Preparing Minds for an Automated Future: How Competence Feedback Shapes AI Self-Efficacy and Acceptance

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Abstract

This thesis explores how competence-oriented feedback can shape employees’ readiness to adopt generative AI by strengthening AI self-efficacy, addressing the research question: how does feedback influence AI self-efficacy, and how does AI self-efficacy in turn affect workplace AI acceptance? Using a sample of 208 participants divided into experimental and control groups, the study employed a survey-based online experimental design to assess whether task-related, competence-oriented feedback after an AI knowledge quiz increases AI self-efficacy and AI acceptance, using validated scales and bootstrapped mediation analysis (PROCESS Model 4). The results show that competence-oriented feedback significantly increases AI self-efficacy, that AI self-efficacy strongly predicts AI acceptance, and that AI self-efficacy significantly mediates the effect of feedback on AI acceptance, with effects robust to demographic and usage covariates. These findings suggest that competence beliefs are a causally relevant and adaptable driver of AI acceptance and can be strengthened through brief, scalable feedback interventions, even when objective task performance is not directly linked to acceptance-related attitudes. This study contributes causal evidence to the emerging literature on AI self-efficacy and AI acceptance and extends technology acceptance research by highlighting competence beliefs as an important psychological factor in AI adoption. Future research should examine the durability of feedback effects over time, compare human- versus AI-generated feedback sources and credibility perceptions, and incorporate behavioral adoption measures to test whether increases in self-efficacy translate into sustained workplace AI use.

Keywords: Artificial intelligence acceptance, AI self-efficacy, competence-oriented feedback, technology acceptance, workplace AI, experimental research, mediation analysis

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Resumo

Esta tese examina como o feedback orientado para a competência molda a disposição dos funcionários para adotar a IA generativa, fortalecendo a autoeficácia da IA. Utilizando uma experiência online baseada em um inquérito com 208 participantes, o estudo testou se o feedback relacionado à tarefa e orientado para a competência após um questionário de conhecimento sobre IA aumenta a autoeficácia da IA e, indiretamente, melhora a aceitação da IA, empregando escalas validadas e análise de mediação bootstrapped (Modelo PROCESS 4). Os resultados mostram que o feedback orientado para a competência aumenta significativamente a autoeficácia da IA, que a autoeficácia da IA prediz fortemente a aceitação da IA e que medeia o efeito do feedback na aceitação da IA, com efeitos robustos para covariáveis demográficas e de uso. Essas descobertas indicam que as crenças de competência são um fator causalmente relevante e maleável para a aceitação da IA, que pode ser fortalecido por meio de intervenções de feedback breves e escalonáveis, mesmo quando o desempenho objetivo da tarefa não está diretamente ligado a atitudes relacionadas à aceitação. Este estudo contribui com evidências causais para a literatura sobre autoeficácia da IA e amplia a pesquisa sobre aceitação da tecnologia, destacando as crenças de competência como um fator psicológico fundamental na adoção da IA. Pesquisas futuras devem examinar a durabilidade dos efeitos do feedback, comparar o feedback gerado por humanos e pela IA e incorporar medidas de adoção comportamental para avaliar o uso sustentado da IA no local de trabalho.

Palavras-chave: Aceitação da inteligência artificial, autoeficácia da IA, feedback orientado para a competência, aceitação da tecnologia, IA no local de trabalho, investigação experimental, análise de mediação

Título: Preparando as mentes para um futuro automatizado:
como o feedback sobre competências molda a autoeficácia e a aceitação da IA

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List of Abbreviations

AI	Artificial Intelligence
AIAS-4	AI Attitude Scale (4-item version)
AILIT-S	Artificial Intelligence Literacy Test – Short form
AIQ	AI Question
b	Regression coefficient
CFI	Comparative Fit Index
CI	Confidence Interval
e.g.	For example (*exempli gratia*)
FIT	Feedback Intervention Theory
GenAI	Generative Artificial Intelligence
GSE-6AI	General Self-Efficacy Scale – AI version (6 items)
H	Hypothesis
IQR	Interquartile Range
IT	Information Technology
KMO	Kaiser–Meyer–Olkin measure of sampling adequacy
M	Mean
Max	Maximum
Mdn	Median
Min	Minimum
M_{ctrl}	Mean of the control group
M_{exp}	Mean of the experimental group
n	Sample size
n_{ctrl}	Control group sample size
n_{exp}	Experimental group sample size
p	Probability value (*p*-value)
PROCESS	PROCESS macro for mediation analysis
Q	Quartile
r	Correlation coefficient
R^2	Coefficient of determination
RMSEA	Root Mean Square Error of Approximation
SD	Standard Deviation
SE	Self-efficacy
SE	Standard Error
SPSS	Statistical Package for the Social Sciences
t	*t*-value (*t*-statistic)
TAM	Technology Acceptance Model

TLI	Tucker–Lewis Index
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Unified Theory of Acceptance and Use of Technology 2
α	Cronbach's alpha
Δ	Change / Difference
λ	Factor loading
ω	McDonald's omega

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This document has been reviewed using AI tools solely for linguistic improvement.

1. Introduction

Since the public release of ChatGPT by OpenAI in late 2022, artificial intelligence (AI) has rapidly transitioned from a largely abstract or experimental technology into a tangible part of everyday work. What was once discussed primarily in futuristic or speculative terms has become embedded in routine organizational practices, reshaping how tasks are performed and how work itself is experienced. AI not only boosts productivity but enables employees to accomplish tasks previously beyond their capabilities.

This development has been particularly accelerated by generative AI (GenAI), which refers to AI systems capable of generating new content, such as text, images, or code. GenAI is increasingly used in workplaces through accessible tools such as ChatGPT and Microsoft Copilot (Feuerriegel et al., 2024). A recent large-scale field experiment by the Boston Consulting Group demonstrated that consultants supported by GenAI completed 12.2% more tasks, worked 25.1% faster, and produced outputs rated more than 40% higher in quality compared to peers without AI assistance (Sack et al., 2024). Beyond these measurable performance improvements, AI also affects how employees experience their work. In the same study, 82% of consultants who regularly used generative AI reported feeling more confident in their roles. These findings indicate that the interaction between AI systems and human users extends beyond measurable performance outcomes to shape employees' psychological work experience.

For businesses, AI offers substantial potential to increase productivity, improve service quality, accelerate decision-making, and generate new revenue opportunities (Struckmann, 2024). When successfully implemented, AI initiatives yield on average 15.2% cost savings and 15.8% revenue growth in their respective areas of application (Sun & Sallam, 2024). Reflecting this potential, around 80% of organizations are currently developing AI use cases, highlighting the importance of AI as a driver of short- and long-term competitiveness (Thamm & Pfitzner, 2024).

Despite these benefits, employees often approach AI with skepticism. Concerns about potential job losses (Frey & Osborne, 2017), fear of being replaced or monitored (Bankins et al., 2023), and the perceived loss of human interaction in technology-mediated work settings (Brougham & Haar, 2018) can hinder acceptance. These attitudes represent not only psychological challenges for workers but also organizational barriers, as the successful implementation of AI depends on employee willingness to adopt and use these systems effectively (Bankins et al., 2023).

These attitudes represent not only psychological challenges for workers but also barriers to effective organizational AI implementation, as negative employee attitudes are associated with resistance and poor uptake of AI systems.

A large body of research has examined how individuals decide whether to adopt new technologies. The Technology Acceptance Model (TAM; Davis, 1989) and its later extensions, such as the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003), identified factors like perceived usefulness, ease of use, and trust as key adoption determinants (Dwivedi et al., 2020; Kelly et al., 2023). Building on these technology acceptance frameworks, recent research highlights self-efficacy as an additional psychological factor that shapes individuals' readiness to engage with AI, influencing both motivation and perceived competence (Luszczynska et al., 2005; Y. Wang & Chuang, 2024). Self-efficacy refers to individuals' beliefs in their capability to organize and execute the courses of action required to manage prospective situations (Bandura, 1977). Applied to the AI domain, AI self-efficacy describes individuals' confidence in their ability to use and interact effectively with AI systems and to make informed decisions when doing so (Woo et al., 2024). While empirical studies linked AI self-efficacy to technology acceptance, much of this evidence remains correlational (Guan et al., 2025; Mao & Liu, 2025; Shao et al., 2024). As Kelly et al. (2023) emphasize in their review, the field lacks experimental and theory-driven approaches in AI acceptance research. This gap is crucial because without causal evidence it remains unclear whether self-efficacy is merely associated with adoption or whether it actively drives it. This thesis aims to address this gap by examining how AI self-efficacy can be manipulated through feedback to study its impact on AI acceptance. Specifically, the following research question is investigated: How does feedback influence AI self-efficacy, and how does AI self-efficacy in turn affect workplace AI acceptance?

The contributions of this research are both academic and practical. Academically, the study provides causal evidence for the role of AI self-efficacy in AI acceptance, extending predominantly correlational literature. Large-scale studies consistently identify AI self-efficacy as a key predictor of acceptance (Iyer & Bright, 2024; Mao & Liu, 2025; Masry Herzallah & Makaldy, 2025; Zeng et al., 2025), while experimental work demonstrates that competence-oriented or AI-generated feedback can increase self-efficacy in related contexts, but without examining acceptance outcomes (Chen et al., 2025; Watanabe et al., 2025). Previous studies have examined psychological mechanisms underlying AI reliance, including trust, confidence calibration, and affective responses

(Blut et al., 2022; Gillath et al., 2021). However, based on the literature review conducted for this thesis, no experimental research has yet manipulated AI self-efficacy to test its causal effect on AI acceptance. Practically, the current study offers insights for organizations seeking to develop effective AI implementation strategies. It highlights how training and feedback mechanisms may serve as concrete measures to strengthen employees' self-efficacy and promote the active use of AI systems. Such initiatives are essential, as the potential benefits of AI can only be realized when employees accept, utilize, and further develop these technologies in their daily work (Bankins et al., 2023).

The remainder of this thesis is structured as follows. Chapter 2 presents the literature review, covering the key determinants of AI acceptance, theoretical foundations of self-efficacy, and the role of feedback as a source of efficacy beliefs. Chapter 3 outlines the methodology, describing the experimental design, measures, and analytical strategy. In Chapter 4, the survey data and manipulation of variables are analyzed, and the mediation model is conducted. Chapter 5 discusses these findings, their implications for future research, academics, and practitioners, as well as limitations. Finally, Chapter 6 concludes this thesis with a summary of the findings and contributions of this research.

2. Literature Review

2.1 AI Acceptance

Artificial intelligence (AI) is reshaping the modern workplace by automating routine tasks, augmenting human capabilities, and supporting complex decision-making across individual, team, and organizational levels, thereby creating both opportunities and challenges. Systematic reviews highlight that AI is already embedded in diverse work contexts, altering job design, decision processes, and skill requirements (Bankins et al., 2023; Borges et al., 2021; Enholm et al., 2022; Langer & Landers, 2021). Other studies confirm that AI adoption is widespread in areas like healthcare, logistics, HR, and customer service, where it improves productivity and decision quality (Murire, 2024; Pereira et al., 2023). However, in order to leverage the benefits of AI, upskilling and adaptation to new forms of human–AI collaboration are required (Bankins et al., 2024).

Successful implementation depends crucially on employee acceptance. Without user buy-in, AI systems risk underuse or failure despite technical potential (Zirar et al., 2023). AI acceptance is commonly conceptualized as an individual's behavioral intention or willingness to use, purchase, or try an AI-enabled product or service (Kelly et al., 2023). Empirical research synthesized in a recent systematic review shows that this intention is shaped by several antecedents, including perceived usefulness, performance expectancy, effort expectancy, attitudes, and trust (Kelly et al., 2023).

Research on technology acceptance has long been shaped by theoretical models that seek to explain such adoption decisions. The Technology Acceptance Model (TAM), introduced by Davis (1989), posits that two primary factors, perceived usefulness and perceived ease of use, determine an individual's intention to use a technology. This model has been widely applied to study technology adoption across domains, including AI, and remains foundational in understanding user acceptance (Greener, 2022). The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), synthesizes elements from eight prior models, adding constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions, as well as moderators like age, gender, and experience (Ali et al., 2025; Blut et al., 2022; Greener, 2022). UTAUT2 further extends the model by incorporating hedonic motivation, price value, and habit, making it more suitable for consumer contexts (Cabrera-Sánchez et al., 2021). and perceived ease of use shaping this attitudinal evaluation (Schepers & Wetzels, 2007).

While these frameworks provide a solid foundation for understanding user adoption, AI acceptance can differ in important respects from general technology acceptance. Unlike traditional IT systems, AI applications often operate with a high degree of autonomy and algorithmic opacity, creating challenges of explainability, fairness, and accountability (Afroogh et al., 2024; Bankins et al., 2023). These characteristics expose the limits of traditional models such as TAM and UTAUT, which insufficiently account for ethical, emotional, and social dimensions of technology use (Davis, 1989; Mansori, 2025; Uren & Edwards, 2023; Venkatesh et al., 2003). Consequently, recent research highlights additional determinants such as trust, perceived threat, and job displacement anxiety, and emphasizes the importance of explainable and ethically aligned AI as prerequisites for acceptance (Angerschmid et al., 2022; Uren & Edwards, 2023). Therefore, AI-specific acceptance models that extend or adapt TAM and UTAUT to address these unique challenges are needed. For instance, Kelly et al. (2023) and other systematic reviews emphasize the importance of trust, attitudes, and perceived risk as additional determinants of AI acceptance (Choung et al., 2023; Kelly et al., 2023). Studies have also introduced constructs such as perceived intelligence, fairness, and ethics to better capture the complexity of AI adoption (Afroogh et al., 2024; Angerschmid et al., 2022; Mansori, 2025). UTAUT2-based studies in AI contexts often add variables like technology fear and consumer trust to account for the emotional and ethical dimensions of AI use (Cabrera-Sánchez et al., 2021). Beyond these model-based determinants, empirical studies reveal a broader set of barriers and drivers of AI adoption operating at multiple levels: Structural and economic factors, such as automation anxiety and concerns about job displacement, are significant obstacles, especially in sectors where AI is viewed as a substitute for human labor. Economic drivers like cost savings and efficiency gains often motivate adoption but can be offset by fears of workforce reduction and skill obsolescence (Cubric, 2020; Mansori, 2025). Organizational factors also play a crucial role in AI adoption: transparency, leadership support, and organizational culture strongly shape acceptance outcomes (Bankins et al., 2023). A lack of transparency in AI decision-making or perceptions of increased monitoring can foster resistance, whereas strong leadership support and clear communication facilitate adoption (Na et al., 2022; Uren & Edwards, 2023). Furthermore, social dynamics influence how individuals interpret and engage with AI (Cabrera-Sánchez et al., 2021). Subjective norms, perceptions of fairness, and the framing of human–AI collaboration affect adoption, while peer influence and broader cultural attitudes toward technology shape employees' responses to AI (Cabrera-Sánchez et al., 2021; Gerlich, 2023). Finally, at the individual level, psychological mechanisms are central. For example, perceived threat, loss of control, and AI-related anxiety hinder adoption, while positive attitudes and self-efficacy promote it (Cabrera-Sánchez et al., 2021; Choung et al., 2023; Gerlich, 2023; Kelly et al., 2023).

In summary, AI acceptance is shaped by a complex interplay of structural, organizational, social, and psychological factors. While external conditions such as transparency, leadership, and communication are essential, internal psychological mechanisms are equally decisive in determining whether employees embrace AI in their daily work. Among these internal factors, self-efficacy has emerged as a particularly interesting determinant, reflecting individuals' belief in their competence to interact effectively with AI systems (Woo et al., 2024). Notably, Davis (1989) explicitly linked TAM to Bandura's (1982) self-efficacy theory by arguing that perceived ease of use reflects beliefs about one's capability to use a system, while perceived usefulness parallels outcome expectations. The following section explores self-efficacy in greater depth and examines how it shapes employees' attitudes and behaviors toward AI in the workplace.

2.2 Self-efficacy

Self-efficacy refers to individuals' beliefs in their capability to organize and execute the actions required to manage difficult tasks or life challenges (Schwarzer, 1998). Within the framework of social cognitive theory, Bandura (1986) emphasized that self-efficacy is part of a triadic system in which cognition, behavior, and environment continuously interact. This conceptualization highlights self-efficacy as a central mechanism of human agency rather than a mere personality trait. It is important to distinguish self-efficacy from self-esteem, which concerns one's overall evaluation of personal worth, although the two constructs are positively related (Judge & Bono, 2001).

The importance of self-efficacy has been well established across educational and occupational contexts: Individuals with strong efficacy beliefs are more likely to perceive difficult situations as challenges that can be mastered rather than threats to be avoided (Abderhalden & Jüngling, 2019). These beliefs foster persistence, enhance learning motivation (Zimmerman, 2000), and protect against stress and burnout (Schwarzer & Hallum, 2008). Further, evidence also links self-efficacy to higher job performance and general psychological well-being (Schwarzer & Jerusalem, 1995). Meta-analytic findings confirm that self-efficacy is not culture-bound but a universal construct, showing consistent associations with coping, well-being, and health behaviors across diverse populations (Luszczynska et al., 2005).

According to Bandura (1997), self-efficacy arises from four sources: mastery experiences, vicarious experiences, verbal persuasion, and physiological states. Mastery experiences are the most influential, as successfully completing tasks provides direct evidence of competence, whereas repeated failure can undermine confidence (Schwarzer & Jerusalem, 1995). Vicarious experiences, such as observing peers succeed, can also enhance self-efficacy, particularly when individuals perceive similarities with the person being observed (Bandura, 1986; Maddux, 1995). Although less potent than direct mastery, such experiences can still encourage individuals to believe that they too can succeed (Bandura et al., 1977; Schunk, 1986). Verbal persuasion, for instance through credible feedback, can further strengthen efficacy beliefs (Bandura, 1986; Bussey & Bandura, 1999). Finally, physiological and affective states play an important role, as experiences of stress and anxiety tend to lower perceived self-efficacy, whereas calmness and emotional stability help support it (Bandura et al., 1997; Maddux, 1995).

These theoretical foundations remain highly relevant in digital and workplace contexts. AI self-efficacy can be defined as the belief in one's competence to interact effectively with AI systems, encompassing confidence in using AI tools and in making informed decisions when relying on AI (Woo et al., 2024). Consistent with Bandura's (1986) social cognitive theory, empirical research demonstrates how core sources of self-efficacy translate to AI-related contexts. For example, Shao et al. (2024) reported that perceived mastery and social persuasion jointly enhanced AI self-efficacy, demonstrating how Bandura's (1986) framework extends to human-AI interaction. Similarly, Wang (2025) found that personalized digital feedback significantly enhanced learners' self-efficacy, underscoring the role of feedback as a form of verbal persuasion. Such increases in AI self-efficacy have been shown to translate into more adaptive responses to technological change, as individuals with higher AI self-efficacy demonstrate greater adaptability and are less affected by adoption-related stress (Kim & Lee, 2024).

Further, more and more studies confirm that AI-related self-efficacy positively predicts AI learning engagement and adoption intentions (Guan et al., 2025; Y. Wang & Chuang, 2024). Moreover, self-efficacy influences acceptance indirectly through trust and cognitive appraisals. Mao & Liu (2025) reported that AI trust mediated the effect of AI self-efficacy on adoption, while hindrance appraisals moderated this relationship. Similarly, Shao et al. (2024) showed that self-efficacy and perceived AI ethics jointly shaped adoption attitudes, and Morales-García et al. (2025) observed that students with higher AI self-efficacy used AI more frequently.

Evidence from workplace contexts supports these findings. Leadership self-efficacy predicts willingness to adopt AI in medical fields (Eminoğlu & Çelikkanat, 2024), and AI-supported training has been shown to enhance both efficacy and readiness for adoption (Lu et al., 2024). However, positive effects of AI use are conditional, as Kuzminska et al. (2024) found that only individuals with medium baseline efficacy showed higher acceptance.

Beyond these findings, self-efficacy also helps explain how external resources lead to positive experiences. Recent work in digital learning settings supports this perspective. For instance, Huang et al. (2024) demonstrated that self-efficacy mediated the effect of AI acceptance and enthusiasm on learners' well-being. Such findings underline the view that self-efficacy does not only operate as an outcome but also as a motivational mechanism that channels technological and social inputs into improved engagement and outcomes.

Although AI self-efficacy is generally associated with more positive attitudes and stronger intentions to use AI, existing research indicates that its effects are context dependent rather than uniformly beneficial. For example, in a team-based learning project where students optionally used AI tools (e.g., ChatGPT or Notion AI) to support project teamwork and group dynamics, Kuzminska et al. (2024) found that self-efficacy improvements were most evident among students with average baseline self-efficacy, whereas students with low or high baseline self-efficacy showed little change. This pattern implies that confidence that is either insufficient or already very high may limit the extent to which individuals benefit from AI-related support. Moreover, the positive effect of AI self-efficacy on AI acceptance depends on how individuals appraise AI in their work context: Mao and Liu (2024) show that when users evaluate AI as obstructive or burdensome, referred to as hindrance appraisal, the typically positive association between self-efficacy, trust, and AI acceptance becomes significantly weaker. Under such appraisals, even individuals who feel capable of using AI may be less willing to adopt it. Together, these findings suggest that while AI self-efficacy generally facilitates adaptation, it may not promote acceptance when confidence is extreme or when AI is perceived as a threat or impediment.

The extant literature consistently shows that self-efficacy is a meaningful predictor of technology-related attitudes and behaviors. In AI-specific contexts, individuals with higher AI self-efficacy report stronger intentions to use AI systems, more positive attitudes toward AI, and greater engagement with AI tools (Guan et al., 2025; Morales-García et al., 2025; Shao et al., 2024; Y. Wang & Chuang, 2024). These findings position AI self-efficacy as a central psychological mechanism in AI adoption, as employees' beliefs about their capability to use AI directly shape their acceptance of such technologies. Building on these insights, this study examines the role of AI self-efficacy as a key predictor of employees' acceptance of AI in the workplace. Thus, I propose the following hypothesis:

H1**:** Higher AI self-efficacy will predict stronger AI acceptance.

As verbal persuasion and feedback are one of Bandura's (1986) core sources of efficacy, the next chapter will explore the literature on feedback. I will examine how different forms of performance information influence self-efficacy.

2.3 Feedback

Feedback has long been recognized as one of the most powerful instructional interventions. Kluger & DeNisi (1996) defined feedback interventions as actions taken by an external agent to provide information about some aspects of an individual's task performance. Similarly, Hattie & Timperley (2007) conceptualized feedback as information about performance or understanding that functions as a consequence of performance and is provided by an agent such as a teacher, peer, or system. Within Bandura's (1986) self-efficacy framework, feedback can be understood as a form of verbal persuasion, one of the four primary sources of self-efficacy. Across these sources, feedback functions as a mechanism for guiding performance, supporting learning, and shaping perceptions of personal competence.

To understand how feedback produces these effects, research differentiates the types of information feedback conveyances and the design principles that determine how recipients process it. Literature is dominated by two influential models. First, Kluger & DeNisi's (1996) Feedback Intervention Theory (FIT) distinguishes between feedback that directs attention to the task and feedback that shifts attention toward the self. Task-focused feedback provides cues, corrective information, or strategies for improvement, thereby supporting performance because it highlights aspects of the task that can be acted upon (Earley, 1986; Hattie & Timperley, 2007; Locke & Latham, 1990). In contrast, person-focused or evaluative messages shift attention to the self and are more likely to elicit self-evaluative or defensive processing, which can impair performance (Hattie & Timperley, 2007).

Second, and complementing the attentional perspective, Hattie & Timperley (2007) differentiate between feedback at the task level (e.g., correctness information or cues), the process level (e.g., strategies and explanations), the self-regulation level (e.g., monitoring or adjusting performance), and the self-level (e.g., praise directed at the person). Task- and process-level feedback generally yield the strongest learning benefits because they provide information that is specific, actionable, and relevant to task improvement (Hattie & Timperley, 2007; Shute, 2008). Self-level feedback is least effective because it lacks information that can guide performance changes (Hattie & Timperley, 2007).

Beyond these structural distinctions, several design principles determine how learners interpret and use feedback. The first principle is valence. Positive and competence-supportive feedback tends to promote learning, motivation, and persistence (Kluger & DeNisi, 1996; Peifer et al., 2020), and neurocognitive findings indicate that positive messages elicit more adaptive performance-monitoring signals (Arbel et al., 2014). Normative feedback, defined as information that compares an individual's performance with peers or a reference standard, illustrates the importance of framing: positively framed comparisons can strengthen motivation and self-efficacy, whereas negatively framed comparisons often trigger defensive reactions (Hartwell & Campion, 2016; Peifer et al., 2020; Wulf et al., 2010)

The second principle concerns the fit between feedback and task characteristics. Feedback is most effective when it provides information that can be directly used for self-regulation, such as adjusting effort or strategies, which is more likely for tasks with clear goals and actionable performance standards (Locke & Latham, 1990). On complex or unfamiliar tasks, simple outcome feedback (e.g., correctness indicators) may hinder learning by triggering unproductive search behavior or distracting from meaningful strategy development (Kanfer & Ackerman, 1989; Wood, 1986). In such cases, explanatory or corrective cues help guide attention toward relevant task features (Kluger & DeNisi, 1996). At the same time, feedback must not be overly detailed or ambiguous. Excessive elaboration can overload working memory or conflict with internal task representations, thereby reducing effectiveness (Ilgen et al., 1979; Shute, 2008).

Finally, effective feedback depends on the presence of explicit performance standards. Clear criteria allow learners to interpret information accurately, whereas ambiguous or missing standards may lead even neutral feedback to be perceived as negative or discouraging (Kluger & DeNisi, 1996; Sadler, 1989). Across studies, these principles: task-focused information, positive or competence-oriented framing, optimal information load, and explicit reference standards emerge as consistent features of feedback that support learning and foster adaptive psychological responses.

As feedback practices increasingly migrate into digital environments, core principles remain relevant but manifest differently: Digital feedback retains key features such as variation in valence, specificity, and task focus. Outcome feedback (e.g., correctness information) and elaborated feedback (e.g., explanations or guidance) parallel long-established categories in traditional feedback research (Narciss, 2004). Furthermore, positive and competence-enhancing digital feedback has been shown to strengthen perceived competence, whereas negative or uninformative feedback can reduce it (Lechermeier & Fassnacht, 2018; Ryan & Deci, 2000). In Addition, digital feedback may overload learners and impair both performance and self-efficacy, when overly complex or frequent (Luo et al., 2021).

At the same time, digital feedback introduces unique characteristics. It is often delivered immediately, and immediate feedback has been found to support learning and self-efficacy more effectively than delayed feedback (Van der Kleij et al., 2015). Digital systems also produce adaptive feedback that adjusts to individual performance and offers personalized guidance (Panadero & Lipnevich, 2022; Shute, 2008). Feedback is conveyed through textual, visual, and symbolic modalities, which shape how learners interpret performance information (Panadero & Lipnevich, 2022). Research in digital quiz environments shows that both corrective and elaborated feedback can improve knowledge retention and confidence (Eghterafi et al., 2022; Rüth et al., 2021), although elaboration does not always lead to better outcomes and may sometimes reduce effectiveness (Rüth et al., 2021). These findings indicate that digital feedback, like traditional feedback, is sensitive to cognitive load, task characteristics, and individual differences. Learners with low self-efficacy may interpret even constructive digital feedback as threatening, while learners with high self-efficacy may benefit less due to existing confidence (Kuzminska et al., 2024).

While digital feedback can support learning and competence when designed appropriately, research also highlights important limitations and unintended consequences. Feedback, while powerful, is not uniformly beneficial. Excessive reliance on external evaluation may undermine intrinsic motivation, particularly when feedback becomes controlling or overly continuous (Kluger & DeNisi, 1996; Ryan & Deci, 2000). Furthermore, in digital work environments, the frequent delivery of automated feedback can evoke perceptions of surveillance and associated stress (Bankins et al., 2023). Positive feedback has also been found to encourage reliance on heuristics rather than careful monitoring, thereby reducing the accuracy of self-regulated learning (Ernst et al., 2024). Individual differences further shape these effects. Middle-ranked performers often benefit most from AI-generated feedback, whereas lower performers may experience cognitive overload and higher performers may develop resistance to algorithmic input (Luo et al., 2021). Nonetheless, well-designed feedback systems can support weaker performers by offering concrete guidance (Bader & Kaiser, 2019), and generative AI tools tend to enhance productivity particularly among novices or less-skilled individuals (Brynjolfsson et al., 2024). Importantly, biased or inaccurate feedback directly affects self-efficacy: inflated feedback increases confidence, whereas deflated feedback reduces it (Ernst et al., 2024).

Feedback not only affects performance and learning but also plays a central role in shaping self-efficacy. Within Bandura's (1986) framework, feedback represents verbal persuasion that signals competence, informs self-appraisal, and reinforces perceptions of capability. Empirical findings consistently support this link. Digital feedback tailored to individual performance has been shown to increase self-efficacy in online learning environments (Wang, 2025), and AI-driven adaptive feedback systems have been found to enhance occupational self-efficacy through competence-oriented information (Watanabe et al., 2025). Feedback also facilitates self-regulation by guiding learners' interpretation of performance and adjustment of goals, thereby supporting sustained motivation and efficacy beliefs (Panadero & Lipnevich, 2022). Studies using positive, competence-focused feedback demonstrate increases in perceived self-efficacy (Brown, 2012), and research on verbal persuasion shows that supportive, mastery-oriented feedback strengthens efficacy beliefs (Achterkamp et al., 2015). These studies vary in their designs but converge on the conclusion that feedback strengthens self-efficacy when it conveys credible, competence-relevant information and reinforces perceptions of progress.

Although prior work demonstrates that feedback can strengthen self-efficacy, comparatively little is known about whether similar mechanisms operate in AI-specific contexts or how they translate into willingness to adopt AI technologies. Given consistent evidence that competence-oriented feedback strengthens self-efficacy (Brown, 2012; Achterkamp et al., 2015; Wang, 2025; Watanabe et al., 2025), and that higher AI self-efficacy predicts more positive attitudes and stronger adoption intentions toward AI (Guan et al., 2025; Shao et al., 2024; Y. Wang & Chuang, 2024), the present study examines whether targeted feedback can increase AI self-efficacy and thereby, indirectly, enhance AI acceptance. Thus, I propose the following two hypotheses:

> H2: Participants receiving competence-oriented feedback will report higher AI self-efficacy than those receiving no feedback.
>
> H3: The effect of feedback on AI acceptance will be mediated by AI self-efficacy.

To empirically examine these hypothesized relationships, the present study applies a mediation framework that positions AI self-efficacy as the key psychological mechanism linking feedback to

AI acceptance. Specifically, it tests whether exposure to competence-oriented feedback enhances participants' AI self-efficacy, which in turn increases their willingness to adopt AI in the workplace. Figure 1 illustrates the conceptual model guiding this investigation.

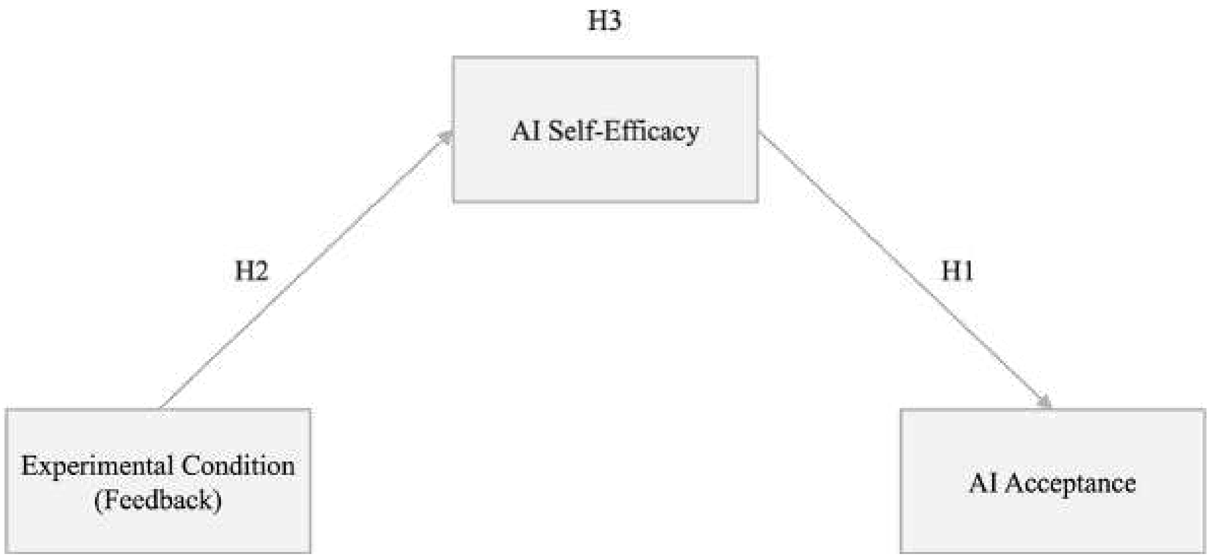

Figure 1: Conceptual Model

3. Methodology

3.1 Research Design

This study aims to experimentally investigate whether providing feedback on performance on an Artificial Intelligence (AI) knowledge test enhances individuals' AI self-efficacy and consequently increases their acceptance of AI. Grounded in self-efficacy theory (Bandura et al., 1997), the study investigates the mediating role of self-efficacy in the relationship between feedback and AI acceptance. This approach enables a systematic assessment of a psychological mechanism that shapes employees' readiness to adopt and use AI systems in the workplace.

A between-subjects experimental design was implemented. The study was conducted as an online experiment using Qualtrics, which enabled efficient data collection, automated randomization, and standardized participation across locations, as well as direct export of responses for statistical analysis (Evans & Mathur, 2018). After completing a short AI-related quiz that provided a realistic context for feedback, participants were exposed to one of two feedback conditions: competence-oriented feedback, designed to enhance self-efficacy (experimental condition), or a neutral message without evaluative content (control condition). Participants were randomly assigned to one of these two conditions using Qualtrics' evenly present elements randomizer, ensuring balanced group sizes and minimizing potential selection bias. No social-comparison or norm-referenced feedback was used, and the manipulation was purely informational and competence-oriented.

Before launching the main data collection, a small pre-test (n = 11; n_{exp} = 5, n_{ctrl} = 6) (Table 2, Table 3, Table 4) was conducted to evaluate the survey procedure, the clarity of instructions, and whether the feedback manipulation produced observable differences in AI self-efficacy and AI acceptance. The pre-test implemented a pre–post design, in which participants completed the AI self-efficacy scale once before receiving feedback (t_0) and again afterwards (t_1), followed by the AI acceptance measure.

On average, the pre-test took 70 minutes, with a median duration of 19 minutes. Completion times were screened for outliers using Tukey (1977) interquartile range (*IQR*) criterion ($Q3 + 1.5 \times IQR$), which yielded an upper threshold of approximately 84 minutes in the pre-test data. Two cases (125 and 491 minutes) exceeded this cutoff and were removed, as both reflected participants who paused the survey and returned later. Excluding these outliers resulted in an adjusted average completion time of 22.05 minutes (Table 5). Several participants indicated that they paused the survey, while those completing it in one sitting reported a duration of approximately 10 minutes. Descriptively, participants in the feedback condition showed higher baseline self-efficacy (M_{exp} = 2.90, M_{ctrl} = 2.53). After the manipulation, post-feedback self-efficacy remained numerically higher in the feedback group (M_{exp} = 2.73, M_{ctrl} = 2.39). A similar pattern emerged for AI knowledge scores, with higher performance in the feedback group (M_{exp} = 7.72, M_{ctrl} = 6.40), and for AI acceptance, which was also slightly higher in the feedback condition (M_{exp} = 7.65, M_{ctrl} = 7.21) (Table 6). An independent-samples t-test comparing post-feedback self-efficacy indicated that this difference was not statistically significant, $t(9) = 1.26$, $p = .24$, although the effect size was large (*Cohen's d* = 0.78; Cohen, 1988; Lakens, 2013) (Table 7). The full descriptive statistics and t-test output for the pre-test are provided in Appendix A.

The pattern of higher baseline self-efficacy among higher performers is consistent with prior findings that confidence correlates positively with test performance (Stankov et al., 2015). Given the small sample size of the pre-test, such baseline differences are likely attributable to random variation rather than systematic effects. To reduce potential pretest sensitization and advice-taking effects that could bias posttest responses, the final experiment therefore adopted a post-only design.

This decision is in line with methodological evidence showing that pretests can bias posttest scores, particularly in short-interval cognitive assessments, and that such effects are not eliminated by conventional statistical controls (Kim & Willson, 2010). Finally, the survey was translated into German to increase accessibility and representativeness in the main study.

3.2 Participants

This study aimed to recruit a minimum of 200 participants (approximately 100 participants per condition) to ensure adequate statistical power for detecting the hypothesized mediation effects (Fritz & MacKinnon, 2007; Schoemann et al., 2017). Based on a Monte Carlo power simulation for a simple mediation model with moderate path coefficients ($r \approx .30$), a minimum of $n \approx 154$ participants was required to achieve 80% power (Schoemann et al., 2017). A target sample size above this threshold was set to account for exclusions and potential covariates, such as quiz performance or language.

Participants were recruited to complete an online experiment hosted on the Qualtrics platform. The study targeted adult participants aged 18 years or older who could complete the questionnaire in English or German. At the beginning of the survey, participants received general information about the study and were asked to provide informed consent. Only those who consented were able to proceed to the questionnaire. An attention-check item was embedded to ensure data quality, and only the data of participants who passed this check were included in the final analyses. Recruitment was conducted through multiple online channels to reach a diverse and international sample. The survey link was distributed via SurveySwap.io and SurveyCircle.com, as well as through postings on social media platforms such as LinkedIn. Participants were also encouraged to share the link within their personal networks to facilitate snowball sampling. In contrast to monetary incentives, participation was voluntary, and as a token of appreciation, €0.50 per valid response was donated to the charity organization Little Bells Nepal (up to €200). This incentive ensures engagement while maintaining complete anonymity of respondents.

A total of 325 individuals accessed the survey. After providing informed consent, 324 participants proceeded to the questionnaire. Cases with incomplete responses were removed, resulting in 256 fully completed surveys. Data quality exclusions were then applied. First, three participants failed the embedded attention-check and were removed. Second, participants were screened using the manipulation-check item. Individuals in the feedback condition who reported with certainty that they had not received feedback ($n = 9$) and individuals in the control condition who reported with certainty that they had received feedback (*n* = 17) were excluded to ensure the integrity of the experimental manipulation. Finally, participants who completed the 10 quiz items at implausibly high speed were removed. Because the distribution of mean quiz-response times in the full dataset was highly right-skewed, conventional statistical outlier rules could not identify any implausibly fast responses. A 2-SD criterion would yield a negative lower bound, and Tukey's (1977) method similarly produced a negative cutoff. Because neither method can detect fast responses when the lower bound falls below zero, an alternative exclusion rule was needed. To ensure data quality, participants in the fastest 5% of the distribution (mean quiz-response time < 2.95 s) were removed. This corresponds to a reading rate of less than 0.1 seconds per word, which would require a reading speed more than twice that of typical adult reading rates of approximately 0.25 seconds per word (Brysbaert, 2019). These cases (*n* = 11) were classified as speeders and excluded. After applying all exclusion criteria, the final valid sample consisted of 208 participants.

The final sample consisted of 50.0% female and 49.5% male participants, while 0.5% selected "prefer not to say" (Table 8). Participants ranged in age from 18 to 84 years (*M* = 32.12, *SD* = 12.12) (Table 12). Regarding occupational status, 35.6% identified as students, 47.6% as employed full-time, and 10.1% as employed part-time. Additional categories included unemployed (2.9%), retired (0.5%,), and other (3.4%) (Table 9). Participants represented 25 nationalities, with the majority coming from Germany (71.2%), followed by the United States (8.2%), and Portugal (3.4%) (Table 11). Social status, measured on a 10-point scale, showed a mean of 6.62 (*SD* = 1.37) (Table 10). A detailed breakdown of all demographic variables is presented in Appendix B.

3.3 Procedure

Upon opening the Qualtrics survey, participants first selected their preferred language (English or German) and were presented with an informed-consent form describing the purpose of the study, the voluntary and anonymous nature of participation, and the charitable donation incentive. Only participants who provided consent were able to proceed.

To control for potential order effects, the demographic section was randomly presented either at the beginning or at the end of the survey. This section consisted of items on age, gender, employment status, and country of residence, as well as subjective social status, measured using the MacArthur scale of subjective social status (Adler et al., 2000). Participants also indicated how frequently they used AI tools at work or in their studies using a single-item six-point Likert scale (1 = "Never" to 6 = "Multiple times a day").

The experimental procedure began with a 10-item AI knowledge test based on the AILIT-S (Hornberger et al., 2025), which provided the basis for the subsequent feedback manipulation.
After completing the quiz, participants were randomly assigned to one of two feedback conditions. The experimental condition received competence-oriented feedback tailored to quiz performance, while the control condition received a neutral completion message without evaluative content.
Immediately following the feedback, participants answered a single attention-check question assessing whether they had received feedback about their quiz performance (1 = "No", 2 = "Not sure", 3 = "Yes"). Afterwards, participants completed the GSE-6AI (Morales-García et al., 2024) self-efficacy measure, recorded on a four-point Likert scale (1 = "Not at all true", 4 = "Exactly true"). Next, they completed the AIAS-4 AI acceptance scale (Grassini, 2023), consisting of four items rated on a 10-point Likert scale (1 = "Not at all", 10 = "Completely agree").
Finally, participants were presented with a debriefing page explaining the full purpose of the study and clarifying the use of different feedback conditions. The debrief reiterated that all responses were anonymous and confidential and provided the researcher's contact information for any inquiries or data withdrawal requests. On average, participation took approximately 15.36 minutes.

3.4 Variables

3.4.1 Independent Variable

The independent variable of this experiment was whether participants received feedback after completing the AI knowledge quiz. In the experimental condition, participants received immediate, competence-oriented feedback that communicated their exact quiz score and included two short statements: one affirming a concept they had answered correctly and one pointing to a concept they had answered incorrectly for further review. These statements were included only in the feedback message shown in the experimental condition. The feedback message was phrased in a neutral, informational manner to provide specific knowledge of results without evaluative or controlling language. The design aimed to deliver feedback in a manner that appeared accurate, credible, and personally relevant, consistent with theoretical evidence that effective feedback combines transparent performance information to enhance credibility (Karl et al., 1993; Peifer et al., 2020), competence-focused statements emphasizing capability rather than judgment (Hattie & Timperley, 2007; Ryan & Deci, 2000), and autonomy-supportive, optional suggestions that sustain intrinsic motivation and perceived self-determination (Anderson & Rodin, 1989; Van der Kleij et al., 2015; Van Dijk & Kluger, 2011). This is an example of the feedback wording:

> You answered 7 of 10 questions correctly.
>
> You recognized data bias correctly – this indicates a good command of the AI concepts covered.
>
> To deepen your understanding, you could review a short example on machine learning if you're interested.

To prevent systematic bias in which specific concepts were displayed, the referenced correct and incorrect concepts were randomly selected from the participant's individual response pattern. This procedure ensured that the feedback was both performance-contingent and personalized while maintaining a consistent structure and message length across all experimental bands.

For participants who answered all items correctly (10/10) or none correctly (0/10), slightly adapted versions were presented that excluded concept-specific references but maintained the same tone and structure. These messages provided either a general statement of mastery (10/10) or a supportive baseline formulation (0/10) to preserve credibility and uphold the competence-oriented framing. Overall, the feedback design followed Bandura's (1986) principle of verbal persuasion as a source of self-efficacy, aiming to elicit an increase in perceived capability through supportive, competence-related communication (Van der Kleij et al., 2015; Van Dijk & Kluger, 2011).

Participants in the control condition received a neutral completion message of identical length and visual format but without competence-related or motivational content (Peifer et al., 2020):

> Thank you for completing this section with 10 questions.
>
> The next part contains a few short questions about your experience.
>
> Please continue when ready.

The complete wording of all feedback messages and their presentation as implemented in Qualtrics are provided in Appendix C.

3.4.2 AI Knowledge Test

To create a realistic context for the feedback manipulation, participants completed a short AI knowledge quiz before receiving feedback. The quiz consisted of the AILIT-S (Hornberger et al., 2025), a ten-item multiple-choice instrument that assesses basic knowledge of AI concepts, applications, and limitations. The AILIT-S was developed as a brief and psychometrically sound measure of AI literacy, demonstrating a high correlation (r = .91) with the full version of the test (10 items) and acceptable internal consistency (α = .61; ω = .64) (Hornberger et al., 2025). Each quiz item provided multiple response options, typically four alternatives from which participants selected the correct answer. One item, however, required participants to order five AI development milestones chronologically and was scored partially, awarding 0.2 points per correctly placed element. Scores were automatically calculated through Qualtrics' built-in scoring function, resulting in a total score ranging from 0 to 10. The quiz served two primary functions: it provided a task that established a realistic context for the feedback manipulation, and it generated individualized performance data on which the feedback manipulation was based. The full item set and scoring scheme are available in Appendix C.

3.4.3 Mediator

The present study measured AI self-efficacy using the GSE-6AI (Morales-García et al., 2024), a validated short form adapted from the General Self-Efficacy Scale (Schwarzer & Jerusalem, 1995). The GSE-6AI demonstrates a unidimensional factor structure with excellent psychometric properties (CFI = 0.99, TLI = 0.98, $RMSEA$ = 0.04) and high internal consistency (α = 0.91; ω = 0.91), as well as factorial invariance across gender (Morales-García et al., 2024). A sample item of the GSE-6AI is: "No matter what comes up, I can usually handle it with the support of artificial intelligence". Participants rated their agreement on a four-point Likert scale (1 = "Not at all true", 4 = "Exactly true"). The complete item set is included in Appendix C.

3.4.4 Dependent Variable

To measure AI acceptance, the present study used the AI Attitude Scale AIAS-4 developed and validated by Grassini (2023). The AIAS-4 is a concise and psychometrically robust instrument for assessing general attitudes toward AI. Across two large international samples, the scale demonstrated a unidimensional structure with excellent psychometric properties (CFI = 0.999, TLI = 0.998, $RMSEA$ = 0.028) and high internal consistency (α = .90; ω = .90), confirming its reliability and suitability for diverse populations. The four items were theoretically grounded in established acceptance frameworks: Two items ("I believe that AI will improve my life"; "I believe that AI will improve my work") reflect perceived usefulness, the central predictor of acceptance in the

Technology Acceptance Model (Davis, 1989; Grassini, 2023). A third item ("I believe AI will improve humanity") captures broader societal evaluations, which Grassini (2023) argues are essential for understanding acceptance in contexts where individuals cannot freely choose whether to use AI. The final item ("I think I will use AI technology in the future") directly measures behavioral intention, the proximal determinant of technology use in TAM and UTAUT (Grassini, 2023; Venkatesh et al., 2003). Together, these items provide a theoretically coherent and empirically validated representation of AI acceptance that integrates personal benefit, societal evaluation, and intention to use. Participants rated their agreement on a 10-point Likert scale (1 = "not at all agree", 10 = "completely agree"). The complete item wording is provided in Appendix C.

3.4.5 Dummy Coding of Categorical Variables

To prepare the dataset for correlational and regression-based analyses, all categorical variables were dummy-coded prior to analysis. Gender was recoded such that male = 1 and female = 0; participants who selected "prefer not to say" or "other" were assigned missing values for this variable due to the very low frequency of these responses. Nationality was dummy coded by creating a variable indicating German nationality, with German = 1 and all other nationalities = 0, as Germany constituted by far the largest subgroup in the sample. Employment status was dummy coded as employed = 1 and not employed = 0, and student status as student = 1 and non-student = 0. A dummy variable was also created for AI use frequency, distinguishing high-frequency AI users (using AI once or multiple times per day = 1) from all other participants (0). Finally, the experimental condition was dummy coded with the feedback condition = 1 and the control condition = 0.

4. Results

4.1 Data Treatment

The data were prepared and analyzed using IBM SPSS Statistics (version 30). Mediation analyses were conducted using the PROCESS macro by Hayes et al. (2025) for SPSS (version 5.0). Before testing the hypotheses, I examined the multi-item scales for internal consistency and factorial validity, in line with established psychometric guidelines that emphasize verifying that items coherently assess one construct before conducting substantive analyses (Clark & Watson, 1995). AI self-efficacy was measured using six items that assessed participants' perceived ability to interact competently with AI systems. The scale demonstrated excellent internal consistency (α = .90) (Table 13). To assess dimensionality, I conducted a principal axis factor analysis. Sampling adequacy was confirmed by a Kaiser–Meyer–Olkin value of .89, which is considered meritorious (Kaiser & Rice, 1974) (Table 14). All individual measures of sampling adequacy exceeded .86, which is well above the recommended minimum of .50 (Lorenzo-Seva & Ferrando, 2021) (Table 15). One factor had an eigenvalue of 4.05, accounting for 67.44% of the total variance (Table 16). All items loaded strongly onto this factor (λ = .69–.83). Based on these results, the items were averaged to form a composite scale score.

AI acceptance was assessed using four items reflecting participants' attitudes toward and intent to use AI. This scale demonstrated excellent reliability (α = .92) (Table 18). Factor-analytic evaluation indicated good sampling adequacy, with an overall Kaiser–Meyer–Olkin value of .85, again within the meritorious range (Kaiser & Rice, 1974) (Table 19), and all individual measures of sampling adequacy values above .81 (Table 20). A single factor emerged with an eigenvalue of 3.26, explaining 81.5% of the variance (Table 21). Item loadings ranged from .82 to .91 (Table 22), supporting a coherent, unidimensional structure. Therefore, a mean score was computed for this measure as well.

Together, these analyses indicated that both scales exhibited strong psychometric properties and were suitable for use as composite variables in subsequent descriptive, correlational, and mediation analyses. The complete scale assessment can be found in Appendix D.

4.2 Descriptive Statistics

Descriptive statistics were computed for all continuous study variables, and the results are presented in Table 1. Participants answered an average of 5.95 quiz items correctly. The AI self-efficacy scale, which ranges from 1 to 4, showed a mean score of 2.52. AI acceptance, measured on a scale from 1 to 10, had a mean of 6.54.

Descriptive statistics

Item	N	Mean	Std. Deviation
Quiz Score	208	5.95	2.25
Social Status	208	6.61	1.37
Self-Efficacy	208	2.53	0.80
AI Acceptance	208	6.54	2.42

Table 1: Descriptive Statistics

AI-use frequency showed substantial variation: 2.9% reported never using AI tools, 10.1% used AI less than once a month, 16.8% less than once a week, 23.1% less than once a day, 21.2% once or twice a day, and 26.0% multiple times per day (Table 23). Assignment to the experimental condition was almost perfectly balanced, with 48.6% participants in the control group and 51.4% participants in the feedback condition (Table 24).

The bivariate correlations among all continuous variables and dummy-coded categorical indicators are shown in Table 25. Condition (0 = control, 1 = feedback) was positively associated with AI self-efficacy ($r = .42$, $p < .001$) and AI acceptance ($r = .43$, $p < .001$). AI self-efficacy showed a positive correlation with AI acceptance ($r = .72$, $p < .001$). Age correlated negatively with AI self-efficacy ($r = -.21$, $p = .002$). Gender showed statistically significant positive correlations with both AI self-efficacy ($r = .18$, $p = .009$) and AI acceptance ($r = .19$, $p = .005$). Daily AI use was associated with higher self-efficacy ($r = .17$, $p = .015$) and higher acceptance ($r = .26$, $p < .001$). Quiz performance showed no meaningful associations with the key psychological constructs (all $|r| < .05$, all $p > .43$). Aside from these effects, no additional correlations of conceptual relevance emerged. Overall, the descriptive and correlational results provide an overview of the relationships among the study variables. The complete correlations table can be found in Appendix F.

4.3 Hypothesis Testing

To test this thesis' three hypotheses, PROCESS Model 4 (Hayes et al., 2025) was used to test whether the effect of the experimental condition (0 = control, 1 = feedback) on AI acceptance was mediated by AI self-efficacy. A schematic overview of this study's mediation model is shown in Figure 2.

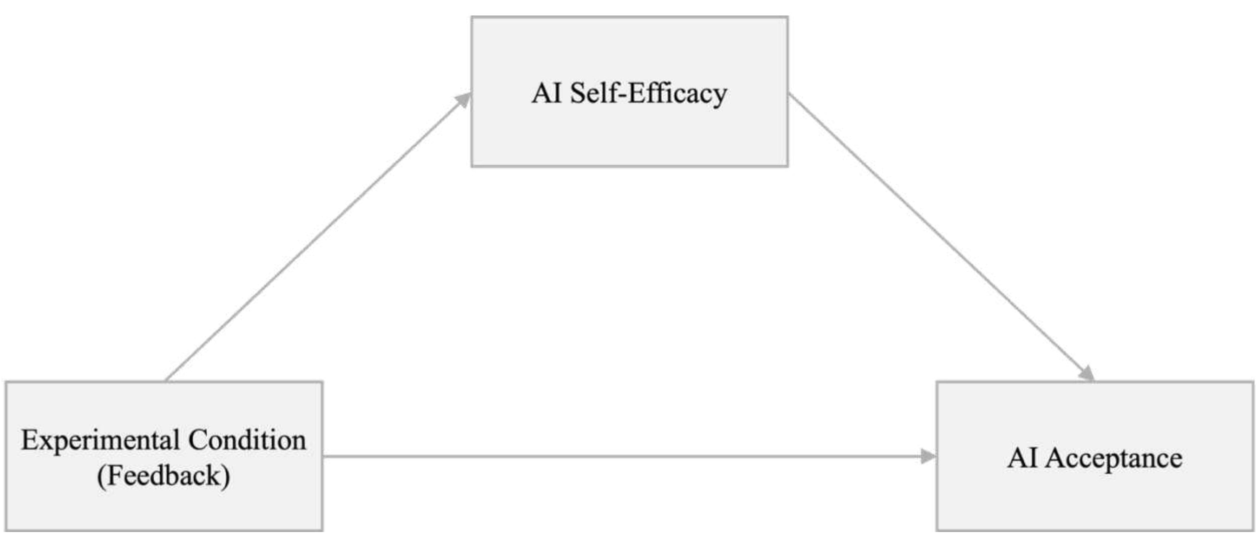

Figure 2: Model 4 of Hayes PROCESS macro for SPSS

I applied bootstrapping with 5,000 resamples and bias-corrected 95% confidence intervals because this method provides robust estimates of indirect effects without assuming normality of the sampling distribution (Waples, 2024). First, all analyses were performed without covariates to test the core hypotheses. Then, a second model was created that included age, employment status, student status, and daily AI use as covariates to examine the robustness of the effects.

In the mediation model without covariates, the experimental manipulation significantly increased AI self-efficacy. Participants who received competence-oriented feedback reported significantly higher AI self-efficacy than those in the control condition ($b = 0.67$, $SE = 0.10$, $p < .001$), supporting H2. In turn, AI self-efficacy strongly predicted AI acceptance ($b = 1.96$, $SE = 0.16$, $p < .001$), providing support for H1. The direct effect of feedback on AI acceptance remained statistically significant when controlling for self-efficacy ($b = 0.79$, $SE = 0.25$, $p = .002$). The total effect of feedback on AI acceptance was also significant ($b = 2.09$, $SE = 0.30$, $p < .001$). The indirect effect of condition on AI acceptance via self-efficacy was statistically significant: The bootstrapped unstandardized indirect effect was 1.31 (*Bootstrapped SE* = 0.24), with the 95% bootstrapped *CI* [0.86, 1.80], which does not include zero. This confirms that the manipulation influenced AI acceptance in part through its effect on AI self-efficacy and therefore supports H3. For the complete PROCESS Output, see Appendix G.

Because four control variables showed correlations with the main study variables, the mediation model was re-estimated including age, employment status, student status, and daily AI use as covariates to reduce potential confounding. When covariates were added to the model, the experimental condition continued to predict AI self-efficacy ($b = 0.68$, $SE = 0.10$, $p < .001$). Thus, even after adjusting for individual differences, participants in the feedback condition reported higher self-efficacy than those in the control group. This supports H2. AI self-efficacy again strongly predicted AI acceptance ($b = 1.91$, $SE = 0.16$, $p < .001$), providing robust support for H1 across both the unadjusted and adjusted models. The direct effect of the experimental condition on AI acceptance also remained statistically significant when controlling for self-efficacy and the covariates ($b = 0.84$, $SE = 0.25$, $p < .001$). The indirect effect of condition on AI acceptance through self-efficacy was statistically significant, with a bootstrapped estimate of 1.29 (*Bootstrapped SE* = 0.24) and a 95% *CI* of [0.84, 1.78], which does not include zero. The final mediation model explained 56.96% of the variance in AI acceptance ($R^2 = .57$). Together, these results indicate that the mediation effect persisted when covariates were included. Therefore, H3 is supported. For the complete PROCESS Output including covariates, see Appendix H.

5. Discussion

5.1 Research Findings

This study explored whether competence-oriented feedback can enhance AI self-efficacy and, consequently, boost AI acceptance. Guided by Social Cognitive Theory and recent technology and AI acceptance research, the study suggested that AI self-efficacy serves as the psychological link between feedback and individuals' acceptance of AI systems. The research thus tested three hypotheses: higher AI self-efficacy predicts greater AI acceptance (H1), competence-oriented feedback increases self-efficacy (H2), and this feedback effect on acceptance is mediated by self-efficacy (H3). All hypotheses were supported, emphasizing the key role of self-efficacy in shaping how people evaluate AI.

One of the main findings is that AI self-efficacy strongly predicted AI acceptance. Participants who felt more capable of using AI tools expressed more positive attitudes toward AI. This pattern aligns with social cognitive theory, which maintains that efficacy beliefs guide approach–avoidance tendencies and shape how individuals respond to new or uncertain situations (Bandura, 2004). In the context of AI, feeling capable appears to encourage more favorable evaluations and greater openness toward future use. This interpretation is consistent with acceptance research showing that attitudes constitute an important component of individuals' readiness to engage with technology (Ajzen, 1991) and with recent evidence demonstrating that users' attitudes toward AI are shaped by self-efficacy and related subjective appraisals (Shao et al., 2024). The present study extends this literature by demonstrating that experimentally increasing self-efficacy leads to more positive evaluations of AI. In doing so, it provides causal evidence to a body of work that has thus far been dominated by correlational findings linking AI self-efficacy to motivation and acceptance-related outcomes (Guan et al., 2025; Morales-García et al., 2025; Y. Wang & Chuang, 2024).

Another important result is that competence-oriented feedback significantly increased AI self-efficacy. Participants who received positively framed, performance-related feedback reported higher self-efficacy than those who did not receive feedback. This effect appeared across all model specifications and aligns with Bandura's (1977) view of feedback as verbal persuasion, one of the key sources from which efficacy beliefs emerge. The feedback used in the experiment followed established design principles from the feedback literature: it was immediate, competence-focused, and tied directly to task performance. Research shows that these characteristics reinforce perceptions of mastery and provide concrete evidence of success (Achterkamp et al., 2015; Hattie & Timperley, 2007; S. Wang, 2025). The current findings extend these insights into the AI domain, demonstrating that even brief digital feedback can meaningfully increase domain-specific self-efficacy.

The mediation results indicate that AI self-efficacy is the psychological mechanism through which competence-oriented feedback increases AI acceptance. Receiving feedback enhanced participants' perceived capability to use AI, which in turn translated into more positive evaluations of AI systems. This finding is consistent with experimental research demonstrating that performance-related feedback can strengthen domain-specific self-efficacy and that self-efficacy can function as a mediating mechanism linking feedback to downstream outcomes such as performance, flow, or affective responses (Peifer et al., 2020). Converging evidence from meta-analytic path models further shows that learners' perceptions of feedback are positively associated with self-efficacy and that feedback effects on outcomes can be transmitted via self-efficacy and related motivational processes (Qi et al., 2024). Extending this line of work, the present study demonstrates that this feedback–self-efficacy mechanism also operates in the context of AI, where strengthening self-efficacy contributes to higher acceptance of AI technologies.

The descriptive results contextualize these findings. Frequent AI users reported higher self-efficacy and more positive attitudes toward AI. This pattern supports the idea that repeated interaction with AI tools provides mastery experiences, which Bandura et al. (1997) identifies as the most influential source of efficacy. Regular practice may therefore build both confidence and openness toward AI. Age was negatively associated with self-efficacy, indicating that older participants felt less capable of using AI tools. This pattern mirrors existing evidence on age-related differences in technology confidence and adoption (Shin & Bang, 2025; Zhang, 2023). Gender showed small positive correlations with both self-efficacy and acceptance, suggesting that males reported slightly higher competence beliefs and more positive attitudes. This modest pattern is consistent with prior work showing small male advantages in self-efficacy across technology-related domains (Huang, 2012). Although modest, these demographic effects demonstrate that AI-related beliefs result from both situational factors and broader individual influences.

A final finding worth mentioning is the lack of a relationship between quiz performance and the psychological constructs of interest. Although quiz results varied with age and social status, they did not correlate with AI self-efficacy or AI acceptance. This pattern suggests that subjective competence beliefs were largely shaped independently of actual task performance. Prior research shows that self-efficacy often relies on motivational and affective cues rather than strictly on objective performance information (Boekaerts, 1991) and that feedback valence can influence self-efficacy without necessarily improving the accuracy of self-assessments (Ernst et al., 2024). Together, these findings indicate that participants' evaluations of their AI-related competence were more affected by feedback and internal cues than by their actual quiz performance.

5.2 Academic Implications

The findings of this study contribute to several academic conversations on AI self-efficacy, technology acceptance, digital feedback, and the psychological mechanisms that shape how individuals engage with AI systems. Recent workplace AI research is organized around five broad themes identified by Bankins et al. (2023): human–AI collaboration, perceptions of competence between humans and algorithms, employee attitudes toward AI, AI as a control mechanism in algorithmic management, and labor market effects such as job displacement and skill shifts. These themes show that competence beliefs and attitudinal evaluations play an important role in how employees experience AI. The present study builds on this foundation by providing new evidence on how competence beliefs can be shaped and how they influence acceptance.

A first contribution concerns the literature on AI self-efficacy. The study provides causal evidence that self-efficacy is a central determinant of AI acceptance. This insight aligns with recent AI-specific research showing that perceived capability meaningfully shapes willingness to adopt AI-enabled tools (e.g., Guan et al., 2025; Morales-García et al., 2025; Wang & Chuang, 2023). The present findings strengthen this literature by showing that increases in self-efficacy lead to more positive evaluations of AI. This supports the view that AI self-efficacy represents a domain-specific extension of social cognitive theory and demonstrates that competence beliefs shape how individuals approach new or uncertain technologies. The results also show that AI self-efficacy is not a static trait but an adaptable psychological resource that targeted interventions can influence.

The findings also have important implications for technology acceptance models. Classic frameworks such as TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003) emphasize perceived usefulness and performance expectancy as primary determinants of acceptance, while treating competence-related beliefs mainly as external or background factors (Davis, 1989; Venkatesh et al., 2003). The present study suggests that in AI-intensive contexts, particularly those characterized by rapid technological change and uncertainty, competence beliefs represent an important psychological factor shaping individuals' evaluations of AI systems. AI self-efficacy emerged as a strong and direct predictor of AI acceptance, even when controlling for demographic and behavioral covariates. This finding indicates that attitudes toward AI are influenced not only by evaluations of the technology itself, but also by individuals' confidence in their ability to work with emerging systems. This perspective is consistent with recent AI-specific research showing that users' perceived capability meaningfully shapes their willingness to adopt AI-enabled tools (Guan et al., 2025; Shao et al., 2024). Rather than replacing established determinants of technology acceptance, these findings highlight the relevance of competence beliefs as an additional factor that warrants explicit consideration in AI acceptance research. Future studies should further examine how AI self-efficacy relates to established constructs such as perceived usefulness and performance expectancy and clarify the extent to which these concepts overlap or interact in shaping AI acceptance.

Another theoretical implication arises for literature on feedback and digital learning. The study demonstrates that competence-oriented feedback can alter self-efficacy even within a brief, experimental digital interaction. Prior research has documented the benefits of feedback for learning, motivation, and confidence (Hattie & Timperley, 2007; S. Wang, 2025). The present findings extend this work by demonstrating that digital feedback can also strengthen competence beliefs related to AI. These insights highlight the importance of feedback-based calibration in digital environments. As AI systems become more widespread in education and work, understanding how feedback shapes confidence and readiness to engage with AI will become increasingly important.

A final conceptual contribution emerges from the distinction between objective performance and subjective beliefs. Quiz performance did not predict AI self-efficacy or AI acceptance, although it varied by age and social status. This dissociation indicates that individuals form competence beliefs independently of their actual performance. Rather than being grounded in objective performance feedback, these beliefs appear to be shaped by external cues such as evaluative feedback, prior experiences with AI, and general confidence. This pattern aligns with research showing that framing, feedback, and interface characteristics can strongly influence subjective appraisals in digital settings (Ernst et al., 2024). Recognizing this gap between performance and belief is important for researchers and practitioners who seek to understand how individuals adopt and use AI systems.

Taken together, these contributions show that self-efficacy plays a central role in shaping AI acceptance, that competence beliefs deserve a more explicit place in technology acceptance models, and that digital feedback can effectively support the development of confidence in AI-related skills.

5.3 Managerial Implications

The findings of this study offer several practical implications for organizations that aim to implement AI systems effectively. As AI tools continue to enter work environments, employee readiness and confidence become increasingly important determinants of successful adoption. The results show that competence-oriented feedback can increase AI self-efficacy and shape employees' willingness to engage with AI, highlighting a concrete lever for organizations during AI rollout and training processes.

A first implication concerns the design of training interventions. The study shows that supportive, performance-related feedback increases AI self-efficacy, which enhances employees' attitudes and acceptance of AI. Research on feedback in digital learning supports this, showing that immediate, competence-focused feedback strengthens confidence and promotes engagement (Hattie & Timperley, 2007; Panadero & Lipnevich, 2022). Managers can use this by designing training activities with timely, constructive feedback. Digital tutorials, interactive practice modules, or guided task demonstrations can help employees recognize progress and build confidence as they begin working with AI systems.

A further implication underscores that organizations should create structured opportunities for hands-on experience with AI tools. Frequent AI users reported higher self-efficacy and more positive attitudes toward AI, suggesting that repeated exposure helps employees develop the competence needed to engage with AI in their daily work. This aligns with social cognitive theory, which identifies mastery experiences as the strongest source of self-efficacy (Bandura et al., 1997), and with research showing that increased AI use predicts higher confidence and acceptance (Morales-García et al., 2025). Pilot environments, experimentation sessions, or supervised practice scenarios, therefore, represent effective ways for employees to gain familiarity with AI systems before adoption becomes mandatory.

Another implication is that competence-building efforts should begin early in the implementation process. Although the study did not directly compare rollout phases, the strong influence of self-efficacy on acceptance suggests that early encounters with AI can have a disproportionate impact. Research on efficacy development shows that initial experiences play a major role in shaping long-term beliefs and attitudes (Bandura et al., 1997). Providing supportive feedback and accessible practice opportunities at the beginning of implementation can prevent negative expectations from forming and lay the foundation for sustained acceptance.

A fourth implication is that AI training should accommodate the diverse needs of the workforce. The descriptive results show that older participants reported lower self-efficacy, and male participants tended to express slightly higher competence beliefs and more positive attitudes. These patterns mirror broader research on demographic differences in technology confidence and adoption (Cabrera-Sánchez et al., 2021; Choung et al., 2023). While these differences are small, they suggest that employees do not enter AI-related learning environments with identical confidence baselines. Managers should therefore avoid one-size-fits-all approaches and instead offer flexible pacing, optional support, and varied instructional formats that allow employees with different levels of prior experience to feel equally capable of using AI tools.

Finally, the results point to the importance of helping employees accurately calibrate their confidence. The study found no relationship between objective quiz performance and either AI self-efficacy or AI acceptance, both in the overall sample and within each experimental condition, indicating that subjective competence beliefs can diverge from actual ability. This pattern is consistent with research demonstrating that digital feedback and interface framing can shape competence judgments independent of performance (Ernst et al., 2024). Managers can address this by providing feedback that is both encouraging and realistic. Such feedback helps employees develop a balanced understanding of their skills and reduces the risk of overconfidence or unnecessary hesitation, both of which can undermine effective AI use.

Taken together, these implications show that competence-building is a central component of successful organizational AI implementation. Supportive feedback, structured experience, early engagement, differentiated training, and accurate confidence calibration can help employees feel prepared to work with AI systems. When employees perceive themselves as capable and supported, they are more likely to adopt AI tools and integrate them into their work in a productive and sustainable manner.

5.4 Limitations and future research

A first limitation concerns the sample's characteristics. Participation was voluntary, and recruitment relied partly on personal and professional networks, which likely resulted in a convenience sample. Individuals with a stronger interest in technology or higher digital affinity may have been more inclined to participate, potentially biasing the results. The use of an online survey reinforces this concern: while online data collection is efficient, it typically faces challenges such as lower response rates, limited control over the completion environment, and reduced representativeness due to self-selection bias (Evans & Mathur, 2018). Moreover, the sample consisted predominantly of German-speaking participants. Although the study does not focus on cross-cultural comparisons, this limitation restricts the generalizability of its findings to other cultural and organizational contexts where attitudes toward AI and technology adoption may differ (Hussain et al., 2025). Future studies should therefore strive to recruit larger and more diverse samples, ideally spanning different industries, cultural backgrounds, and levels of AI exposure.

Another limitation concerns the reliance on self-report measures. AI self-efficacy and AI acceptance were assessed through questionnaires, which may be influenced by self-awareness and motivational factors that affect how individuals regulate and present their responses (Baumeister & Vohs, 2007; Hutton & Baumeister, 1992). These biases may lead to inflated estimates of confidence or positive attitudes toward AI. Because both AI self-efficacy and AI acceptance were assessed using self-report measures, future research may benefit from explicitly addressing potential social desirability bias. Prior research shows that socially desirable responding can systematically distort self-reported attitudes and confidence judgments, even in anonymous online surveys (Larson, 2019). Incorporating short social desirability scales, indirect questioning techniques, or statistical controls for socially desirable responding could therefore help ensure that reported levels of AI self-efficacy and acceptance more accurately reflect individuals' genuine beliefs rather than normative response tendencies.

In addition, although the scales used in this study demonstrated strong psychometric properties, future research would benefit from complementing self-reported measures of AI acceptance with objective indicators of AI adoption, such as actual AI usage data, longitudinal usage patterns, or task-level interaction metrics. Such measures would allow researchers to more directly capture how individuals engage with AI systems in practice and to examine whether self-reported acceptance translates into sustained and observable AI use over time.

The conceptualization of AI acceptance presents an additional limitation. In this study, acceptance was measured using the AI Attitude Scale, which captures general AI acceptance, including evaluations of AI's usefulness, perceived societal impact, and future intentions to use AI (Ajzen, 1991; Grassini, 2023), rather than workplace-specific adoption behavior. While intentions are central components of models such as the Theory of Planned Behavior and are generally thought to correlate strongly with actual behavior (Ajzen, 1991), this relationship is not perfect. As a result, intention-based measures do not fully capture how individuals use AI tools in practice. Future research should therefore incorporate behavioral indicators, such as longitudinal usage patterns or task-level interaction data, to examine whether increases in AI self-efficacy translate into sustained and observable AI use over time.

Another limitation is the lack of realism in the experimental manipulation. The competence-oriented feedback was brief and standardized, and it was only delivered once. In real organizational settings, feedback is usually iterative, contextualized, and embedded within broader training and support structures. While the study included a manipulation check to confirm that participants noticed the feedback, it did not assess whether the feedback was perceived as credible or an accurate reflection of individuals' performance. Since perceived credibility is essential for feedback to meaningfully influence efficacy beliefs (Bandura, 1977), future research should incorporate direct measures of credibility or compare different sources of feedback, such as AI-generated versus human-generated messages, to better understand the conditions under which competence-oriented feedback is most effective.

The online setting of the study limited experimental control over participants' attentional engagement. Research on survey methodology shows that attentional engagement and response quality can vary in online questionnaires due to response fatigue and question order effects (Egleston et al., 2011). However, one would expect such variability to attenuate rather than inflate the influence of feedback on self-efficacy. Therefore, observing a significant effect despite these minimal and potentially distracting conditions suggests that the reported findings represent a conservative estimate of the impact of competence-oriented feedback. Future research conducted in more controlled or ecologically valid settings may help determine whether stronger or more sustained effects emerge when feedback is delivered repeatedly under conditions of higher engagement. The absence of longitudinal data provides an additional limitation. Self-efficacy and acceptance were measured immediately after the feedback manipulation, which limits conclusions about their durability. It remains unclear whether increases in self-efficacy persist over time or diminish once the feedback context is removed. Longitudinal or repeated-measures designs would enable researchers to examine whether brief feedback interventions lead to sustained changes in competence beliefs or long-term adoption of AI technologies.

A further limitation concerns the use of a donation-based incentive. For each completed questionnaire, a €0.50 donation was made to a charitable organization. Although such incentives are commonly used in online research to increase participation, they may have influenced participants' motivation and attentional engagement, potentially encouraging satisficing behavior. Future studies could examine whether similar findings emerge without incentives or under alternative incentive structures.

Another limitation relates to the translation of all study materials into German. Despite careful translation procedures, subtle differences in wording or interpretation cannot be fully ruled out, particularly for constructs such as self-efficacy and AI acceptance. Future research should therefore assess measurement equivalence across languages or replicate the findings in multilingual samples.

Beyond the limitations discussed above, future research should consider additional psychological and contextual predictors that may complement AI self-efficacy in explaining AI acceptance. Although the final mediation model explained a substantial proportion of variance in AI acceptance (approximately 57%), a considerable share remains unexplained. Established technology acceptance frameworks, such as the Technology Acceptance Model and UTAUT, highlight factors including perceived usefulness, performance expectancy, and effort expectancy as central determinants of adoption (Davis, 1989; Venkatesh et al., 2003). Because these constructs were not measured in the present study, it remains unclear to what extent they overlap with, mediate, or potentially outweigh the effects of self-efficacy. For instance, individuals who feel more capable of using AI may also perceive it as more useful, suggesting conceptual interdependencies between self-efficacy and perceived usefulness that future studies should explicitly examine (Davis, 1989; Mansori, 2025; Uren & Edwards, 2023; Venkatesh et al., 2003). Recent research also highlights additional determinants of AI acceptance, such as trust in AI systems, perceived threat, and job displacement anxiety, and emphasizes the importance of explainable and ethically aligned AI as prerequisites for acceptance (Angerschmid et al., 2022; Uren & Edwards, 2023). More broadly, the findings underscore the need for future research to examine how subjective assessments, rather than objective performance alone, shape individuals’ readiness to engage with AI in learning and workplace contexts.

6. Conclusion

This thesis shows that competence-oriented feedback shapes individuals' relationships with AI. A brief, targeted feedback intervention increased AI self-efficacy, in turn leading to more positive attitudes toward AI. These results show that AI self-efficacy is a key psychological factor in acceptance and a flexible resource that organizations can enhance through straightforward, scalable interventions. By clarifying how feedback influences competence beliefs and how these beliefs shape attitude towards AI, this research provides an evidence-based mechanism to support employee readiness in a rapidly evolving technological landscape.

7. References

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8. Appendix A

Results from Pre-Test:

Statistics

Age

N	Valid	11
	Missing	0
M		25.67
Min		22
Max		36

Table 2: Pre-Test Descriptive Statistics – Demographics Age

How do you describe yourself? - Selected Choice

	N	%
Male	6	0.54
Female	5	0.46

Table 3: Pre-Test Descriptive Statistics – Demographics Gender

Condition

	N	%
Experimental	5	0.46
Control	6	0.54

Table 4: Pre-Test Descriptive Statistics – Condition

Statistics

Completion Time

N	Valid	11
	Missing	0
M		69.71
Mdn		19.37
Min		11
Max		491

Table 5: Pre-Test Descriptive Statistics – Completion Time

Pre-Test Descriptive Statistics by Experimental Condition

Measure	Feedback (n = 5)	Control (n = 6)
Mean Self-Efficacy (t_0)	2.90	2.53
Mean Self-Efficacy (t_1)	2.73	2.39
Δ Self-Efficacy ($t_0 \rightarrow t_1$)	-0.17	-0.14
Mean AI Quiz Score	7.72	6.40
Mean AI Acceptance	7.65	7.21

Table 6: Pre-Test Descriptive Statistics – Mean Differences by Experimental Condition

Independent-Samples t-Test for Post-Feedback Self-Efficacy (t_1)

Statistics	Values
M (Feedback)	2.73
M (Control)	2.39
t(9)	1.26
p	.24
Cohen's d	0.78

Table 7: Pre-Test Descriptive Statistics – Independent-Samples t-Test

9. Appendix B

Demographics:

What is your gender?

	N	%
Male	103	49.5
Female	104	50.0
Prefer not to say	1	0.5

Table 8: Demographics - Gender

What is your current employment status?

	N	%
Employed full time	99	47.6
Employed part time	21	10.1
Unemployed	6	2.9
Retired	1	.5

Student	74	35.6
Other	7	3.4

Table 9: Demographics - Employment

Perceived social status

	N	%
1.00	0	0%
2.00	2	1.0
3.00	4	1.9
4.00	7	3.4
5.00	21	10.1
6.00	56	26.9
7.00	70	33.7
8.00	34	16.3
9.00	11	5.3
10.00	3	1.4

Table 10: Demographics – Social Status

List of Countries

	N	%
Afghanistan	1	.5
Australia	2	1.0
Austria	2	1.0
Belgium	2	1.0
Czech Republic	1	.5
France	2	1.0
Gabon	1	.5
Germany	148	71.2
Greece	1	.5
India	2	1.0
Italy	3	1.4
Lithuania	1	.5
Netherlands	6	2.9
Pakistan	2	1.0

Table 11: Demographics – Country

Age

N	Valid	208
	Missing	0
M		32.11
Med		26.00
Min		18
Max		84

Table 12: Demographics - Age

10. Appendix C

Start of Block: InformedConsent

Consent Welcome to this experiment on **interactions with artificial intelligence (AI)**.

The study will take **about 10 minutes** to complete and consists of completing a short task and answering several individual questions.

I will donate **€0.50 to Little Bells Orphanage (Nepal) for every response** that is fully usable (up to €200). No personal data is required for the donation.

This survey contains **SurveySwap.io credits** to get free survey responses and provides **SurveyCircle points** for participation.

Please **answer as honestly as possible**. All answers will be kept **strictly confidential and are anonymous**.

I, Leonard Keck, am conducting this experiment as part of my Master Thesis at Católica Lisbon School of Business and Economics, under the supervision of Prof. Cristina Mendonça. The purpose is to gain insight into **how individuals engage with AI systems** and make decisions when working with or learning about such technologies. Your participation will contribute to research on human–AI interaction.

The data collected will be used for research purposes only and may be presented in my thesis or disseminated in academic journals, always in aggregated form and never about any individual response.

I ask you to take the study in one go, without interruptions. There are no expected side effects of participating in this study beyond those associated with looking at a computer screen for approximately 10 minutes. You may change your mind and drop out at any point during the study.

If you have any **questions about this study, please email Leonard Keck (s-lkeck@ucp.pt)**.

Thank you for participating!

Q_Consent Do you agree to participate in this study?

○ No (1)

○ Yes (2)

End of Block: InformedConsent

Start of Block: Demographics

Intro_Demographics In the following, we will ask you to answer a few short **questions about yourself**. Please respond as accurately as you can. When you are ready, click the arrow button below to continue.

Page Break

Gender What is your gender?

- ◯ Male (1)
- ◯ Female (2)
- ◯ Other (3) ____
- ◯ Prefer not to say (6)

Page Break

Age How old are you?

____

Page Break

Employment What is your current employment status?

- ◯ Employed full time (1)
- ◯ Employed part time (2)
- ◯ Unemployed (3)
- ◯ Retired (4)
- ◯ Student (5)
- ◯ Other (6) ____

Page Break

Social Status Think of a ladder that represents where people stand in society. At the top of the ladder are the people who are the best off, those who have the most money, most education, and best jobs. At the bottom are the people who are the worst off, those who have the least money, least education, worst jobs, or no job. Where you think you stand on the ladder? Please select a number between 1 (bottom) and 10 (top).

	1	2	3	4	5	6	7	8	9	10
()										

Page Break

Country In which country do you currently reside?

▼ Afghanistan (1) ... Zimbabwe (1357)

Page Break

AC_1 To show that you are paying attention, please select “Rarely” below.

- Never (1)
- Sometime (2)
- Rarely (3)
- Always (4)

Page Break

AI_UseFreq How often do you use AI?

- Never (1)
- Less than once a month (2)
- Less than once a week (3)
- Less than once a day (6)
- Once or twice a day (7)
- Multiple times a day (4)

End of Block: Demographics

Start of Block: AI_Quiz

Intro_AIQ In the upcoming passage, you will complete a **short test about your knowledge of artificial intelligence**. Please answer each question as best as you can.
When you are ready, click the arrow button below to begin.

Page Break

AIQ1 In which of these areas is AI typically applied?

- Detecting credit card fraud (1)
- Cryptocurrency mining (2)
- Web tracking (3)
- Encryption for instant messaging services (4)

Page Break

AIQ2 Which of the following interdisciplinary research fields is also a subfield of AI?

○ Blockchain (1)

○ Natural Language Processing (2)

○ Psychology of Learning (3)

○ Bioinformatics (4)

Page Break

AIQ3 For which task was AI first shown to be superior to human experts?

○ Detecting tumors (1)

○ Conducting software projects (2)

○ Translating novels (3)

○ Designing cancer therapies (4)

Page Break

AIQ4 How does supervised learning differ from unsupervised learning?

○ in supervised learning, the output values of the training data are known (1)

○ in supervised learning, humans must supervise the AI during learning and intervene if necessary (2)

○ in supervised learning, all computational steps are documented (3)

○ in supervised learning, stricter legal regulations apply (4)

Page Break

AIQ5 Sort the process steps in supervised learning into the correct order by selecting which step (1–5) each action represents:

Train model with training data (1)	▼ 1. Step (1) ... 5. Step (5)
Predict test data with the model (2)	▼ 1. Step (1) ... 5. Step (5)
Collect and prepare data (3)	▼ 1. Step (1) ... 5. Step (5)
Divide data into training and test data (4)	▼ 1. Step (1) ... 5. Step (5)
Calculate accuracy of prediction (5)	▼ 1. Step (1) ... 5. Step (5)

Page Break

AIQ6 How do AI developers most typically shape the results of the machine learning process?

○ Through calculation of the accuracy of the prediction (1)

○ Through randomized division into test and training data (2)

○ Through selection of the model (3)

○ Through abstraction of the model (4)

Page Break

AIQ7 What primarily determines the behavior of AI systems?

- ◯ AI systems strive for autonomy (1)
- ◯ AI systems pursue a goal that has been given to them by humans (2)
- ◯ AI systems perform behaviors randomly (3)
- ◯ AI systems seek out goals independently (4)

Page Break

AIQ8 You are testing a machine learning model that is supposed to classify images of animals. You notice that the model is better at recognizing cats than dogs. What could be the reason for this?

- ◯ Dogs are more difficult to recognize than cats, since there are fewer images of dogs on the internet (1)
- ◯ Small objects (cats) are better recognized than large ones (2)
- ◯ Most models are generally better at recognizing cats than dogs (3)
- ◯ The training data of the dogs were not representative of all dog breeds (4)

Page Break

AIQ9 What is the black box problem?

- ◯ AI entails a residual risk that is hard to calculate (1)
- ◯ It is often difficult to determine how an AI system makes decisions (2)
- ◯ Users are often not informed that an AI system is being used (3)
- ◯ Many users have little knowledge about AI (4)

Page Break

AIQ10 What is a central risk in using AI for predictive policing?

◯ Vulnerability to hacking (1)

◯ Discrimination against suspects based on origin and status (2)

◯ Lack of legal certainty in the event of an AI failure (3)

◯ Undermining the authority of police officers (4)

End of Block: AI_Quiz

Start of Block: Feedback_Perfect

Feedback_Timing_Perf Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

Feedback_Perfect

You answered **${e://Field/QuizScore} out of 10** questions correctly.

Your answers on **${e://Field/concept_correct_EN} were accurate** - this reflects a solid grasp.

To deepen your understanding, you could explore an advanced example on an AI topic of your choice.

End of Block: Feedback_Perfect

Start of Block: Feedback_High

Feedback_Timing_High Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

Feedback_High

You answered **${e://Field/QuizScore} out of 10** questions correctly.

Your answers on **${e://Field/concept_correct_EN} were accurate** - this reflects a solid grasp.

To deepen your understanding, you could review a short advanced example on ${e://Field/concept_focus_EN}.

End of Block: Feedback_High

Start of Block: Feedback_Mid

Feedback_Timing_Mid Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

Feedback_Mid

You answered **${e://Field/QuizScore} out of 10** questions correctly.

You applied **${e://Field/concept_correct_EN} correctly** - this is a good foundation.

To deepen your understanding, you could revisit a brief example on ${e://Field/concept_focus_EN}.

End of Block: Feedback_Mid

Start of Block: Feedback_Low

Feedback_Timing_Low Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

Feedback_Low

You answered **${e://Field/QuizScore} out of 10** questions correctly.

You recognised **${e://Field/concept_correct_EN} correctly** - this is a useful baseline.

To deepen your understanding, you could start with a short overview on ${e://Field/concept_focus_EN}.

End of Block: Feedback_Low

Start of Block: Feedback_zero

Feedback_Timing_Zero Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

Feedback_Zero

You answered **${e://Field/QuizScore} out of 10** questions correctly.

This provides a useful baseline for building your understanding of AI concepts.

To deepen your understanding, you could review a short introductory example about how AI systems work.

End of Block: Feedback_zero

Start of Block: Feedback_Control

Feedback_Cont_Timing Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

Feedback_Control

Thank you for completing this section with 10 questions.

The next part contains a few short questions about your experience.

Please continue when ready.

End of Block: Feedback_Control

Start of Block: Post-feedback exposure check

feedback_exposure_po Please indicate below if you received feedback about your quiz performance.

○ Yes (1)

○ Not sure (3)

○ No (6)

End of Block: Post-feedback exposure check

Start of Block: SelfEfficacy_t1

Intro_SE_t1 Now, we would like to ask you to rate **how true each of the following statements feels** to you regarding **your ability to use artificial intelligence** effectively. When you are ready, click the arrow button below to continue with these statements.

Page Break

SE_t1 Please indicate how much you agree with each statement.

	Not at all true (1)	Hardly true (2)	Moderately true (3)	Exactly true (4)
If someone opposes me, I can find means and ways to get what I want by using artificial intelligence. (1)	○	○	○	○
It's easy for me to stay true to my goals and achieve my objectives with the help of artificial intelligence. (2)	○	○	○	○
I am confident that I could efficiently face unexpected events by using artificial intelligence. (3)	○	○	○	○
Thanks to my resourcefulness supported by artificial intelligence, I know how to handle unforeseen situations. (4)	○	○	○	○
I can stay calm when facing difficulties because I trust in my coping skills backed by artificial intelligence. (5)	○	○	○	○
No matter what comes up, I can usually handle it with the support of artificial intelligence. (6)	○	○	○	○

End of Block: SelfEfficacy_t1

Start of Block: AI_Acceptance

Intro_AIA Next, you will see a few new statements about **your overall views on artificial intelligence**. These questions focus on **your broader perspective** rather than your confidence in using AI. When you are ready, click the arrow button below to continue.

Page Break

AIA Please indicate how much you agree with each statement.

	Not at all 1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	8 (8)	9 (9)	Completely agree 10 (10)
I believe that AI will improve my life (1)	○	○	○	○	○	○	○	○	○	○
I believe that AI will improve my work (2)	○	○	○	○	○	○	○	○	○	○
I think I will use AI technology in the future (3)	○	○	○	○	○	○	○	○	○	○
I think AI technology is positive for humanity (4)	○	○	○	○	○	○	○	○	○	○

End of Block: AI_Acceptance

Start of Block: Debrief

Debrief Thank you for your participation in this study.

In this study, I aimed to understand how completing short AI-related tasks and receiving different types of information can shape people's experiences and confidence in using AI. To ensure natural and unbiased responses, I did not disclose the full goal of the study beforehand, as doing so could have influenced participants' behavior and rendered the results less informative.

All data remain completely anonymous and will be analyzed only at the group level. If you have any questions or would like to withdraw your data, please contact **Leonard Keck (s-lkeck@ucp.pt)**.

If you wish, you may provide comments or feedback about your experience in the text box below. Your input helps us improve future studies.

End of Block: Debrief

11. Appendix D

Scale reliability GSE-6AI

Cronbachs alpha - GSE-6AI

Reliability Statistics

Cronbach's Alpha	N of Items
.90	6

Table 13: Reliability Statistics – GSE-6AI

Factor analysis - SE

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.89
Bartlett's Test of Sphericity	Approx. Chi-Square	715.75
	df	15
	Sig.	<.001

Table 14: Factor Analysis – GSE-6AI

Anti-image Correlation

Item	1	2	3	4	5	6
1	.932[a]	-.246	-.102	-.141	-.138	-.030
2	-.246	.898[a]	-.216	-.246	-.229	.011
3	-.102	-.216	.910[a]	-.274	-.019	-.217
4	-.141	-.246	-.274	.904[a]	-.221	-.118
5	-.138	-.229	-.019	-.221	.864[a]	-.453
6	-.030	.011	-.217	-.118	-.453	.870[a]

a. Measures of Sampling Adequacy(MSA)

Table 15: Factor Analysis – GSE-6AI

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.05	67.44	67.44	3.67	61.09	61.09
2	0.56	9.36	76.80			
3	.46	7.64	84.44			
4	.38	6.28	90.71			
5	.31	5.18	95.89			
6	.25	4.11	100.00			

Extraction Method: Principal Axis Factoring.

Table 16: Factor Analysis – GSE-6AI

Factor Matrix

	Factor
Item	1
1	.692
2	.800
3	.765
4	.832
5	.834
6	.757

Extraction Method: Principal Axis Factoring.[a]

a. 1 factors extracted. 5 iterations required.

Table 17: Factor Analysis – GSE-6AI

AI Acceptance Scale

Cronbachs alpha - AIAS-4

Reliability Statistics

Cronbach's Alpha	N of Items
.92	4

Table 18: Reliability Statistics – AIAS-4

Factor analysis - AIAS-4

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.85
Bartlett's Test of Sphericity	Approx. Chi-Square	639.88
	df	6
	Sig.	<.001

Table 19: Factor Analysis – AIAS-4

Anti-image Correlation

Item	1	2	3	4
1	.813[a]	-.434	-.199	-.439
2	-.434	.832[a]	-.367	-.195
3	-.199	-.367	.888[a]	-.148
4	-.439	-.195	-.148	.866[a]

a. Measures of Sampling Adequacy(MSA)

Table 20: Factor Analysis – AIAS-4

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.26	81.48	81.48	3.02	75.46	75.46
2	0.33	8.34	89.82			
3	0.24	5.90	95.71			
4	0.17	4.29	100.00			

Extraction Method: Principal Axis Factoring.

Table 21: Factor Analysis – AIAS-4

Factor Matrix

	Factor
Item	1
1	0.91
2	0.90
3	0.82
4	0.84

Extraction Method: Principal Axis Factoring.[a]

a. 1 factors extracted. 6 iterations required.

Table 22: Factor Analysis – AIAS-4

12. Appendix E

Descriptive Statistics:

How often do you use AI?

	N	%
Never	6	2.9
Less than once a month	21	10.1
Less than once a week	35	16.8
Multiple times a day	54	26.0
Less than once a day	48	23.1
Once or twice a day	44	21.2

Table 23: Demographics – AI Use

Condition

	N	%
Control	101	48.6

Table 24: Demographics – Condition

13. Appendix F

Correlations:

Correlations

	N	M	SD	1	2	3	4	5	6	7	8	9	10	11
1 Age	208	32.11	12.12	–										
2 SocialStatus	208	6.61	1.37	.15*	–									
3 Quiz Score	208	5.95	2.25	.21**	.22**	–								
4 AI Self-efficacy	208	2.52	0.80	-.21**	.03	.04	–							
5 AI Acceptance	208	6.54	2.41	-.09	.12	-.02	.72**	–						
6 Daily AI Use	208	0.47	0.50	-.15*	.05	-.03	.17*	.26**	–					
7 Male	208	0.49	0.50	.07	.17*	.14*	.18**	.19**	.03	–				
8 Employed	208	0.57	0.49	.42**	.29**	.23**	-.03	-.01	-.09	.13	–			
9 Student	208	0.35	0.47	-.48**	-.17*	-.22**	.07	.02	.06	-.17*	-.87**	–		

10 Condition	208	0.51	0.50	-.03	-.03	.01	.42**	.43**	-.01	.02	-.09	.070	–	
11 German	208	0.71	0.45	.06	-.09	-.05	-.06	.02	.11	.04	.08	-.10	-.02	–

Table 25: Correlation table

**p* < .05. ***p* < .01.

14. Appendix G

PROCESS Matrix Output – without covariates

```
Run MATRIX procedure:

Copyright 2013-2025 by Andrew F. Hayes. ALL RIGHTS RESERVED.
This version of PROCESS requires SPSS version 26 or later
Workshop schedule available at haskayne.ucalgary.ca/CCRAM
In SPSS 29 and later, change default output font to Courier New for tidier
output. More information about PROCESS at processmacro.org/faq.html.
This beta release has not been completely tested. Use at your own risk.



***************** PROCESS Procedure for SPSS Version 5.0 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
  Model: 4
      Y: AIA_mean
      X: CondB
      M: SE_mean

Sample
Size:  208

Variable descriptive statistics
       AIA_mean      CondB    SE_mean
Mean     6.5445      .5144     2.5272
SD       2.4175      .5010      .8036
Min      1.0000      .0000     1.0000
Max     10.0000     1.0000     4.0000

Variable intercorrelations (Pearson r)
           AIA_mean      CondB    SE_mean
AIA_mean     1.0000      .4337      .7199
CondB         .4337     1.0000      .4150
SE_mean       .7199      .4150     1.0000
```

****

OUTCOME VARIABLE:
SE_mean

Model Summary

R	R-sq	MSE	F	df1	df2	p
.4150	.1722	.5372	42.8567	1.0000	206.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	2.1848	.0729	29.9584	.0000	2.0410	2.3286
CondB	.6656	.1017	6.5465	.0000	.4652	.8661

Some regression diagnostics

	Min.	Max.
fitted	2.1848	2.8505
residual	-1.8505	1.8152
t-resid	-2.5710	2.5211

Shape of residuals

	Skewness	Kurtosis
Value	-.2294	-.5478
se	.1686	.3357

Bonferroni-corrected p for largest t-residual

t-resid	p-value	casenum
-2.5710	1.0000	200.0000

Most influential observations

	casenum	dfbeta
constant	68.0000	.0182
CondB	68.0000	-.0182

Variable tolerance and VIF

	Tol.	VIF
CondB	1.0000	1.0000

Breusch-Pagan test of heteroskedasticity

	Chi-sq	df	p
Normal	.1966	1.0000	.6574
Robust	.2738	1.0000	.6008

****

OUTCOME VARIABLE:
AIA_mean

Model Summary

R	R-sq	MSE	F	df1	df2	p
.7350	.5402	2.7132	120.4445	2.0000	205.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	1.1811	.3793	3.1136	.0021	.4332	1.9290
CondB	.7869	.2512	3.1330	.0020	.2917	1.2821
SE_mean	1.9620	.1566	12.5302	.0000	1.6533	2.2708

Some regression diagnostics

	Min.	Max.
fitted	3.1432	9.8162
residual	-5.3352	5.3758
t-resid	-3.3403	3.3689

Shape of residuals

	Skewness	Kurtosis
Value	-.1024	.6163
se	.1686	.3357

Bonferroni-corrected p for largest t-residual

t-resid	p-value	casenum
3.3689	.1876	178.0000

Most influential observations

	casenum	dfbeta
constant	200.0000	.1645
CondB	200.0000	.0922
SE_mean	200.0000	-.0753

Variable tolerance and VIF

	Tol.	VIF
CondB	.8278	1.2080
SE_mean	.8278	1.2080

Breusch-Pagan test of heteroskedasticity

	Chi-sq	df	p
Normal	13.2546	2.0000	.0013
Robust	10.3033	2.0000	.0058

********************* TOTAL EFFECT MODEL*************************

OUTCOME VARIABLE:
AIA_mean

```
Model Summary
     R       R-sq        MSE         F       df1       df2         p
  .4337     .1881     4.7679   47.7334    1.0000   206.0000    .0000

Model
         coeff      se        t          p       LLCI       ULCI
constant   5.4678    .2173   25.1658    .0000     5.0395    5.8962
CondB      2.0929    .3029    6.9089    .0000     1.4957    2.6902
-----------
Some regression diagnostics

              Min.       Max.
fitted       5.4678     7.5607
residual    -5.8107     4.5322
t-resid     -2.7147     2.1032

Shape of residuals
        Skewness   Kurtosis
Value     -.3683     -.7396
se         .1686      .3357

Bonferroni-corrected p for largest t-residual
    t-resid    p-value    Casenum
    -2.7147     1.0000   184.0000

Most influential observations
            casenum      dfbeta
constant    71.0000       .0453
CondB      184.0000      -.0548

Variable tolerance and VIF
            Tol.         VIF
CondB     1.0000      1.0000

Breusch-Pagan test of heteroskedasticity
           Chi-sq         df          p
Normal     6.5992     1.0000       .0102
Robust    10.5642     1.0000       .0012


********* TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y *********

Total effect of X on Y
   Effect      se          t          p       LLCI       ULCI
   2.0929      .3029     6.9089      .0000     1.4957     2.6902

Direct effect of X on Y
   Effect         se          t          p       LLCI       ULCI
    .7869      .2512     3.1330      .0020      .2917     1.2821
```

```
Indirect effect(s) of X on Y:
            Effect     BootSE   BootLLCI   BootULCI
SE_mean     1.3060      .2440      .8621     1.7957

Cases with greatest influence on indirect effect(s):
           casenum     dfb_ie
SE_mean   200.0000     -.0857

***************** ANALYSIS NOTES AND ERRORS ******************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
```

15. Appendix H

PROCESS Matrix Output – with covariates

```
Run MATRIX procedure:

Copyright 2013-2025 by Andrew F. Hayes. ALL RIGHTS RESERVED.
This version of PROCESS requires SPSS version 26 or later
Workshop schedule available at haskayne.ucalgary.ca/CCRAM
In SPSS 29 and later, change default output font to Courier New for tidier
output. More information about PROCESS at processmacro.org/faq.html.
This beta release has not been completely tested. Use at your own risk.



************ PROCESS Procedure for SPSS Version 5.0 *************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

****************************************************************
  Model: 4
      Y: AIA_mean
      X: CondB
      M: SE_mean

Covariates:
 Age      EmployB  StudB    DyAiUse

Sample
```

Size: 208

Variable descriptive statistics

	AIA_mean	CondB	SE_mean	Age	EmployB	StudB	DyAiUse
Mean	6.5445	.5144	2.5272	32.1154	.5769	.3558	.4712
SD	2.4175	.5010	.8036	12.1216	.4952	.4799	.5004
Min	1.0000	.0000	1.0000	18.0000	.0000	.0000	.0000
Max	10.0000	1.0000	4.0000	84.0000	1.0000	1.0000	1.0000

Variable intercorrelations (Pearson r)

	AIA_mean	CondB	SE_mean	Age	EmployB	StudB	DyAiUse
AIA_mean	1.0000	.4337	.7199	-.0923	-.0125	.0186	.2612
CondB	.4337	1.0000	.4150	-.0249	-.0921	.0790	-.0080
SE_mean	.7199	.4150	1.0000	-.2124	-.0316	.0687	.1682
Age	-.0923	-.0249	-.2124	1.0000	.4194	-.4829	-.1484
EmployB	-.0125	-.0921	-.0316	.4194	1.0000	-.8678	-.0885
StudB	.0186	.0790	.0687	-.4829	-.8678	1.0000	.0631
DyAiUse	.2612	-.0080	.1682	-.1484	-.0885	.0631	1.0000

****

OUTCOME VARIABLE:
SE_mean

Model Summary

R	R-sq	MSE	F	df1	df2	p
.4957	.2457	.4992	13.1624	5.0000	202.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	2.3243	.2710	8.5767	.0000	1.7899	2.8586
CondB	.6755	.0985	6.8608	.0000	.4814	.8696
Age	-.0145	.0047	-3.0952	.0022	-.0237	-.0052
EmployB	.2830	.2002	1.4132	.1591	-.1119	.6778
StudB	.1206	.2139	.5636	.5736	-.3012	.5423
DyAiUse	.2410	.0995	2.4223	.0163	.0448	.4372

Some regression diagnostics

	Min.	Max.
fitted	1.6533	3.1913
residual	-1.8911	1.5131
t-resid	-2.7503	2.1868

Shape of residuals

	Skewness	Kurtosis
Value	-.1207	-.5657
se	.1686	.3357

Bonferroni-corrected p for largest t-residual

t-resid	p-value	casenum
-2.7503	1.0000	10.0000

Most influential observations

	casenum	dfbeta
constant	5.0000	-.1229
CondB	200.0000	-.0175
Age	208.0000	.0021
EmployB	5.0000	.0849
StudB	5.0000	.0966
DyAiUse	200.0000	-.0249

Variable tolerance and VIF

	Tol.	VIF
CondB	.9911	1.0090
Age	.7526	1.3287
EmployB	.2452	4.0782
StudB	.2289	4.3696
DyAiUse	.9731	1.0277

Breusch-Pagan test of heteroskedasticity

	Chi-sq	df	p
Normal	15.0790	5.0000	.0100
Robust	21.2512	5.0000	.0007

****

OUTCOME VARIABLE:
AIA_mean

Model Summary

R	R-sq	MSE	F	df1	df2	p
.7547	.5696	2.5903	44.3391	6.0000	201.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	.6240	.7210	.8654	.3878	-.7978	2.0458
CondB	.8410	.2491	3.3769	.0009	.3499	1.3321
SE_mean	1.9095	.1603	11.9132	.0000	1.5934	2.2255
Age	.0124	.0109	1.1392	.2560	-.0091	.0339
EmployB	-.0880	.4584	-.1920	.8479	-.9919	.8159
StudB	-.1756	.4876	-.3602	.7191	-1.1372	.7859
DyAiUse	.8003	.2299	3.4809	.0006	.3469	1.2536

Some regression diagnostics

	Min.	Max.
fitted	2.9676	10.3857
residual	-4.7702	5.5417
t-resid	-3.0678	3.5808

Shape of residuals

	Skewness	Kurtosis
Value	-.1247	.5673
se	.1686	.3357

Bonferroni-corrected p for largest t-residual

t-resid	p-value	casenum
3.5808	.0895	178.0000

Most influential observations

	casenum	dfbeta
constant	24.0000	.2397
CondB	160.0000	.0857
SE_mean	160.0000	-.0653
Age	207.0000	-.0037
EmployB	24.0000	-.1731
StudB	24.0000	-.1931
DyAiUse	200.0000	.0676

Variable tolerance and VIF

	Tol.	VIF
CondB	.8038	1.2441
SE_mean	.7543	1.3258
Age	.7185	1.3917
EmployB	.2428	4.1185
StudB	.2285	4.3764
DyAiUse	.9456	1.0575

Breusch-Pagan test of heteroskedasticity

	Chi-sq	df	p
Normal	17.4920	6.0000	.0076
Robust	13.8547	6.0000	.0313

************************** TOTAL EFFECT MODEL ****************************

OUTCOME VARIABLE:
AIA_mean

Model Summary

R	R-sq	MSE	F	df1	df2	p
.5155	.2657	4.3975	14.6214	5.0000	202.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI

L

constant	5.0621	.8044	6.2934	.0000	3.4761	6.6482
CondB	2.1308	.2922	7.2916	.0000	1.5546	2.7071
Age	-.0152	.0139	-1.0964	.2742	-.0425	.0121
EmployB	.4523	.5943	.7610	.4475	-.7196	1.6242
StudB	.0546	.6349	.0859	.9316	-1.1973	1.3064
DyAiUse	1.2604	.2953	4.2684	.0000	.6782	1.8427

Some regression diagnostics

	Min.	Max.
fitted	4.5115	8.5562
residual	-5.1051	4.6694
t-resid	-2.4985	2.2711

Shape of residuals

	Skewness	Kurtosis
Value	-.2462	-.8985
se	.1686	.3357

Bonferroni-corrected p for largest t-residual

t-resid	p-value	Casenum
-2.4985	1.0000	184.0000

Most influential observations

	casenum	dfbeta
constant	145.0000	-.3023
CondB	155.0000	.0522
Age	207.0000	-.0046
EmployB	145.0000	.2468
StudB	120.0000	-.2532
DyAiUse	190.0000	-.0548

Variable tolerance and VIF

	Tol.	VIF
CondB	.9911	1.0090
Age	.7526	1.3287
EmployB	.2452	4.0782
StudB	.2289	4.3696
DyAiUse	.9731	1.0277

Breusch-Pagan test of heteroskedasticity

	Chi-sq	df	p
Normal	7.4573	5.0000	.1888
Robust	13.6302	5.0000	.0181

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

```
Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     2.1308      .2922     7.2916      .0000     1.5546     2.7071

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      .8410      .2491     3.3769      .0009      .3499     1.3321

Indirect effect(s) of X on Y:
            Effect     BootSE   BootLLCI   BootULCI
SE_mean     1.2898      .2329      .8637     1.7765

Cases with greatest influence on indirect effect(s):
           casenum     dfb_ie
SE_mean   160.0000     -.0764

********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
```