construction of EI. Thus, scholars could aim to answer the following questions:

- How does AI adoption reshape EI in different institutional environments?
- How does AI adoption transform EI as a process compared to as a property?

5.6 Conclusion

This study explores how entrepreneurs in the distinct institutional contexts of Germany and Japan perceive and respond to the isomorphic pressures surrounding AI adoption. Drawing on 32 semi-structured interviews, we identify institutional enablers and barriers across the regulative, normative, and cultural–cognitive pillars, and reveal how the strategies entrepreneurs adopt reflect varying degrees of compliance and identity transformation. Our framework links institutional pressures, strategic responses, and identity reconstruction to show that AI adoption is not merely a technological or economic decision but a deeply institutional process. The four profiles derived in our typology—visionary, conformer, skeptic, and rebel—illustrate how entrepreneurs make sense of, accommodate, and/or resist institutional demands. By highlighting how institutional contexts shape entrepreneurial engagement with AI, our study bridges digital entrepreneurship and institutional theory, offering actionable insights for entrepreneurs and policymakers.

6 Concluding Discussion of the Dissertation

To address the overarching research question ***“How do stakeholders react to ADM, and how do these reactions vary depending on interaction and system characteristics, company types, and institutional contexts?”***, this dissertation consists of four essays. The following sections summarize the research findings and discuss the theoretical and practical implications of each essay on a higher level. This is followed by a reflection on the limitations of the dissertation and a discussion of potential avenues for future research.

6.1 Summary of Research Findings

Essay I presented a meta-analysis of research on ADM within HRM, offering a comprehensive synthesis of stakeholder reactions to ADM and introducing an overarching theoretical framework. The findings indicated that algorithm aversion is more prevalent than algorithm appreciation. Stakeholders tended to react more negatively to ADM compared to HDM, both in terms of system-related (i.e., justice, fairness, trust, and trustworthiness) and organization-related (i.e., organizational attractiveness, job pursuit intention) reactions. These relationships were dependent on specific boundary conditions. Stakeholder reactions were particularly unfavorable when decisions were automated rather than augmented (i.e., extent of decision), and when individuals were personally affected by the ADM decision compared to when they were not directly affected (i.e., psychological distance). Building on these findings, Essay I introduced an overarching theoretical framework and outlined a research agenda to guide future work. In particular, the essay highlighted the need to investigate cultural variation in ADM reactions, further differentiation of the level of psychological distance of algorithmic decisions, and the type of tasks where ADM is introduced.

Building on these gaps, *Essay II* explored how ADM and psychological distance to ADM decisions affect positive and negative stereotypes. By means of text analysis of scraped articles from seven German newspapers and interviews, Essay II derived the most prevalent positive (i.e., innovativeness, performance, speed) and negative (i.e., unfairness, distrust, creepiness) ADM stereotypes. The findings in Study 1 showed that ADM elicited both positive and negative stereotypes simultaneously in individuals. Study 2 investigated the role of psychological distance and found that individuals who are directly affected by the decision of ADM (i.e., low distance) reported stronger negative stereotypes and fewer positive ones, whereas those who were more distant were more likely to have more positive stereotype perceptions. Furthermore, these stereotypes mediated the relationship between ADM and organizational attractiveness as well as between psychological distance and organizational attractiveness. While Essay I demonstrated that algorithm aversion is more prevalent in response to ADM, Essay II added a nuance by showing that ADM can also elicit positive stereotypes and that they exist at the same time as negative stereotypes, indicating a certain internal conflict. Thus, this essay introduces the term algorithm ambivalence, which refers to the simultaneous perceptions of ADM as positive and negative. This challenges prior findings which stated that either algorithm aversion or appreciation is prevalent in individuals, but not both at the same time. Thereby, Essay II calls for a more integrated perspective of ADM reactions.

Essay III investigated how algorithm transparency and the type of managerial task shape employee reactions to AM. Drawing on the ARM (Zhang, 2013), this essay revealed that high levels of algorithm transparency elicited negative reactions (i.e., perceived data security, opportunity to perform, emotional creepiness), particularly in managerial tasks which require emotional and intuitive decision components (i.e., training allocation, performance evaluation). While prior research found that transparency can improve AM reactions by providing insights into the black box that is AM (Friedrich et al., 2022), Essay III highlighted that these effects were not universal and depend on the type of information that is given about the algorithm and the type of task where it is introduced. In doing so, the essay advances the understanding of the transparency paradox and extends the ARM in the context of AM reactions.

Essay IV investigated how entrepreneurs view AI-related institutional changes, which pressures arise from these changes, and which strategies they apply in order to deal with these pressures through the lens of institutional theory (Scott, 2014). Based on interviews from Germany and Japan, this essay found that entrepreneurs saw disruptions of AI along the regulative, normative, and cultural–cognitive pillars, which ultimately resulted in coercive, normative, and mimetic isomorphism. The entrepreneurs responded differently to these new pressures, by (partially) conforming (e.g., adhering to all AI-related laws and regulations), avoiding (e.g., not talking to their peer group about AI, leaving the country), or rejecting (e.g., openly contesting AI regulations) the institutional demands. In addition, Essay IV showed that entrepreneurs experience a shift in their EI through AI-related institutional pressures. The essay synthesized all of these findings into a comprehensive framework, thereby providing guidance for future research. Moreover, Essay IV identified a typology of entrepreneurial profiles (i.e., the visionary, the conformer, the skeptic, the rebel), which vary in the degree of compliance with institutional demands and the level of EI transformation. The profiles also showed cultural variations, as not all profiles were found uniformly among interviewees in the two countries. For example, the conformer was rather present in Japan, whereas the rebel was more frequently found in Germany. The essay presented future research questions on AI and institutional theory in entrepreneurship.

6.2 Theoretical Implications

6.2.1 Extension of CASA

The first contribution of this dissertation lies in extending the CASA framework (Nass & Moon, 2000) by applying it to the context of ADM. Originally developed to demonstrate that individuals treat computers and simple machines as social actors, the dissertation extends CASA here to show that similar reactions emerged in interactions with ADM systems. Essay I demonstrated that theories traditionally used to explain human–human interaction can also be meaningfully applied to human–algorithm interactions. This addresses a key issue in the existing ADM literature (i.e., the fragmented use of theories and models) and supports the development of a more coherent, unifying framework. The CASA framework, together with the frameworks developed in Essay I and this dissertation, provide a theoretical lens to explain both algorithm aversion, appreciation, and its boundary conditions. Specifically, algorithm aversion emerges because stakeholders apply human-like expectations to ADM systems—expectations that are often violated due to the absence of interpersonal communication, such as empathy or intuition (Glikson & Woolley, 2020).

However, findings from Essay II and Essay IV revealed that stakeholders may also express algorithm appreciation. Here, CASA also provides explanatory mechanisms. Just as expectations toward other humans are not always fulfilled in human–human interaction, ADM systems may sometimes perform better in meeting these expectations (Gambino et al., 2020). For example, entrepreneurs in Essay IV reported that they prefer using AI tools in certain tasks over relying on employees or colleagues due to the speed and instant feedback of these systems. Similarly, Essay II identified the decision speed as a positive stereotype of ADM. In such cases, ADM systems fulfill expectations more consistently than human counterparts (e.g., in the form of real-time feedback). Altogether, CASA functions as an overarching framework that explains both algorithm aversion and appreciation, by conceptualizing ADM systems as social actors which are subject to the same expectations as human decision-makers.

6.2.2 Insights into Different Stakeholder Perspectives

The second contribution of this dissertation is that it provides insights into how different stakeholders react to ADM and the underlying mechanisms that shape these reactions. Essay I offered initial evidence that HR professionals, employees, and applicants differ systematically in their responses to ADM. While employees and applicants (i.e., second parties) reported more negative reactions to ADM compared to HDM, HR professionals (i.e., first parties) did not show these differences. Essay II further demonstrated that employees and applicants (i.e., second parties) perceived ADM more negatively than third-party observers. Essay IV complemented this perspective by showing that entrepreneurs (i.e., first parties) tended to be more positive about AI implementation, as they interact with these tools regularly and directly benefit from the efficiency gains. These findings support Langer and Landers' (2021) work, which distinguishes between first, second, and third parties. First parties (e.g., entrepreneurs, HR professionals) directly interact with ADM systems and use them to make decisions about others, second parties (e.g., employees, applicants) are confronted with decisions made by ADM but do not interact with the system itself, and third parties (e.g., observers) are exposed to ADM only indirectly, with no personal consequences.

Two central mechanisms help explain why these stakeholder groups react differently. First, stakeholder reactions vary based on proximity to the system. First parties are typically users of the systems and tend to become familiar with them over time, which has been shown to improve ADM reactions (Horowitz et al., 2024). Furthermore, they may attribute more control to the implementation of ADM systems, as they can shape their use and degree of involvement (Deci & Ryan, 2012; Gonzalez et al., 2022). In contrast, second and third parties do not use ADM themselves and thus may perceive less control over the process. These stakeholders may have fewer insights into the system (e.g., how it is designed, which decision criteria are selected to make decisions) and therefore perceive it as opaque or as a "black box" (Langer & König, 2023; Schlicker et al., 2021). This may lead to less favorable ADM reactions.

Second, these roles differ in terms of the psychological distance to the decision and the following consequences. For instance, second parties are closer to algorithmic decisions compared to first or third parties, because the decisions have direct implications for their lives (e.g., hiring, performance evaluation). In contrast, first parties make decisions, which have consequences for other individuals (e.g., applicants, employees), which may reduce the closeness of the decision for them. However, they may still need to justify their decisions to these individuals and may develop their own decision rationale. Thus, they are not completely separated from the individuals who face the decisions. The least psychologically close are third parties, who only observe ADM usage. This leads to the evaluation of ADM systems in a more abstract manner and tends to result in more favorable reactions (Braun et al., 2022). In sum, this dissertation provided important insights on how stakeholders differ in ADM reactions and calls on future research to expand the scope to additional stakeholders (e.g., customers, investors) that are involved in the ecosystem of ADM introduction.

6.2.3 Multi-Level Analysis of Boundary Conditions

This dissertation contributes to the literature by identifying key boundary conditions that shape stakeholder reactions to ADM. Across the essays, several boundary conditions emerged for explaining variation in ADM reactions. Essay I and II highlighted the importance of psychological distance as a boundary condition of ADM reactions. When people are not affected by algorithmic decisions, they can focus on a more neutral interpretation of ADM implementation. However, when the outcomes directly affect individuals' lives, this leads individuals to interpret ADM in a more detailed and context-specific way. Thus, both essays stress the importance of incorporating psychological distance in future work.

Moreover, Essay I and III demonstrated that algorithm transparency and type of managerial task (mechanical vs. human tasks) shape ADM reactions. Importantly, the findings showed that introducing both boundary conditions together (i.e., Essay III), compared to analyzing them in isolation, yielded additional insights. Moreover, the results highlighted that transparency is not always beneficial, particularly when ADM is introduced in tasks which are associated with human skills, such as making decisions in performance evaluation, and with detailed information about the algorithm. This strengthens the importance of analyzing several boundary conditions at once to provide a more comprehensive understanding of ADM introduction in organizations. Previous research has mostly introduced one boundary condition within their studies (e.g., transparency, type of task, differing countries; Kleinlogel et al., 2023; Lee, 2018; Von Eschenbach, 2021), which is important for gaining an initial understanding of the influencing factors of ADM reactions, but limits the holistic understanding of these reactions. Boundary conditions may influence or counteract each other, which can only become visible once they are analyzed together. Therefore, Essay III provides a first attempt at bridging different boundary conditions and urges future scholars to put more emphasis on this integration.

Finally, Essay IV identified institutional differences as a boundary condition. Here, this essay showed that the development of AI has consequences not only for managers or organizations, but also for the institutional landscape as a whole. As AI disrupts this landscape, new pressures and demands emerge, which entrepreneurs and organizations need to deal with in order to remain successful in the future. In particular, this study showed that entrepreneurs in varying institutional settings react differently to these new demands. These findings underscore that stakeholder reactions cannot be fully understood without attending to the broader institutional logics in which ADM is embedded. Thus, this study contributes to the literature by extending institutional theory (Scott, 2014) to the AI field and shows that not only individual or organizational factors impact stakeholder reactions, but also the larger institutions they operate in.

In sum, these findings underscore that influencing factors of ADM reactions can occur on the *micro-level*, that is, related to the system itself, (e.g., transparency of the system; Essay III), on the *meso-level*, related to the organizational implementation (e.g., type of task, extent of decision; Essay I and II), and on the *macro-level* (e.g., institutions; Essay IV). Previous literature underscored the importance of such multi-level analyses (Carretero et al., 2015; Groen, 2005). However, in the field of ADM, this is still underrepresented, with the exception of one review of Bankins et al. (2024). As Essay III showed, understanding different levels of ADM implementation together is needed, as it may challenge prior conclusions drawn from studies focused on only one level of analysis.

6.3 Practical Implications

This dissertation yields several practical implications for organizations, managers, entrepreneurs, policymakers, and developers engaged in the design, implementation, and governance of ADM systems. First, organizations and managers should be aware that ADM leads to algorithm aversion in some instances and algorithm appreciation in others. However, as Essay I showed, algorithm aversion may currently be more prevalent; hence, organizations should be cautious and aware of the potential downsides of ADM introduction.

Based on these insights, tailored interventions are essential to improve stakeholder reactions to ADM, depending on the stakeholder group involved. For first parties, such as HR professionals, organizations should prioritize developing effective human–ADM collaboration. This can be achieved by offering training programs that are developed with

ADM specialists or providers (Köchling et al., 2023), the establishment of peer support networks (Sharma et al., 2023), and inclusive implementation processes that actively involve first parties in decision-making (Weber et al., 2023). In particular, such training programs should focus on improving familiarity with the system and provide an overview of the system functionalities. However, besides this technical focus, organizations could also offer programs which focus more on the social and psychological side of ADM implementation, answering questions such as: How can I develop my role so that the use of ADM works for me? Which resources do I have available to reduce the increase of cognitive load or technostress? What do I do if I feel overwhelmed by ADM? In line with this, regular meetings or events for users could be organized to provide safe spaces to exchange challenges and best practices. Furthermore, involving first parties in decisions about tool selection, implementation procedures, and feature prioritization fosters a greater sense of control and ownership, which may in turn increase acceptance and positive engagement (De Vreede et al., 2021; Deci & Ryan, 2012). Entrepreneurs, as another category of first parties, typically exercise greater autonomy in deciding which ADM systems to adopt and how to integrate them. Still, they too benefit from exchange with their peer group. As highlighted in Essay IV, many entrepreneurs actively build informal networks to stay informed, share experiences, and enhance their proficiency in using AI in the long run.

For second parties, such as (potential) employees, organizations need to take additional steps to reduce concerns and improve acceptance of ADM. As shown in Essays I and II, these groups are more likely to experience algorithm aversion because ADM decisions directly affect them. To address this, organizations should clearly explain how decisions are made, ensure human oversight is present, and offer ways to appeal decisions (Langer et al., 2025). ADM could be introduced in a transparent way, which highlights the decision criteria and human involvement in the decision (Friedrich et al., 2022). However, as Essay III highlights, transparency does not always yield positive ADM reactions. Providing too much or overly technical information can confuse users and lead to negative reactions. Therefore, it is important that organizations involve affected stakeholders in deciding how much and what kind of information to share when introducing ADM systems. In addition, ADM could be designed to improve perceived control or agency over its implementation. For example, ADM systems could offer interactive elements that involve employees or applicants where they have the option to give preferences or feedback to the system's decisions (Park et al., 2021). This way, second parties may shift to becoming first parties as they are still confronted with the decision, but actively use the system before and after receiving the decision. Moreover, second parties would also benefit from support networks. Potentially, they could attend regular meetings dedicated to users, allowing both sides to share concerns and suggestions.

For third parties, ADM is often perceived more positively, as they are not directly affected by its decisions. However, these individuals may eventually transition into second-party roles—for instance, by applying to an organization that uses ADM and subsequently being subject to its decisions. Thus, organizations should proactively shape public perceptions by communicating their ADM practices in a positive light. Specifically, information about ADM use could be spread through the news, the company website, or social media. This can reduce potential skepticism when third parties become directly impacted. In addition, doing so would also help entrepreneurs gain legitimacy as consumers are an important group who legitimize new ventures and would already be accustomed to ADM systems being employed (Wang et al., 2014).

Across all stakeholder groups, developers and policymakers should consider these perspectives when designing ADM systems or drafting AI regulations to ensure that the diverse expectations and concerns of affected parties are addressed. This includes acknowledging that first parties need to be consulted to understand which features of the interface are particularly useful and which are not. Second parties would benefit from more interactive elements of ADM to improve their sense of control over the decision. Policymakers should focus on creating context-sensitive regulatory frameworks that account for all stakeholder perspectives. A promising step in this direction is the EU AI Act (European Commission, 2021), which introduces a risk-based classification system. By categorizing AI applications into levels such as unacceptable, high, limited, and minimal risk, the EU AI Act explicitly acknowledges the varying societal impacts of different AI use cases. For example, ADM in recruiting is labeled as a high-risk context as the decisions affect individuals heavily. This approach helps align stakeholder expectations with regulatory guidance. However, findings from Essay IV also show that entrepreneurs express dissatisfaction with the AI Act's regulations on technical implementation, as they criticize its limited practical utility. This suggests that future regulatory efforts should find ways to mitigate conflicting interests of stakeholders, specifically related to those who need to implement the guidelines themselves (i.e., organizations and entrepreneurs). Policymakers could also provide additional guidance materials tailored to entrepreneurs and small ventures, as this stakeholder group often lacks the resources to navigate complex regulatory documents such as the AI Act. As a result, it is often unclear to them what is expected in terms of compliance.

Furthermore, this dissertation highlights the importance of considering boundary conditions on all three levels when designing, implementing, or governing ADM systems. On the micro-level, system features, such as transparency, should not be seen as universally beneficial. For example, Essay III showed that when too much information is provided about ADM, it can lead to more negative employee reactions, particularly in human tasks (e.g., performance evaluation). Thus, organizations should derive the most appropriate level of transparency depending on the context and the respective stakeholder involved.

On the meso-level, organizations should assess the compatibility of ADM with the type of organization in which ADM is employed. As findings from Essay II showed, the company type was not a significant moderator for reactions to ADM, however, established ventures were perceived more unfair and creepier compared to new ventures. Therefore, established organizations should pay particular attention to how they introduce, communicate, and justify the use of ADM systems to not potentially enforce these perceptions. Essay IV adds how new ventures can utilize AI under the specific constraints they face. Here, new and established organizations could engage in a systematic exchange of learnings and best practices. This might be particularly useful for established organizations which strive to include intrapreneurial processes and thus could directly apply insights from entrepreneurs and the other way around.

Finally, on the macro level, institutional environments should be considered when introducing ADM. Essay IV illustrates that stakeholder reactions are embedded in broader institutional logics, which vary significantly across countries. In Japan, entrepreneurs tended to exhibit more compliant reactions and demonstrated a higher degree of trust in governmental authority. While this trust facilitates policy implementation, it also underscores the responsibility of policymakers to design ADM systems and regulations that genuinely reflect the expectations of all affected stakeholders and do not exploit this trust. In contrast, entrepreneurs in Germany expressed more critical views and skepticism toward government initiatives. While the EU AI Act represents a strong first step in regulating AI, some entrepreneurs in Germany felt that the Act constrains innovation and fails to adequately capture entrepreneurial perspectives on what AI can and should do. Thus, policymakers should actively engage with entrepreneurs to better understand their needs. Such dialogue could foster greater acceptance, prevent misinterpretation, and bridge the gap between policymakers and entrepreneurs.

6.4 Limitations

While this dissertation offers valuable theoretical and practical insights into stakeholder reactions to ADM, several limitations must be acknowledged. First, this dissertation investigated reactions to ADM in hypothetical or controlled settings, particularly through experimental vignette studies in an online format as seen in Essays II and III. While such designs offer high internal validity and allow for causal inference, they may limit ecological validity and generalizability (Aguinis & Bradley, 2014). Real-world interactions with ADM systems are typically more complex, iterative, and embedded in organizational routines than the employed scenarios that only tested one point in time. In addition, the online format may not accurately depict how stakeholders view ADM introduction in an actual organization due to lack of immersion and artificiality. Nevertheless, robustness checks in Essay I did not reveal significant differences between vignette and field experiments, suggesting that study design may not substantially impact the results.

Second, Essay IV offered insights through semi-structured interviews, which is an appropriate method for investigating complex and new phenomena (Bluhm et al., 2011). However, the findings from this essay are limited in their generalizability, as they focus on the experiences and perspectives of 32 entrepreneurs in two cultural settings. In the next step, it would be valuable to adopt methods which allow a bigger sample size, such as surveys or experiments, to analyze the impact of institutions on how legitimate stakeholders are perceived.

Third, this dissertation does not include a longitudinal study, which may limit the extent to which it captures the development of ADM reactions over time. Although measuring reactions at a single point in time may be appropriate in recruitment contexts, where applicants typically encounter ADM at a specific stage (e.g., during resume screening), this approach is less suitable for employees or HR professionals, who are confronted with or interact with ADM systems continuously. These repeated interactions, whether through receiving decisions or directly using the system, can influence perceptions and attitudes long-term. Prior research suggests that experience with AI may lead to more favorable evaluations (Horowitz et al., 2024). Future research should therefore incorporate longitudinal designs to better understand how stakeholder responses develop and change over time.

Fourth, the studies in this dissertation rely largely on self-reported data on ADM reactions, which may lead to problems of participants answering what they deem socially desirable or may not accurately reflect actual behaviors or outcomes. While self-report measures are both common and necessary in assessing individuals' reactions to a stimulus (Spector, 1994), they can be influenced by individual, contextual, or cultural norms. For instance, interviewees from Japan in Essay IV may express more favorable attitudes toward AI and governmental regulations due to cultural norms of harmony, deference to authority, and reluctance to express open criticism (Yokozawa et al., 2021), thereby potentially masking more critical or ambivalent views. Such tendencies underscore the need for caution when interpreting self-reported attitudes, especially in culturally diverse samples. In addition, entrepreneurs reported their perceived changes in institutions compared to providing an overview of actual institutional changes with the development of AI. Future research should therefore seek to triangulate self-reported data with behavioral or organizational indicators, such as actual usage patterns or behaviors (i.e., actual turnover instead of turnover intention) or AI adoption outcomes within firms, to provide a more comprehensive understanding of stakeholder reactions and the corresponding broader consequences.

6.5 Future Research Avenues

Building on the findings and limitations of this dissertation, several avenues for future research emerge that can extend and deepen the understanding of ADM in organizational settings.

6.5.1 Research Avenue 1: Reactions of Different Types of Stakeholders

This dissertation focuses on specific stakeholders, while the perspectives of other relevant actors, such as (line) managers, policymakers, investors, and customers, remain underexplored. Yet, ADM systems operate in complex socio-technical environments where multiple stakeholder groups play critical roles in shaping adoption and legitimacy. Essay I already pointed to potential variation in stakeholder reactions, showing initial evidence that employees, applicants, and HR professionals differ in how they evaluate ADM. In addition, all essays together provide further insights into how stakeholders differ in ADM reactions: The essays showed that first and third parties are more favorable towards ADM, but because of different reasons. First parties can use ADM themselves and shape their usage accordingly, whereas third parties are not personally affected by ADM introduction (i.e., high psychological distance).

Moreover, Essay IV highlighted how entrepreneurs respond to institutional pressures surrounding AI use, but it did not investigate how other stakeholders evaluate entrepreneurs' AI introduction. Given that actors such as customers, regulators, and investors are key audiences in determining the legitimacy of organizational practices (DiMaggio & Powell, 1983), it is essential to better understand how such stakeholders perceive AI introduction and its impact on legitimacy. Their evaluations may be shaped by diverging expectations regarding fairness, transparency, efficiency, or innovation, resulting in competing legitimacy demands. To advance research on AI in complex stakeholder environments, future work should investigate additional stakeholder perspectives that capture these differing viewpoints and potential tensions. Research questions that future research could investigate are as follows:

- How do additional stakeholder groups (e.g., line managers, consumers) react to ADM? How do these reactions differ to the findings from the stakeholders of this dissertation?
- How do different stakeholders (e.g., customers, investors, regulators) evaluate the legitimacy of ADM systems in organizational contexts?
- How do new ventures and established organizations manage competing legitimacy demands when adopting ADM in environments with multiple stakeholder expectations?

6.5.2 Research Avenue 2: Shift in Stakeholders' Professional Identities

Future research should investigate how the increasing integration of ADM systems may trigger shifts in stakeholder identities, for example, among entrepreneurs, managers, and employees. Essay IV provided initial evidence that entrepreneurs are experiencing tensions between traditional role expectations and emerging demands from AI, suggesting that AI adoption can disrupt how they define their EI. As AI becomes more deeply embedded in decision-making processes, such identity shifts are likely to extend beyond entrepreneurship into broader organizational contexts.

Identity theory (Burke & Stets, 2009) posits that individuals construct self-meanings based on the roles they occupy and that these identities guide their behavior. When technological change disrupts the content or relevance of a role, individuals may experience a dissonance with their previous professional identity. This could lead to a reconfiguration of their identity and result in identity transformation. For example, a manager whose identity is built upon making decisions for others may feel displaced when this is delegated to ADM systems. Similarly, employees who engaged in creative tasks, such as generating content for social media, or in analytical tasks, such as generating code, may feel that their core tasks are taken away from them by AI (in this case, also specifically generative AI). Understanding how stakeholders reconstruct their identities in response to the development of AI is essential, as identity shifts can influence a wide range of reactions and shape stakeholders' job satisfaction or perceptions of organizational attractiveness. Accordingly, the following research questions emerge:

- How does the introduction of AI reshape stakeholders' (e.g., managers, entrepreneurs) professional identities?
- What forms of identity conflict emerge when core role functions are altered by AI?

6.5.3 Research Avenue 3: Multi-Level Analysis of ADM Reactions

A promising avenue for future research lies in the investigation of additional boundary conditions across different levels of analysis. There is a need for a more comprehensive framework that integrates micro-, meso-, and macro-level factors to explain the heterogeneous reactions to ADM. At the *micro level*, previous literature investigated ADM features and mechanisms, such as transparency or human-in-the-loop (De Fine Licht & De Fine Licht, 2020), but put less emphasis on specific design features of the system which may change ADM reactions. For first parties, scholars showed how ADM can be designed to engage users more efficiently, for example, through displaying human-like competencies (Chandra et al., 2022) or with options of personalization (Teepapal, 2025), however, these insights are rather focused on general users and not specifically targeted to users within organizations (e.g., managers, employees). In this specific context, users have less control over whether to engage in ADM, as this may be a decision that is communicated top-down. Thus, it is important to investigate potentially differing user demands in organizations. In addition, these insights are transferred to second or third parties only to a limited extent. However, it is likely that different design elements (e.g., anthropomorphism, interactivity) may shift ADM reactions in one or the other way.

At the *meso level*, future research should examine how organizational structures, cultures, and industry contexts shape stakeholder reactions to ADM. For instance, an organizational culture that emphasizes innovation and technological openness may foster more favorable attitudes toward ADM, influencing both acceptance and usage. Similarly, industry-specific norms, practices, and the level of dynamism likely affect how ADM is perceived, as this has been shown for previous technologies as well (Engelen et al., 2022). While Essay II found no moderating effect of company type (established firms vs. new ventures), this may be attributable to the hypothetical nature of the experimental design. In contrast, Essay IV revealed that entrepreneurs tend to adopt and view AI more positively than stakeholders in more established organizations (e.g., employees), as shown in Essay I. These findings suggest that ADM reactions may differ by industry type (e.g., traditional vs. high-tech) or company maturity. Another promising but underexplored avenue concerns leadership style and leader–member communication. Leaders who engage in transparent, supportive communication may facilitate more effective ADM implementation and mitigate resistance over time. This organizational-level perspective remains underrepresented in the ADM literature and warrants further investigation.

At the *macro level*, Essay IV showed initial insights on the role of institutions in the development of AI, specifically comparing Germany and Japan. However, this comparison is limited in scope. In addition, Essay I showed that the ADM literature is focused on a few mainly Western countries (e.g., U.S., Germany) which should be expanded to underrepresented regions of South America, Africa, Asia, and other parts of Europe. Such diversity is essential for developing a more holistic and context-sensitive approach on ADM implementation.

Moreover, regulatory developments provide a timely opportunity for comparative and longitudinal studies. For instance, the EU AI Act introduces a framework which categorizes decisions and tasks based on their level of risk. This emphasizes transparency, accountability, and human oversight for high-stakes ADM applications, such as recruiting (European Commission, 2021). In contrast, the U.S. remains largely self-regulatory (Mökander et al., 2022). Studying how these frameworks shape ADM implementation and reactions—before and after enforcement—would yield important insights into the role of formal institutions in shaping ADM use. Relevant research questions may include:

- How do specific ADM design features impact stakeholder reactions, particularly those of second and third parties, to ADM?
- How do varying organizational structures, cultures, and industries impact stakeholder reactions to ADM?
- What role does the leadership style and team communication play in the adoption and successful integration of ADM systems?
- How do regional cultural values impact stakeholder reactions to ADM beyond Western contexts?
- How do differences between regulatory environments (e.g., EU vs. U.S.) affect the legitimacy and implementation of ADM systems over time?

6.5.4 Research Avenue 4: Future Advancements of AI and the Human Role

Recently, AI agents have become popular, which are capable of performing complex tasks with minimal human input (Hughes et al., 2025). These AI agents are implemented across domains, such as customer service, software development, or forecasting. However, it remains unclear how different stakeholder groups respond to AI agents in comparison to previous ADM systems, what contexts are most suitable for their deployment, and how human–agent collaboration should be designed to ensure positive reactions to them. A particularly critical issue in this regard is the changing role of the human in using AI agents. Earlier ADM systems often involved a human “in-the-loop,” providing oversight of the system’s recommendations and making the final decision. However, the role of the human “on-the-loop” becomes increasingly more important, which refers to monitoring AI activities, rather than being further involved in making decisions (i.e., the system works more autonomously). For instance, the EU AI Act specifically mentions this role of an observer who is “on-the-loop” to be legally binding for high risk AI systems by the time the EU AI Act comes into force in 2026 (European Commission, 2025). Thus far, research has not differentiated between these two forms of human involvement (i.e., in-the-loop versus on-the-loop), which may complicate the introduction of AI agents in organizations on a theoretical and practical level.

Beyond these developments, research should remain attentive to the rapid advancements of AI that may introduce entirely new forms of intelligent systems. To ensure that scholarly insights remain relevant and forward-looking, future research must continuously examine how stakeholders respond to evolving forms of AI, including not only ADM and AI agents but also emerging hybrid forms of automation. To advance this research avenue, future studies should address the following research questions:

- What are stakeholder reactions to AI agents? Do they differ from reactions to ADM systems and if so, why?
- What are effective strategies for implementing AI agents in organizations? In which contexts are AI agents particularly useful?
- How do stakeholder reactions to human-in-the-loop and on-the-loop differ? How can an on-the-loop design be implemented most effectively?
- What are emerging AI tools and how can we improve the predictability of new AI advancements?

6.6 Conclusion

This dissertation aimed to examine how stakeholders react to, interact with, and integrate ADM systems across various organizational contexts by drawing on an extending CASA. Accordingly, the dissertation investigated system-related (e.g., fairness, creepiness) and organization-related (e.g., organizational attractiveness) reactions to ADM. In doing so, this dissertation builds a bridge between human–human and human–algorithm contexts to explain how reactions to ADM form. Here, this dissertation demonstrates that algorithm aversion and appreciation can occur simultaneously within individuals, as ADM leads to specific stereotypes that serve as cognitive shortcuts to make sense of the system. Accordingly, ADM introduction led to both an increase in perceptions of innovativeness and distrust, showing the complex nature of how ADM systems are perceived. These system-related reactions had further consequences for the organizations, for example, resulting in increased or decreased organizational attractiveness. In addition, several boundary conditions were found to have an impact on ADM reactions: type of stakeholder, psychological distance, algorithm transparency, type of task, and institutional differences. These findings highlighted that algorithm aversion and appreciation depend largely on additional factors, such as, how close the algorithmic decision is to stakeholders or how transparently the ADM system is introduced. Overall, this dissertation provided several important implications for theory and practice and outlines multiple future research avenues.

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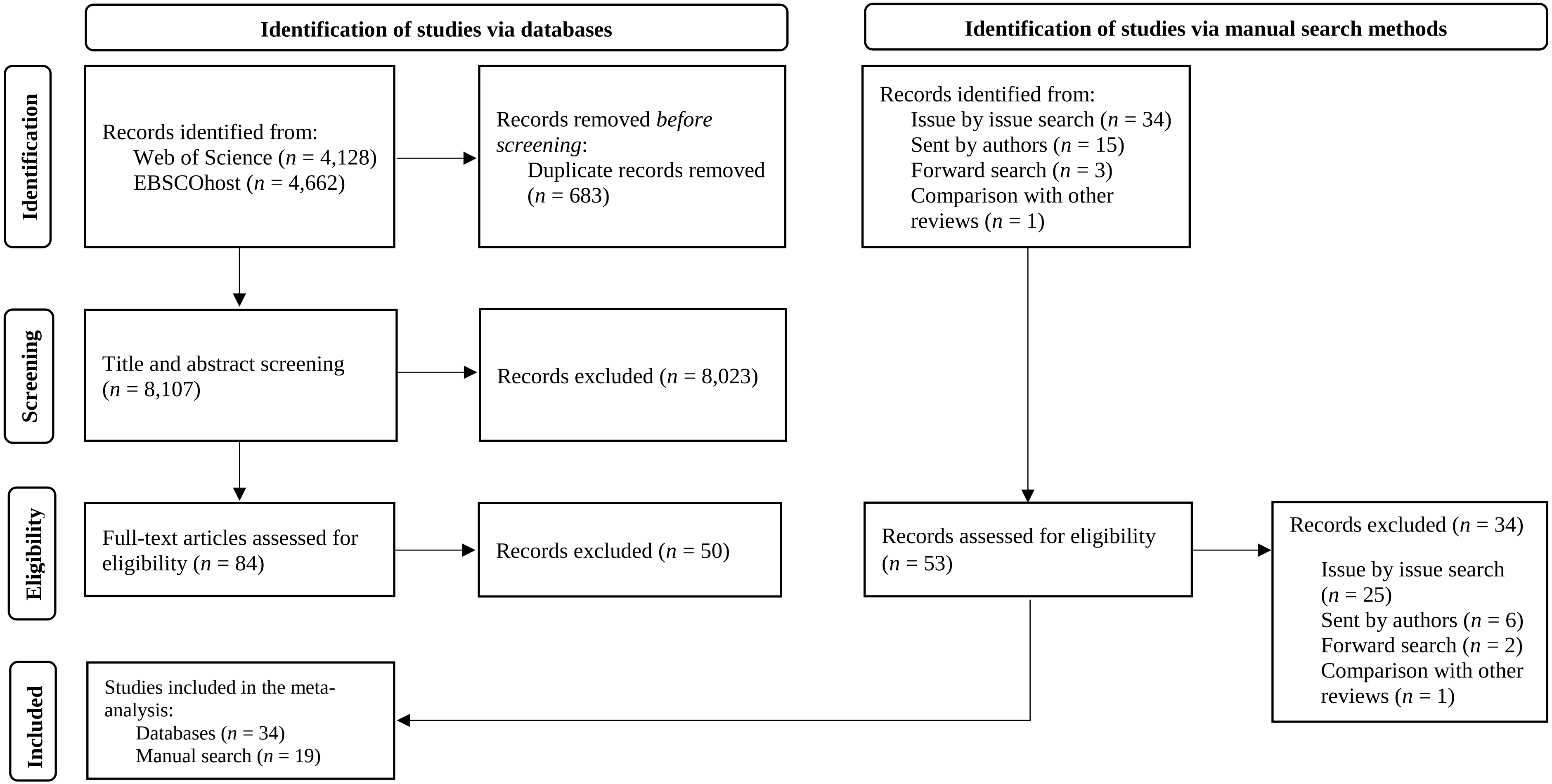
8 Appendix

Appendix A1 (Essay I). Flow Diagram



Note. The 53 studies included a total of 73 samples.

Appendix A2 (Essay I). Overview of Included Studies

Author(s), Year	Journal	Sample Size	Type of Stakeholder	Type of Interaction	Type of Task	Extent of Decision	Psych. distance	Random-ization
Acikgoz et al. (2020)	International Journal of Selection and Assessment	Study 1: 298, study 2: 225	Applicants	Confrontation	Interviews	Decision support	Low	Yes
Acikgoz et al. (2024)	Unpublished	Interview sample: 276, screening sample: 274	Applicants	Confrontation	Interview sample: interviews, screening sample: screening	Sole decision entity	Low	Yes
Bankins et al. (2022)	Information Systems Frontiers	446	Employees	Confrontation	Career development	Sole decision entity	Low	Yes
Bedemariam and Wessel (2023)	Computers in Human Behavior	309	Applicants	Confrontation	Recruiting	Sole decision entity	Low	Yes
Canagasuriam and Lukacik (2025)	International Journal of Selection and Assessment	245	Applicants	Collaboration	Interviews	Decision support	Low	Yes
Chacon et al. (2024)	Unpublished	336	Applicants	Confrontation	Recruiting	Decision support	Low	Yes
Choi and Chao (2024)	Personality and Social Psychology Bulletin	Study 1: 177, study 2: 421, study 3a: 248, study 3b: 638, study 5: 1,092	Employees	Confrontation	Conflict resolution	Sole decision entity	Low	Yes
Choung et al. (2024)	International Journal of Human-Computer Interaction	235	Applicants	Collaboration	Screening	Decision support	High	Yes
Deriu et al. (2024)	Journal of Business Research	108	Applicants	Both	Interviews	Sole decision entity	Low	Yes
Dong et al. (2024)	Technovation	504	Employees	Confrontation	Career development	Sole decision entity	Low	Yes
Dutta and Mishra (2025)	Personnel Review	1,179	Employees	Collaboration	Career development	Decision support	Low	No

Author(s), Year	**Journal**	**Sample Size**	**Type of Stakeholder**	**Type of Interaction**	**Type of Task**	**Extent of Decision**	**Psych. distance**	**Random-ization**
Feldkamp et al. (2024)	European Journal of Work and Organizational Psychology	215	HR professionals	Collaboration	Screening	Decision support	High	Yes
Fumagalli et al. (2022)	Research Policy	1,725	Applicants	Confrontation	Recruiting	Sole decision entity	Low	Yes
Gonzalez et al. (2019)	Personnel Assessment and Decisions	192	Applicants	Confrontation	Recruiting	Sole decision entity	Low	No infor-mation
Gonzalez et al. (2022)	Computers in Human Behavior	Study 1: 183, study 2: 163	Applicants	Confrontation	Recruiting	-	Low	Yes
Höddinghaus et al. (2021)	Computers in Human Behavior	333	Employees	Confrontation	Career development	Sole decision entity	Low	Yes
Kares et al. (2023)	International Journal of Selection and Assessment	Study 1: 170, study 2: 154	HR professionals	Collaboration	Study 1: screening, study 2: Career development	Decision support	High	Yes
Keppeler (2023)	Journal of Public Administration Research and Theory	415 (reduced *N* for our included correlations)	Applicants	Confrontation	Sourcing	-	Low	Yes
Keppeler et al. (2024)	Unpublished	Study 2: 538	HR professionals	Collaboration	Screening	Decision support	High	Yes
Kleinlogel et al. (2023)	International Journal of Selection and Assessment	Study 1: 151, study 2: 148[14]	Applicants	Confrontation	Interviews	Decision support	Low	Yes
Koch-Bayram et al. (2023)	International Journal of Selection and Assessment	Study 1: 209, study 2: 302	Applicants	Confrontation	Interviews	Sole decision entity	Low	Yes
Koch-Bayram and Kaibel (2024)	Human Resource Management Journal	Study 1: 259, study 2: 342	Applicants	Confrontation	Screening	Sole decision entity	Study 1: high, study 2: low	Yes

[14] We operationalized the study by Kleinlogel et al. (2023) as two studies due to the given data basis.

Author(s), Year	Journal	Sample Size	Type of Stakeholder	Type of Interaction	Type of Task	Extent of Decision	Psych. distance	Random-ization
Köchling and Wehner (2023)	International Journal of Selection and Assessment	200	Applicants	Confrontation	Recruiting	Decision support	Low	Yes
Köchling et al. (2023)	Review of Managerial Science	160	Applicants	Confrontation	Recruiting	Decision support	Low	Yes
Köchling et al. (2025)	Review of Managerial Science	280	Employees	Confrontation	Career development	Decision support	Low	Yes
Lacroux and Martin-Lacroux (2022)	Journal of Business and Psychology	694	HR professionals	Collaboration	Screening	Decision support	High	Yes
Langer , König and Hemsing (2019)	Journal of Managerial Psychology	124	Applicants	Confrontation	Interviews	Sole decision entity	Low	Yes
Langer, König and Papathanasiou (2019)	International Journal of Selection and Assessment	123	Applicants	Confrontation	Interviews	-	High	Yes
Langer, König, Sanchez, et al. (2019)	Journal of Managerial Psychology	148	Applicants	Confrontation	Interviews	-	Low	Yes
Langer et al. (2023)	Journal of Business and Psychology	121	HR professionals	Collaboration	Screening	Decision support	High	Yes
Lavanchy et al. (2023)	Journal of Business Ethics	Study 1: 249, study 2: 272, study 3: 282, study 4: 270	Applicants	Confrontation	Screening	Sole decision entity	Low	Yes
Liu et al. (2023)	Journal of Computer-Mediated Communication	134	Applicants	Collaboration	Interviews	Sole decision entity	Low	Yes
Luo and Zhang (2023)	Academy of Management Proceedings	302	Employees	Confrontation	Interviews	Sole decision entity	Low	Yes

Author(s), Year	**Journal**	**Sample Size**	**Type of Stakeholder**	**Type of Interaction**	**Type of Task**	**Extent of Decision**	**Psych. distance**	**Random-ization**
Maasland and Weissmueller (2022)	Frontiers in Psychology	156	HR professionals	Collaboration	Administrative	Decision support	High	Yes
Mirowska (2020)	Journal of Personnel Psychology	184	Applicants	Confrontation	Interviews	Sole decision entity	Low	Yes
Moritz and Schmidt (2024)	European Conference on Information Systems Proceedings	173	Employees	Confrontation	Management tasks	Sole decision entity	Low	Yes
Moritz et al. (2024)	Academy of Management Proceedings	416	Applicants	Confrontation	Recruiting	Sole decision entity	Low	Yes
Moritz et al. (2025)	Academy of Management Proceedings	252	Applicants	Confrontation	Recruiting	Decision support	Low	Yes
Nagtegaal (2021)	Government Information Quarterly	Study 1: 109, study 2: 126	Employees	Confrontation	Study 1: administrative & career development, study 2: administrative & recruiting	Sole decision entity	High	Yes
Noble et al. (2021)	International Journal of Selection and Assessment	360	Applicants	Confrontation	Screening	Sole decision entity	Low	Yes
Oostrom et al. (2024)	Journal of Occupational and Organizational Psychology	Study 1: 172, study 2: 276	Applicants	Confrontation	Recruiting	Sole decision entity	Low	No infor-mation
Pomrehn, Göttel, and Wehner (2024)	Unpublished	405	Applicants	Confrontation	Recruiting	Decision support	Low	Yes

Author(s), Year	**Journal**	**Sample Size**	**Type of Stakeholder**	**Type of Interaction**	**Type of Task**	**Extent of Decision**	**Psych. distance**	**Random-ization**
Pomrehn Schmodde, and Wehner (2024)	Unpublished	HR professionals sample: 205, employees sample: 202	HR professionals sample: HR professionals, Employees sample: employees	HR professionals sample: collaboration, employees sample: confrontation	Recruiting, Layoff	Decision support	HR professionals sample: high, employees sample: low	Yes
Pomrehn and Wehner (2025)	Hawaii International Conference on System Sciences (HICSS)	190	Employees	Confrontation	Career development	Sole decision entity	Low	Yes
Renier et al. (2021)	Computers in Human Behavior	439	Applicants	Confrontation	Recruiting	Sole decision entity	High	Yes
Schlicker et al. (2021)	Computers in Human Behavior	209	Employees	Confrontation	Administrative	Sole decision entity	Low	Yes
Shulner-Tal et al. (2025)	International Journal of Human-Computer Interaction	3,068	HR professionals	Collaboration	Screening	Sole decision entity	High	Yes
Sondern et al. (2025)	Unpublished	291	Applicants	Collaboration	Negotiation	Sole decision entity	Low	No infor-mation
Suen and Hung (2023)	Computers in Human Behavior	152	Applicants	Confrontation	Interviews	Sole decision entity	Low	Yes
Suen et al. (2019)	Computers in Human Behavior	180	Employees	Confrontation	Interviews	Sole decision entity	Low	Yes
Wesche et al. (2024)	European Journal of Work and Organizational Psychology	270	Employees	Confrontation	Career development	Sole decision entity	Low	Yes
Yan et al. (2024)	Journal of Business Ethics	Study 1: 192, study 2: 206	Employees	Confrontation	Layoff	Sole decision entity	High	Yes
Zhang and Amos (2024)	Behavior & Information Technology	95	Employees	Confrontation	Career development	Sole decision entity	High	Yes

Note. Psych. = psychological. Recruiting means that the study included screening as well as interviews in the hypothetical scenario. High psychological distance means that participants were not directly affected by the decision (i.e., others were affected), a low psychological distance means that participants were directly affected by the decision.

Appendix B1 (Essay II). Scenario Descriptions for Both Studies

Manipulation	Scenarios
Study 1	
Human decision-making	You are currently looking for a job and come across a job posting from a company that perfectly matches your skills and expectations for a position. The company describes itself in the job posting as follows: [Scenario for new ventures:] *AUREONA is a **young company** founded in 2019. It currently consists of a team of around **12 employees** who are working on the development of the company's products. AUREONA plans to grow in the coming years and is therefore preparing to **raise capital** from well-known investors in a funding round at the end of the year.* [Scenario for established company]: *AUREONA is a **well-established company** founded in 1972 with a decades-long tradition. With approximately **112,000 employees**, it is one of the largest and most **successful manufacturers** in the world.* After reading the company description, you decide to apply for the position offered by AUREONA. Before submitting your resume, you read the following information about the application process on AUREONA's career website: After you submit your resume, your application will be reviewed by **our HR staff**. You will receive an email notification if you are invited to a **personal interview**. In this face-to-face interview, we aim to get to know you, your personality, and your motivation for joining AUREONA. During the interview, an HR representative and the team lead will ask you both personal and professional questions. Based on your answers, they will jointly prepare an individual written personality profile. The final hiring decision will be made **exclusively by human decision-makers**.
Algorithmic decision-making	Before reading the following scenario, please first look at this definition of artificial intelligence (AI): *Artificial Intelligence is defined as the capability of a system to correctly interpret external data, learn from such data, and use those learnings to flexibly achieve specific goals and tasks. Examples include chatbots like ChatGPT or image-generating AI tools like DALL·E.* You are currently looking for a job and come across a job posting from a company that perfectly matches your skills and expectations for a position. The company describes itself in the job posting as follows: [Scenario for new ventures:] *AUREONA is a **young company** founded in 2019. It currently consists of a team of around **12 employees** who are working on the development of the company's products. AUREONA plans to grow in the coming years and is therefore preparing to **raise capital** from well-known investors in a funding round at the end of the year.*

	[Scenario for established company]: *AUREONA is a **well-established company** founded in 1972 with a decades-long tradition. With approximately **112,000 employees**, it is one of the largest and most successful manufacturers in the world.* After reading the company description, you decide to apply for the position offered by AUREONA. Before submitting your resume, you read the following information about the application process on AUREONA's career website: Once you have submitted your resume, your application will be reviewed by **an AI system**. You will receive an email notification if you are invited to **an asynchronous video interview**. An asynchronous interview is a specific type of interview in which applicants and employers are not present at the same time. You will record your answers to predefined questions via video and will always have the option to do a trial run for each question. The HR department can review your recorded responses at a time that suits them. In our asynchronous interview, we aim to get to know you, your personality, and your motivation for joining AUREONA. You may start the interview at **any time** within the next 14 days. Once you begin, the AI system will present the questions. Further details will be provided at the start of the interview. The AI system supports the HR team by analyzing your answers and creating a personality profile based on your verbal and nonverbal communication. It then generates a list of the most suitable candidates and makes a recommendation regarding who should be offered the position. The final hiring decision, however, will be made by **the HR department and the team lead**.
Study 2	
High psychological distance	Before reading the following scenario, please first look at this definition of artificial intelligence (AI): *Artificial Intelligence (AI) is a technology that enables machines to imitate human intelligence.* As usual, you open your news app in the morning and a headline catches your attention. You click on an interesting article to read further. [Scenario for recruiting]: *The article reports on a company that **uses AI to screen résumés** for specific keywords. Applicants who meet the initial criteria are invited to **an asynchronous video interview**. In this type of interview, applicants are asked questions by an AI and respond via recorded video. These responses are then evaluated by the AI based on both **verbal and nonverbal communication**, such as facial expressions and gestures. After the asynchronous interview, candidates are invited to a **face-to-face interview** where they meet the team and the HR manager. The final hiring decision is **made by a human**, not the AI.* [Scenario for bonus payments]: *The article reports on a company that **uses AI to determine the annual bonus payments** for its employees. The AI generates a decision proposal based on employees' **performance goals** achieved during the previous*

	*year and their **job position**. However, the final decision on the bonus amount is **made by a human**, not the AI.* [Scenario for employee layoff]: *The article reports on a company that will need to eliminate 10% of its workforce in the near future. The company has decided to **use AI to help identify which positions** are potentially affected. The decision proposal is based on employees' current **job position**, **tenure** at the company, and their **social circumstances**. However, the final decision on which jobs will be eliminated is **made by a human**, not the AI.* After reading the article, you prepare your breakfast and continue with your normal daily routine.
Low psychological distance	Before reading the following scenario, please first look at this definition of artificial intelligence (AI): *Artificial Intelligence (AI) is a technology that enables machines to imitate human behavior.* [Scenario for recruiting]: *You are currently looking for a job and come across a job posting online. The position seems highly attractive to you, as it matches all of your criteria. You visit the company's career website to learn more about the application process. On the website, you learn that the company **uses AI to screen résumés** for specific keywords. The evaluation is based on your **verbal and nonverbal communication** during the interview. If your application passes this step, the first interview will be conducted **asynchronously by an AI**. This means you will receive predefined questions from the AI and respond via video. Your answers are recorded and then evaluated by the AI. After this asynchronous interview, you will be invited to an **in-person interview** to meet the team and the HR manager. The final hiring decision will be **made by a human**, not the AI.* [Scenario for bonus payments]: *You work at a company and are satisfied with your current position. During a team meeting, your manager announces that **AI will be used going forward to determine annual bonus payments**. The AI will generate a decision proposal based on the **performance goals** you achieved in the past year and **your job position**. However, the final decision on the bonus amount will be **made by a human**, not the AI.* [Scenario for employee layoff]: *You work at a company and are satisfied with your current position. During a team meeting, your manager announces that 10% of the total workforce will need to be reduced in the near future. The company has decided **to use AI to help identify which positions** are potentially affected. The decision proposal is based on **your job position**, your **tenure** at the company, and your **social circumstances**. However, the final decision on which jobs will be eliminated is **made by a human**, not the AI.*

Appendix B2 (Essay II). Balance Check of Random Assignment of Participants

	Scenario	Number of participants per scenario
Study 1	1	99
	2	100
	3	100
	4	106
	Mean	101
Study 2	1	54
	2	54
	3	51
	4	54
	5	50
	6	54
	Mean	53

Appendix B3 (Essay II). Variables, Item Measurements, and Factor Loadings

Variable	Item	FL Study 1	FL Study 2
Innovativeness	This company takes new approaches to making decisions.	.954	.829
	This company integrates innovative technologies.	.962	.853
	The decision-making processes in this company are innovative.	.914	.810
Performance	Using AI in the decision-making process improves the company's performance.	.806	.822
	Using AI in the decision-making process improves the company's efficiency.	.851	.871
	The use of AI in the decision-making process increases productivity.	.853	.842
Speed	The decision-making processes in this company are fast.	.922	.872
	This company makes decisions quickly.	.962	.949
	Decisions are made promptly in this company.	.914	.813
Unfairness	I think the company described in the scenario makes (un)fair decisions.	.947	.932
	I think the way the company described in the scenario makes decisions is (un)fair.	.941	.953
	I think the decisions of the company described in the scenario are (un)fair.	.947	.961
Distrust	I would (not) heavily rely on the company described in the scenario.	.830	.788
	I would (not) trust the company described in the scenario completely/at all.	.922	.940
	I would (not) feel comfortable relying on the company described in the scenario.	.932	.875
Emotional creepiness	During this situation, I had a queasy feeling.	.846	.848
	I had a feeling that there was something shady about this situation.	.784	.768
	I felt uneasy during this situation.	.852	.858
	I had an indefinable fear during this situation.	.805	.799
	This situation somehow felt threatening.	.817	.826
Creepy ambiguity	I did not know how to judge this situation.	.785	(.576)
	During this situation, I did not know exactly what was happening to me.	.786	.780
	During this situation, things were going on that I did not understand.	.706	(.667)
	I did not know exactly how to behave in this situation.	.824	.780
	I did not know exactly what to expect of the situation.	.816	(.659)

Variable	Item	FL Study 1	FL Study 2
Organizational attractiveness (study 1)	*General Attractiveness*		
	This company is attractive to me as a place for employment.	.891	
	I would gladly accept a job offer from this company.	(.349)	
	This company is a good place to work.	.898	
	I would recommend this company as an employer to my friends.	.749	
	Intention to Pursue Employment		
	I would make this company one of my first choices as an employer.	.889	
	I would try to obtain a job at this company.	.829	
	I can see myself working at this company.	.854	
	Prestige		
	Employees are probably proud to say they work at this company.	.845	
	This company probably has a reputation as being an excellent employer.	.840	
	I would find this company a prestigious place to work.	(.612)	
	There are probably many who would like to work at this company.	.816	
	This is a reputable company to work for.	.776	
	This company has a reputation as an employer that offers a great work environment.	.865	
	This company is well regarded by its employees.	(.661)	
Organizational attractiveness (study 2)	This would be a good company to work for.		.943
	I would like to have such a company in my environment.		.930
	I would like to work for this company.		.933
	This company takes care of its employees.		.786
	I find this company very attractive.		.928

Note. FL = factor loading. Items in brackets were dropped for further analyses due to low factor loading (< .70).

Appendix B4 (Essay II). Model Fit Comparisons

Model Indices	**First-Order Factor CFA Model**	**Second-Order Factor CFA Model**	**First-Order Factor SEM Mediation**	**Second-Order Factor SEM Mediation**	**First-Order Factor SEM Moderation**	**Second-Order Factor SEM Moderation**
Study 1						
χ^2	982.27	1,283.75	2,011.16	1,386.88	1,454.89	1,698.64
Df	499.00	515.00	546.00	548.00	587.00	615.00
p-value	.00	.00	.00	.00	.00	.00
CFI	.96	.94	.89	.94	.94	.92
RMSEA	.05	.06	.08	.06	.06	.07
AIC	37,222.00	37,492.00	37,823.58	37,195.30	37,211.51	37,399.26
BIC	37,302.00	37,812.00	38,155.90	37,519.61	37,651.93	37,727.58
Study 2						
χ^2	491.36	767.22	1,473.53	800.64	432.34	741.65
Df	296.00	314.00	336.00	338.00	264.00	301.00
p-value	.00	.00	.00	.00	.00	.00
CFI	.98	.94	.86	.94	.97	.92
RMSEA	.05	.07	.10	.07	.05	.07
AIC	22,615.32	22,855.17	23,515.38	22,838.49	19,050.45	19,285.75
BIC	22,923.55	23,095.75	23,774.74	23,090.34	19,422.58	19,518.81

Note. CFA = confirmatory factor analysis, SEM = structural equation modeling, CFI = comparative fit index, RMSEA = root mean square error, AIC = Akaike information criterion, BIC = Bayesian information criterion, Df = degrees of freedom. Study 1: *n* = 405; Study 2: *n* = 317.

Appendix B5 (Essay II). Results of the First-Order Factor Structural Equation Modeling (Study 1)

Variables			***B***	***SE***	***β***	***p*-value**
Treatment effects (Path A)						
Decision-entity	→	Innovativeness	2.34***	.13	.70***	< .001
Company type	→	Innovativeness	0.17	.17	.05	.317
Decision-entity	→	Performance	0.13	.12	.05	.304
Company type	→	Performance	0.16	.18	.07	.354
Decision-entity	→	Speed	0.75***	.11	.33***	< .001
Company type	→	Speed	0.09	.16	.04	.558
Decision-entity	→	Distrust	1.31***	.12	.51***	< .001
Company type	→	Distrust	0.10	.16	.04	.541
Decision-entity	→	Unfairness	1.02***	.13	.37***	< .001
Company type	→	Unfairness	0.36	.19	.13	.050
Decision-entity	→	Emotional creepiness	1.14***	.14	.39***	< .001
Company type	→	Emotional creepiness	0.46*	.20	.16*	.019
Decision-entity	→	Creepy ambiguity	0.90***	.13	.37***	< .001
Company type	→	Creepy ambiguity	0.44*	.17	.18*	.011
Two-way interactions for moderator						
Innovativeness: Decision-entity	→	Company type	−0.30	.22	−.12	.174
Performance: Decision-entity	→	Company type	−0.23	.25	−.09	.362
Speed: Decision-entity	→	Company type	−0.30	.22	−.12	.172
Distrust: Decision-entity	→	Company type	0.14	.23	.01	.950
Unfairness: Decision-entity	→	Company type	−0.22	.26	−.07	.398
Emotional creepiness: Decision-entity	→	Company type	−0.32	.28	−.10	.245
Creepy ambiguity: Decision-entity	→	Company type	−0.33	.24	−.12	.164
Effects of the mediators (Path B)						
Innovativeness	→	Org. attractiveness	0.04	.04	.06	.233
Performance	→	Org. attractiveness	0.17***	.04	.18***	< .001
Speed	→	Org. attractiveness	0.04	.04	.04	.357
Distrust	→	Org. attractiveness	−0.49***	.04	−.58***	< .001
Unfairness	→	Org. attractiveness	−0.20***	.03	−.25***	< .001
Emotional creepiness	→	Org. attractiveness	−0.07*	.03	−.10*	.017
Creepy ambiguity	→	Org. attractiveness	0.03	.04	.04	.385
Indirect effects of the mediators (Path A*B)						
Innovativeness	→	Org. attractiveness	0.10	.08	.05	.234
Performance	→	Org. attractiveness	0.02	.02	.01	.316
Speed	→	Org. attractiveness	0.03	.03	.01	.362
Distrust	→	Org. attractiveness	−0.64***	.08	−.30***	< .001
Unfairness	→	Org. attractiveness	−0.20***	.04	−.09***	< .001
Emotional creepiness	→	Org. attractiveness	−0.09*	.04	−.04*	.022
Creepy ambiguity	→	Org. attractiveness	0.03	.03	.01	.388
Direct effects (Path C)						
Decision-entity	→	Org. attractiveness	−0.16	.14	−.15	.267

Note. *B* = unstandardized effect, *SE* = standard error, *β* = standardized effect, org. = organizational, *n* = 405, decision-entity: human decision-making = 0, algorithmic decision-making = 1, company type: established company = 1, new venture = 0. * *p* < .05; ** *p* < .01; *** *p* < .001.

Appendix B6 (Essay II). Results of the First-Order Factor Structural Equation Modeling (Study 2)

Variables			***B***	***SE***	***β***	***p*-value**
Treatment effects (Path A)						
Psychological distance	→	Innovativeness	−0.33**	.12	−.16**	.007
Recruiting	→	Innovativeness	−0.05	.19	−.02	.808
Employee layoff	→	Innovativeness	−0.28	.22	−.13	.210
Psychological distance	→	Performance	−0.31*	.14	−.13*	.025
Recruiting	→	Performance	−0.31	.21	−.14	.144
Employee layoff	→	Performance	0.15	.22	.07	.508
Psychological distance	→	Speed	−0.33**	.11	−.17**	.003
Recruiting	→	Speed	0.24	.19	.11	.215
Employee layoff	→	Speed	−0.21	.18	−.10	.239
Psychological distance	→	Unfairness	0.34**	.14	.14**	.012
Recruiting	→	Unfairness	0.64***	.17	.29***	< .001
Employee layoff	→	Unfairness	−0.20	.19	−.09	.299
Psychological distance	→	Distrust	0.24	.13	.11	.064
Recruiting	→	Distrust	0.46*	.18	.21*	.012
Employee layoff	→	Distrust	−0.10	.19	−.04	.618
Psychological distance	→	Emotional creepiness	0.59***	.17	.20***	< .001
Recruiting	→	Emotional creepiness	0.48**	.17	.22**	.004
Employee layoff	→	Emotional creepiness	0.10	.20	.04	.628
Psychological distance	→	Creepy ambiguity	0.70***	.19	.24***	< .001
Recruiting	→	Creepy ambiguity	0.29	.21	.13	.163
Employee layoff	→	Creepy ambiguity	−0.02	.21	−.01	.920
Two-way interactions for moderators						
Innovativeness						
Psychological distance	× Recruiting		0.31	.27	.11	.255
Psychological distance	× Employee layoff		−0.27	.31	−.10	.372
Performance						
Psychological distance	× Recruiting		0.37	.29	.14	.197
Psychological distance	× Employee layoff		−0.22	.31	−.08	.475
Speed						
Psychological distance	× Recruiting		0.05	.28	.02	.855
Psychological distance	× Employee layoff		−0.32	.28	−.12	.260
Unfairness						
Psychological distance	× Recruiting		−0.31	.25	−.11	.215
Psychological distance	× Employee layoff		−0.02	.29	−.01	.941
Distrust						
Psychological distance	× Recruiting		0.27	.27	.10	.314
Psychological distance	× Employee layoff		−0.23	.30	−.08	.444
Emotional creepiness						
Psychological distance	× Recruiting		−0.26	.14	−.09	.050
Psychological distance	× Employee layoff		0.17	.24	.06	.469
Creepy ambiguity						
Psychological distance	× Recruiting		0.26	.20	.09	.206

Variables			***B***	***SE***	***β***	***p*-value**
Psychological distance	× Employee layoff		0.45	.27	.16	.096
Effects of the mediators (Path B)						
Innovativeness	→	Org. attractiveness	0.01	.05	.01	.922
Performance	→	Org. attractiveness	0.25***	.05	.26***	< .001
Speed	→	Org. attractiveness	0.07	.05	.06	.164
Unfairness	→	Org. attractiveness	−0.18	.04	−.20	< .001
Distrust	→	Org. attractiveness	−0.56***	.05	−.56***	< .001
Emotional creepiness	→	Org. attractiveness	−0.17***	.04	−.22***	< .001
Creepy ambiguity	→	Org. attractiveness	0.09*	.04	.13*	.027
Indirect effects of mediators (Path A*B)						
Innovativeness	→	Org. attractiveness	0.00	.02	.00	.922
Performance	→	Org. attractiveness	−0.08*	.04	−.03*	.038
Speed	→	Org. attractiveness	−0.03	.02	−.01	.206
Unfairness	→	Org. attractiveness	−0.06*	.03	−.03*	.029
Distrust	→	Org. attractiveness	−0.13	.07	−.06	.066
Emotional creepiness	→	Org. attractiveness	−0.10**	.04	−.05**	.005
Creepy ambiguity	→	Org. attractiveness	0.07*	.03	.03*	.048
Direct effects (Path C)						
Psychological distance	→	Org. attractiveness	0.33**	.11	.15**	.003

Note. *B* = unstandardized effect, *SE* = standard error, *β* = standardized effect, *n* = 317, org. = organizational, psychological distance: high distance = 0, low distance = 1. For the moderators bonus payments and employee layoff (= 1), the recruiting scenario is taken as the reference (= 0). * $p < .05$; ** $p < .01$; *** $p < .001$.

Appendix C1 (Essay III). Scenario descriptions

Scenarios	Description
In AM scenarios, this description was given before the scenario:	Artificial intelligence (AI) describes a computer system that solves tasks, which would require intelligence when solved by humans. In the following situation, an AI makes a decision autonomously without human intervention.
Work allocation	*Low transparency:* In a manufacturing company, **an AI/a manager** assigns employees tasks to **inspect and replace specific machine components** to prevent critical operational failures. The assignment is based on data showing **how often different components have worn out and failed in the past.** *High transparency:* In a manufacturing company, **an AI/a manager** assigns employees tasks to **inspect and replace machine components to prevent** critical operational failures. The assignment follows an adaptive process where the AI/manager evaluates data in three-week cycles. If the deformation gradient—a second-order tensor based on continuum mechanics—falls **below a critical threshold**, the AI/manager identifies potential wear or defects. *Explanation:* Tensors provide a linear mapping of geometric vectors in three-dimensional Euclidean space. Failure probabilities of individual components are monitored and compared against manufacturer specifications. *Scenario:* Chris works in a manufacturing plant. The AI/The manager assigns Chris to inspect a particular machine component, and Chris performs maintenance on it.
Training allocation	*Low transparency:* In a consulting firm, **an AI/a manager** assigns presentation training of **varying durations and intensities** to consultants based on an **analysis of their speech**, **gestures**, and **facial expressions** during client presentations. *High transparency:* In a consulting firm, **an AI/a manager** assigns presentation training of **varying durations and intensities** to consultants based on an **analysis of their speech**, **gestures**, and **facial expressions** during client presentations. The analysis includes data on **speech rate, vocal intensity**, and **eye and body movements**. Using principles from **articulatory and acoustic phonetics**, the sinusoidal vibrations of speech are decomposed to analyze their amplitudes. The **speed and strength of body movements**, as well as the frequency of eye contact with the audience, are evaluated and compared against benchmarks provided by linguists and movement scientists. *Scenario:* Chris works in a management consulting firm. Based on his previous client presentations, the AI/the manager assigns specific presentation training programs.
Performance evaluation	*Low transparency:* In a customer service center, an AI/a manager evaluates employees by analyzing the **content and tone of their conversations** with customers.

High transparency: In a customer service center, a manager evaluates employees by analyzing the **content and tone of their customer interactions**. The analysis involves an adaptive process in which data are assessed iteratively. **Speech characteristics** such as sinusoidal vibrations are broken down, and the amplitudes of individual components are analyzed. Using Fourier analysis, conversations are **graphically represented as spectrograms**, and the resonant properties of the speech are evaluated as reliable indicators of performance.

Scenario: Chris works in this customer service center. Based on previous call recordings, the AI/the manager evaluates his performance and compares it to previously set goals. At the end of the year, Chris receives an evaluation of his performance.

Notes. The scenarios of work assignment and performance evaluation were taken from Lee (2018) and slightly adapted. The scenario of training assignment was developed accordingly.

Appendix C2 (Essay III). Balance Check of Group Sizes

Group		**Number of participants**
Context	**Algorithm transparency**	
Work allocation	Low	59
Work allocation	High	59
Training allocation	Low	54
Training allocation	High	65
Performance evaluation	Low	58
Performance evaluation	High	59
Total		**354**

Appendix D1 (Essay IV). Interview Guide

Part 1: Introduction

Business-related

- When have you founded your company?
- Which industry is your company based in?
- Which position do you have in your company?
- If you have any employees working for you, how many are there?
- How old are you?
- What is your nationality?
- What is your highest educational background?
- What gender do you identify as?

AI-related

- How would you describe AI in general?
- What is your opinion about AI in general?
- Has your opinion about AI changed over time?
- I would like to know which AI you are working with in your company?
- How long have you been using this AI?
- Please shortly explain why you specifically you use this AI compared to other providers.

Part 2: Main Part

<u>Functionalities of AI:</u>

- For which purpose(s) and in which area(s) is the AI applied?
- How has the development of AI changed your approach to build your business?
- How has the development of AI influenced your wellbeing/job satisfaction as an entrepreneur?
- Has the development of AI influenced which products/services you want to pursue with your business and if so, how?

<u>Advantages of AI:</u>

- How does the use of AI help you and your company?
- Are there any specific features of AI that accelerate your usage?
- Which other advantages of AI do you perceive?

<u>Disadvantages of AI:</u>

- How does the use of AI hinder you and your company?
- Are there any specific features of AI that hinder your usage?
- Which other disadvantages of AI do you perceive?

<u>Wishes and Future:</u>

- Do you plan to implement other AI tools in your processes?
    - If so, in which processes?
- Have you heard about other AI-based systems that you would like to incorporate but cannot at this moment?
    - for example: barriers of costs, data usage etc.

- If you could design your dream AI for your business, which features would it cover? Which processes would you like to incorporate this AI into?

Part 3: Institutional specificities

<u>Regulative institutions:</u>

- How do you feel supported by the government of your country to use AI?
    - Are there any legal regulations that support you with using AI as an entrepreneur?
    - Which opportunities do you perceive does your country create, specifically in terms of AI?
- How do you feel the government of your country hinders AI usage for you?
    - Are there any legal regulations that hinder you with using AI as an entrepreneur (i.e., data privacy)?
- Do you feel overwhelmed or pressured by legal regulations regarding AI?

<u>Normative Institutions:</u>

- How is the general perception of AI within your peer group (specifically regarding other entrepreneurs)?
- How is the general perception of AI within your country (specifically regarding other entrepreneurs)?
- How does the opinion of your peer group influence you to use AI?
- Are there specific industry norms related to AI that influence your work?
- Are there any AI-related expectations from customers or investors you work with?

<u>Cultural–cognitive institutions:</u>

- How is your long-term planning influenced by AI introduction?
- How does AI help you to avoid uncertainty?
- How do you feel that AI helps/hinders to overcome gender differences in your country?
- How do you deal with the pressures that you are facing regarding the development of AI?

Appendix D2 (Essay IV). Overview of AI-Tools Used

Category	Sub-Category	AI-Tool	Use Cases for Interviewees
Large Language Models (LLMs)		ChatGPT Microsoft Copilot Gemini Claude Perplexity	Conversational AI for generating or translating texts, answering questions, brainstorming, developing codes, creating marketing/ social media plans, and/or conducting benchmarking
Content generation	Text generation/ editing	Jenny.AI	Assisting in writing texts
	Image generation	Dall-E Midjourney Firefly Flux AI Lookx.AI DaVinci	Generating pictures for websites, blogposts, social media posts
	Video generation	DeepBrain AI	Generating text to video content
		Synthesia	Generating AI-based videos with voiceovers
	Building websites	Durable 10Web	AI website builder
	Presentations and graphics	Slides.AI Tome Gamma Wepik	Automating presentation slides generation (especially for pitch decks)
		Canva	Simplifying graphic design with AI tools for layouts, branding, and visual content
	Voice generation	11laps	Creating text to speech (AI voice generator)
		Murf.AI	Creating voiceovers with the option to edit and translate
Administrative tasks	Tools for meetings	Otter.AI	Transcribing meetings and generating automated notes
		Fathom tl;dv	Recording, transcribing, and summarizing meetings
		Notion	Chatting with documents, meeting notes, etc.; task management
	Code development	Cursor	Developing codes, helping with errors in coding system
	Translations	DeepL	Translating texts (e.g., for e-mails, products descriptions) into various languages
Marketing & sales		Jasper AI	Offering solutions for specific marketing purposes (e.g., product marketing, content marketing, public relations)
		HubSpot	Automating customer relationship management (CRM) and marketing operations
		Luca AI	Smart pricing and helping with promotional decisions
		SessionLab	Creating workshops
Business process automation		Zapier	Connecting and automating workflows between apps and tools
		Amazon	Providing cloud-based AI services for

Category	Sub-Category	AI-Tool	Use Cases for Interviewees
		Web Services (AWS)	infrastructure, analytics, and development
		Sortify	Automating data organization and file sorting tasks
Brainstorming		Miro AI	Visual collaboration for brainstorming and project mapping
		Feedly	Personalized feed based on interests
Research		AI scientist	Automating hypothesis testing

Declaration of co-authorship - Essay I

Declaration of relative contributions to the paper titled:

A Meta-Analysis on Reactions to Algorithmic Decision-Making in Human Resource Management

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Co-author	Wehner	Marius C.	10

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She conceptualized the research question and wrote the initial manuscript draft. She further contributed to reviewing and editing the initial draft, and interpreting and integrating the editor's and reviewers' comments.

The first author **Josephine Moritz** conceptualized the research question, conducted the initial database search, wrote the initial manuscript draft, reviewed and edited the initial draft, interpreted and integrated the editor's and reviewers' comments, led discussions at conferences, and submitted the initial version to the journal.

Co-author **Holger Steinmetz** calculated the analysis, contributed to reviewing and editing the initial draft, and interpreting and integrating the editor's and reviewers' comments.

Co-author **Marius C. Wehner** contributed to conceptualizing the research question, reviewing and editing the initial draft, and interpreting and integrating the editor's and reviewers' comments.

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Declaration of co-authorship - Essay II

Declaration of relative contributions to the paper titled:

The Bright and Dark Sides of Algorithmic Decision-Making (ADM): The Role of Stereotypes and Psychological Distance of ADM in Organizational Attraction

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Declaration of co-authorship - Essay III

Declaration of relative contributions to the paper titled:

Too Much Information? The Role of Algorithm Transparency and Type of Task in Employee Reactions to Algorithmic Management

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Declaration of co-authorship Essay IV

Declaration of relative contributions to the paper titled:

Navigating Institutional Pressures in the Age of Artificial Intelligence: A Typology of Entrepreneurial Responses

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She developed the research idea, conducted the interviews, transcribed and translated the data, and carried out the coding and analysis. She also conceptualized the paper's frameworks, wrote the manuscript, led discussions at conferences, and submitted the initial version to the journal. In the future, she will interpret and integrate the editor's and reviewer's comments.

Co-author **Toru Yoshikawa** assisted in coding the interviews and strengthening the theoretical contributions and frameworks of the paper. Additionally, he revised the manuscript to meet the international journal publication standards. In the future, he will assist in interpreting and integrating the editor's and reviewer's comments.

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Eidesstattliche Versicherung

Ich, Frau Larissa Pomrehn, versichere an Eides statt, dass die vorliegende Dissertation von mir selbstständig und ohne unzulässige fremde Hilfe unter Beachtung der „Grundsätze zur Sicherung guter wissenschaftlicher Praxis an der Heinrich-Heine-Universität Düsseldorf“ erstellt worden ist.

Düsseldorf, der 16. Juli 2025

L. Pomrehn

Unterschrift