AI Usage, Self-Efficacy, and Employee Performance: Balancing Productivity Gains and Unintended Consequences

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02nd June 2025

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Abstract

This research explores how frequent AI usage influences employee performance. While literature has focused on how AI improves efficiency, this study attempts to analyze its impact on overall performance, including counterproductivity. Based on Bandura's self-efficacy theory and the Technology Acceptance Model, it was assumed that AI usage frequency influences employee performance through work self-efficacy. Data were gathered from 185 employees using an online questionnaire. The analysis confirmed that frequent AI use leads to higher positive performance by enhancing work self-efficacy. This supports the assumption that AI usage makes employees feel more confident in their ability to perform work tasks, through which they are likely to perform better across different performance dimensions. Finally, there was no significant negative indirect effect of frequent AI use on counterproductive work behaviors through self-efficacy. The study highlights the psychological mechanism at play in improving work performance by using AI and discusses implications for ethical responsibility and future research.

Introduction

In the past decades, there have been astonishing advances in science and technology that have enhanced human productivity (Naqbi et al., 2024). However, the recent improvements in artificial intelligence (AI) reach beyond just efficiency gains, as they have begun to reshape how people perform tasks (Jutel, 2023). Unlike previous technologies that primarily supported cognitive processes, such as thinking, decision making, and problem solving, AI independently executes and automates these tasks (Wang et al., 2023). This development might influence employees' confidence and work behavior in ways that lead to both opportunities and challenges in their individual work performance. Yet, little attention has been given to the different dimensions of job performance, especially to counterproductivity.

Researchers primarily argue that using AI has the potential to improve efficiency, but it might also enhance other work eras. For example, it can release employees from routine tasks and thereby free up their time to focus on more strategic or collaborative tasks (Huang & Rust, 2018). The technology can also help them learn new skills and adjust to evolving job roles more easily (Babashahi et al., 2024). In these ways, AI could enhance collaboration, engagement, and agility for employees.

It is further unclear, whether AI usage might simultaneously increase counterproductive work behaviors. These are workplace behaviors, that negatively affect the organizational performance (Peterson, 2002). Whereas the traditional definition of counterproductive work behavior focuses on purposeful actions, such as intentionally working slowly, AI usage might lead to unintended negative performance outcomes. For instance, studies suggest that employees rely too much on AI and make mistakes that otherwise would not have occurred (Macnamara et al., 2024). This can happen because users tend to prioritize input from automated systems over human expertise, even when the recommendations are contradictory or incorrect (Mosier et al., 1997). Other studies further argue that using AI might reduce employees' mental effort and engagement by decreasing their thinking capacity and therefore making them "lazy" (Ahmad et al., 2023). As a result of not using specific skills, proficiency in those skills may decline over time (Morandini et al., 2023). Nevertheless, these unintended effects of using AI remain underexplored in current literature.

Specifically, how AI usage can result in both improvements and declines in employee performance at once remains unclear. Insights from psychological frameworks, such as Bandura's construct of self-efficacy are valuable for understanding the mechanisms underlying AI's contradicting effects. The concept describes an individual's belief about being capable of performing an activity or mastering a particular task (Bandura, 1988). It was found that the use of AI can enhance self-efficacy as it improves confidence and perceived efficiency in performing required tasks (Zhang and Xu, 2024). Generally, individuals with greater self-efficacy are found to reach higher performance achievements, because they feel more in control of achieving their goals (Bandura, 1982). Thus, by enhancing work self-efficacy, AI usage could enhance individual work performance.

Yet, at the same time, employees might establish inefficiencies and behavioral setbacks. Researchers have raised the possibility that higher work self-efficacy, which is generally linked to better performance, might reduce motivation to put in further effort or attention to detail (Vancouver et al., 2001). This could heighten the likelihood of overlooking errors in AI systems or it might lead to skill deterioration over time (Rabenu et al., 2017). Therefore, while AI systems are likely to boost the employee's confidence and performance up to a certain threshold, it is not yet known whether and how they may affect human behavior in a way that could diminish the foreseen benefits (Malik et al., 2021).

Taken together, while existing literature has shown the potential of using AI to improve efficiency, there is a lack of research on its influence on various performance outcomes, particularly on counterproductivity. Moreover, there is a lack of understanding of the psychological mechanism underlying these contradicting effects. This study attempts to fill this gap by contributing to a holistic approach to performance improvement by using AI. Therefore, the purpose of this study is to investigate the relationship between AI usage frequency, self-efficacy, and employee's positive and counterproductive performance.

Specifically, it aims to answer the following research question: How does the frequent use of AI affect employee performance? In this way, the present study contributes to the ongoing debate on how AI should be implemented in the workplace. It advocates for strategies that do not only focus on efficiency but also the mitigation of possible risks. Through this sustainable and balanced perspective on the integration of AI within the workplace, it aims to ensure general employee performance and satisfaction.

Understanding Employee Performance and the Role of AI

Employee performance. Employee performance can be defined as employee behavior that helps an organization reach its predefined goals in terms of job quality, quantity, and time (Na-Nan et al., 2018). Job quality refers to meeting the set criteria and standards for acquiring, manufacturing, and delivering products or services. Job quantity, on the other hand, refers to the units of output generated by employees' behavior in terms of product amounts, waste quantities, and sales numbers. Finally, the time spent to complete the work-related activities in relation to their degrees of difficulty is called work time. Employees achieve their at-work time goals if the necessary tasks are completed correctly and in a reasonable period (Peterson & Plowman, 1953).

While the dimensions job quality, quantity, and time may offer valuable insights, it can be argued that they do not capture the complexity and full range of behaviors that make up an employee's performance at work (Campbell, 1990). Koopmans et al. (2011) offer a more heuristic conceptual framework of individual work performance, consisting of the three positive performance dimensions, task, contextual, and adaptive performance.

Task performance refers to the effectiveness with which central job tasks are executed. The aforementioned aspects of performance, job quality, quantity and time, could be considered task performance (Koopmans et al., 2011). Contextual performance can be described as actions that facilitate the organizational, social, and psychological environment in which the technical core operates (Borman et al., 1993). It includes voluntary actions exceeding the obligations of an official role and aimed at helping particular individuals, groups, or the organization (Lavelle, 2010). As a third dimension, adaptive performance refers to an employee's ability to adapt to changes in a work system or work roles. It includes, for example, dealing with uncertain or unpredictable work situations, learning new tasks and technologies, and being flexible and open-minded to others (Koopmans et al., 2011). These three dimensions capture not only the execution of core responsibilities but also the ability to contribute to the broader organizational environment and adapt to evolving demands.

Furthermore, Koopmans et al.’s (2001) individual work performance framework includes a fourth dimension, counterproductive work behaviors, which address negative performance indicators. They are characterized by behaviors that negatively impact the organization’s effectiveness, such as absenteeism, avoiding tasks, or doing them incorrectly (Koopmans et al., 2011). These actions are considered to be voluntary activities that harm customers, colleagues, and managers (Spector & Fox, 2005). In this regard, the key feature of counterproductive work behavior is its intentionality as it stems from an employee’s will to act in a way that is damaging either to the organization or to any of its members (Sypniewska, 2020).

Together, Koopmans et al. (2011) four dimensions, task, contextual, adaptive performance, and counterproductive work behavior provide a holistic framework for this study to evaluate AI’s overall impact on employee performance. In order to understand this impact better, the core functions and capabilities of AI should be defined first.

Artificial Intelligence. Although AI as a field has existed for decades, its impact has become more significant in recent years (Haenlein & Kaplan, 2019). This is due to advances in technology and data availability (Brynjolfsson & McAfee, 2017). Moreover, its accessibility to the general public and integration into the workforce have allowed non-experts to interact with the technology in real time (Shrestha et al., 2019). Therefore, AI has become more integrated into everyday tasks and business processes.

The term AI refers to systems that perform human cognitive tasks, such as reasoning, learning, and solving problems (Rrussel & Norvig, 2016). For this, AI relies on several technologies, including machine learning, deep learning, and natural language processing. While this study aims to examine the overall impact of AI technologies on employee performance and does not differentiate between the effects of the different AI models, it will briefly explain how these technologies work and are applied in the workforce.

The machine learning process involves the selection and application of algorithms that enable computers to learn from data and make predictions (Tyagi & Rekha, 2019). For instance, employees working in sales and marketing might use those systems to analyze customer data and predict purchases (Al-Ebrahim et al., 2023). Deep learning is a subset of machine learning and can handle much more complex tasks (Jiang et al., 2024). Compared to machine learning algorithms, it is able to learn from unstructured data, such as images or audio, without the need for human intervention (Chauhan et al., 2021). For instance, employees can use deep learning-based tools, which can scan resumes and evaluate candidates based on the job's requirements (Priyanka & Parveen, 2023). Natural language processing focuses on understanding, processing, and generating human language (Jerfy et al., 2024). For example, an AI-powered virtual assistant such as Siri can understand spoken language and respond with relevant information (Madushan et al., 2023).

The most prominent example of an AI tool is ChatGPT. It is a natural language processing model that uses machine learning and deep learning algorithms to communicate with users in a conversational manner. It offers numerous advancements over traditional bots or voice assistants as it can understand complex questions and respond more accurately (George et al., 2023). It is also a type of Generative AI, which means that beyond analyzing data it can to produce new content (Feuerriegel et al., 2024). Since it has recently been introduced to the public, it had a profound impact on employees of various types of industries (Pereira et al., 2023). Within slightly over two months, it has garnered over 100 million users and has been considered the quickest-growing online platform in history as it surpassed Instagram, Facebook, Netflix, and TikTok (Leiter et al., 2024). This extraordinarily high usage rate can be explained by theoretical frameworks, such as the Technology Acceptance Model (TAM) (Davis, 1989).

AI Usage. TAM aims to provide a general explanation of how users accept and use technology by identifying two core factors: perceived usefulness and perceived ease of use (Davis, 1989). These factors significantly influence the user's attitude toward technology and, consequently, their intention to use it (Davis, 1989). Perceived usefulness refers to the extent to which a user views the technology as beneficial to their daily activities (Davis, 1989). More use reinforces the perception of whether the technology is beneficial or not (Rafique et al., 2019). Meanwhile, perceived ease of use relates to a user's perception of how easy a technological device would be to use (Davis, 1989). According to TAM, when employees find AI tools useful and easy to use, they are more likely to integrate them into their work processes and engage with them more frequently (Czarnitzki et al., 2023).

AI systems like ChatGPT are designed with user-friendly interfaces that do not require specialized technical knowledge to use (Choudhury & Shamszare, 2024). This simplicity reduces cognitive effort and thus enhances perceived user-friendliness (Czarnitzki et al., 2023). Additionally, AI technologies offer various advancements in how employees operate, the prime example being efficiency (Jutel, 2023). This contributes to the users' perception of the technology's usefulness and, together with the perceived ease of use, influences their intention to use it (Davis, 1989). The frequency of using AI has further several effects on employees performance.

AI Usage Frequency and Positive Performance. When discussing AI's positive effects on workplace performance, the focus is often on task performance as it directly improves quality, quantity, and time spent to complete core job responsibilities (Purwati, 2024). For example, a medical practitioner can enhance the quality of his work and take into consideration AI aggregated expert knowledge to come to a well-informed diagnosis (Heilig & Scheer, 2023). AI technologies can further automate processes and execute business processes rapidly without needing much manual effort, enhancing job quantity (Ramachandran et al., 2021). This can be helpful for, for instance, the processing of invoices. AI-powered tools can extract data from invoices, match them to relevant orders in real time, and schedule payments automatically (Jain & Pandey, 2019). AI's effects on task performance were shown across various sectors, such as manufacturing, healthcare, and agriculture (Chen et al., 2024).

Research has also demonstrated that AI usage improves contextual performance (Bruni A., 2021). AI tools, which automate processes, can free up employees from routine tasks and thereby allow them to engage in extra-role activities (Huang & Rust, 2018). It can also inspire workers and enhance creativity in employee engagement by offering new ways to contribute positively to their organizations (Jia et al., 2023). In a recent case study, the integration of generative AI tools like ChatGPT within an organizational setting led to the creation of an internal knowledge-sharing platform (Ameen et al., 2022). These findings show how AI fosters employee engagement and motivation beyond their core responsibilities.

Finally, AI can improve adaptive performance by offering resources to learn and adjust to new skills or job roles (Babashahi et al., 2024). For instance, employees using AI-powered learning platforms can receive personalized training modules that are tailored to their specific skill gaps. Intelligent technologies, such as LinkedIn Learning, adjust the learning content to the learner's performance, progress, or knowledge (Bayly-Castaneda et al., 2024). Chatbots, like ChatGPT, can further help employees access real-time feedback and data that helps them understand a specific subject faster (Cacicio & Riggs, 2023). These examples demonstrate how AI enhances adaptive performance by providing personalized learning opportunities and real-time support.

Given the evidence about AI improving the positive performance dimensions, task, contextual, and adaptive performance, it can be assumed that a higher frequency of using the technology can maximize these effects. The more frequently employees interact with AI tools, they can streamline core job tasks, drive creative problem-solving, and enable continuous skill development with personalized learning. Drawing from TAM, as users engage more frequently with the technology, over time they view the technology as easier to use and more useful for executing their tasks (Davis, 1989). This leads to a positive feedback loop of increased use and a better understanding of how to use the technology effectively, compounding its positive effects over time (Saadé, 2007). Therefore, this study assumes that AI usage frequency enhances positive performance.

Self-Efficacy as a Mediator between AI Usage Frequency and Positive Performance. Bandura's construct of self-efficacy provides a further explanation for the psychological mechanisms involved in this relationship. It indicates an individual's confidence in their capacity to reach one's own goals (Bandura, 1988). This trust in oneself significantly influences perceptions, actions, and decision making (Bandura, 1997). In this way, self-efficacy also acts as an antecedent in TAM as it influences both, the perceived ease of use and perceived usefulness of a new technology (Alharbi & Drew, 2018). People who generally feel more capable, are more likely to use a new technology (Kulviwat et al., 2014).

Overall, the construct serves as a foundation for motivation and accomplishments in every facet of life (Momeni et al., 2014).

This study assumes that using AI frequently enhances an employee's work-related self-efficacy. As aforementioned, AI technologies can take over repetitive tasks or help employees solve complex problems (Malik et al., 2021). Therefore, it can be seen as a job resource, which helps them to manage their job demands (Bakker & Demerouti, 2017). With more resources at their disposal, employees who use AI are able to solve problems more effectively and save time when working on tasks. Thus, they develop the belief in their ability to succeed in their goals (Bakker et al., 2014).

The effect of AI usage on work-related self-efficacy was demonstrated by various research findings (Huang et al., 2024). For example, Noy and Zhang (2023) showed that AI increases self-efficacy among a number of professions, from HR professionals and managers to writers, marketers, and consultants. Zhang and Xu (2024) further revealed that frequent AI use improves an individual's confidence and efficiency in performing tasks. Over time and through repeated successful experiences in completing tasks with AI tools, employees begin to see themselves as more competent and effective in their roles overall (Bandura, 1997).

It is further assumed that work self-efficacy, which is built by using AI often, enhances employees' different positive performance dimensions. For example, individuals with greater work self-efficacy are found to perform more efficiently, improving task performance (Stajkovic & Luthans, 1998). It was also found to enhance motivation and engagement to engage in extra-role behaviors, therefore contributing to contextual performance (Kappagoda, 2018). Additionally, employees with high self-efficacy are more likely to believe in their ability to acquire new knowledge, which impacts their adaptive performance (Nobels, 2024).

These findings indicate that AI usage enhances work-related self-efficacy, which in turn influences employees' positive performance dimensions, task, contextual, and adaptive performance. Thus, the first hypothesis of this study is that:

H1: AI usage frequency has a positive relationship with employees' positive performance (task, contextual, and adaptive performance), and this is mediated by self-efficacy.

AI Usage Frequency and Unintended Counterproductive Work Behavior. While AI usage enhances employees' confidence and offers several benefits on employee performance outcomes, its influence can be context dependent. This study assumes that using AI enhances performance, while at the same time leading to unintended consequences that can negatively impact it. Specifically, it may indirectly encourage counterproductive work behaviors, the fourth dimension of the individual work performance framework (Koopmans et al., 2011).

As previously mentioned, the construct is traditionally defined as actions that intentionally harm the organization such as theft or absenteeism (Özbağ, 2019). However, the integration of AI in the workforce has established unintended consequences on employees' behaviors and outcomes that hinder workplace effectiveness (Malik et al., 2021). Therefore, the current study extends the definition to include those unintended behaviors that emerge from the use of AI. These are not outcomes of deliberate misconduct but result from psychological mechanisms. This extension aligns with Dizard (1985), who states that all technological innovations carry unforeseen consequences on human behavior. In this study, we categorize these as "unintended counterproductive work behaviors". By reframing the fourth dimension of the individual work performance framework, this research aligns with the broader goal of providing a comprehensive view of how AI shapes employee's overall performance.

One prominent example of such a behavior is overreliance on AI, which is defined as excessively relying on AI advice and accepting its incorrect recommendations (Passi et al., 2021). Generally, reliance can positively impact performance, if users trust the system to execute on one part of the work so they can focus on other aspects of the task (Macnamara et al., 2024). Nevertheless, all AI systems can produce errors (Bansal, 2019). Often, the information provided by automated systems, can change a user's visual scanning behavior (Rezazade Mehrizi et al., 2023) and decrease the frequency with which they verify them (Manzey et al., 2012). This behavioral shift is linked to automation bias, where users tend to prioritize input from automated systems over human expertise, even when the recommendations are contradictory or incorrect (Mosier et al., 1997). An example of AI tools causing biases in employees can be seen in recruiting, where the technology is used to screen job candidates and evaluate them for positions through the usage of algorithms (Yarger, 2020). Algorithms can disadvantage employees based on race, gender, or other protected attributes (Chen, 2023). These discriminatory outcomes could be overlooked or ignored by employees due to the wrong assumption that AI systems are inherently objective and unbiased (Kim & Bodie, 2021). Overreliance on AI can even lead users to perform worse on tasks compared to the performance of the user alone or AI working alone (Bansal et al., 2020).

Another example of how AI impacts counterproductivity is its potential to reduce employee effort by diminishing their active engagement and motivation at work (Ahmad et al., 2023). Because the technology has made performing tasks easier and faster, it has made employees impatient and passive (Krakauer, 2016). Instead of improving their own abilities, employees use AI tools to solve problems, which, over time, can lead to a decline in motivation (Farrow, 2022). This growing use of AI technologies not only undermines personal growth but also risks diminishing overall productivity in the long term (Gerrie, 2008).

This reduced engagement not only affects motivation but also might also impact the retention of essential skills over time (Macnamara et al., 2024). Among researchers, there is an ongoing debate about AI undermining critical thinking and problem-solving skills (Kasneci et al., 2023). Furthermore, studies into skill degradation indicate that after a period of non-use of specific skills, proficient performance decreases (Ackerman & Tatel, 2023). For example, Casner et al. (2014) examined the manual flying skills of pilots trained for manual flight, who then spent most of their careers using high levels of automation. Significant declines in cognitive skills were observed, including failures to maintain situational awareness, track the next steps, and make planned adjustments to the route (Casner et al., 2014). This evidence suggests that the overuse of AI systems can reduce motivation and hinder skill retention and personal competence.

Self-Efficacy as a Mediator Between AI Usage and Unintended Counterproductive Work Behavior. Self-efficacy, the same mechanism, that enhances employee performance, could paradoxically negatively impact it at the same time. As previously established, high work-related self-efficacy can lead to improved task, contextual, and adaptive performance by empowering employees and making them feel more capable (Bandura, 1988). Generally, self-efficacy is seen as a positive psychological construct that encourages performance outcomes (Bandura, 1982). However, it could contribute to an exaggerated belief in one’s abilities, where individuals perceive themselves as more competent than they actually are (Moores & Chang, 2009). When this overconfidence is built up alongside using AI, it may contribute to unintended counterproductive work behavior such as making errors due to overreliance, reduced effort, and skill decay.

Because employees can achieve their work goals with the technology, it reduces their awareness for verifying its outputs (Klingbeil et al., 2024). Generally, humans persist in the behaviors that generate these positive feelings and this sense of accomplishment (Brenner et al., 2021). McLuhan (1977) explains that when we use technology so often, we stop noticing how it affects us, similar to how we don't think about our hands when we grab something or our mouths when we speak. Our focus is usually on the goal we're achieving, not the tools we're using to do it (McLuhan 1977). Therefore, when the belief in achieving our goals is high, the awareness of technological activities becomes unnoticed (Gerrie, 2008). When users do not monitor the outcome of automated systems, they allow system errors and other malfunctions to go undetected and therefore negatively affect their performance (Risko & Gilbert, 2016).

Furthermore, when individuals have high self-efficacy, they may reduce their effort when working on tasks (Moores & Chang, 2009). This is because they may prematurely assume they have already reached their goal and reduce their motivation to put in further effort or attention to detail (Vancouver et al., 2001). In this way, AI is reducing humans' independence by substituting their decisions with its decisions and causing them to become lazy in various aspects of life (Danaher, 2018). As a result, this laziness and diminished attentiveness can result in notable declines in performance (Spatola, 2024). This has been confirmed by Moores & Chang (2009), who revealed that overconfidence from high self-efficacy leads to a significant negative relationship between self-efficacy and subsequent performance.

Finally, repeated exposure to efficient and convenient tools, may gradually lead to skill deterioration because of a dependency on these tools (Kumar et al., 2024). Users who use automated systems instead of their own knowledge for an extended period are found to experience a decrease in their abilities once these systems are not available (Ackerman & Tatel, 2023). Furthermore, confident individuals may be less inclined to seek feedback or engage in continuous learning, assuming AI systems are sufficient already (Morandini, 2023). This attitude can prevent them from recognizing and addressing areas where their skills may be declining (Arthur & Day, 2020). Taking these considerations together, these patterns reveal how self-efficacy can act as a double-edged sword, enhancing positive performance while simultaneously contributing to counterproductive behaviors such as overreliance on AI, reduced effort, and skill decay.

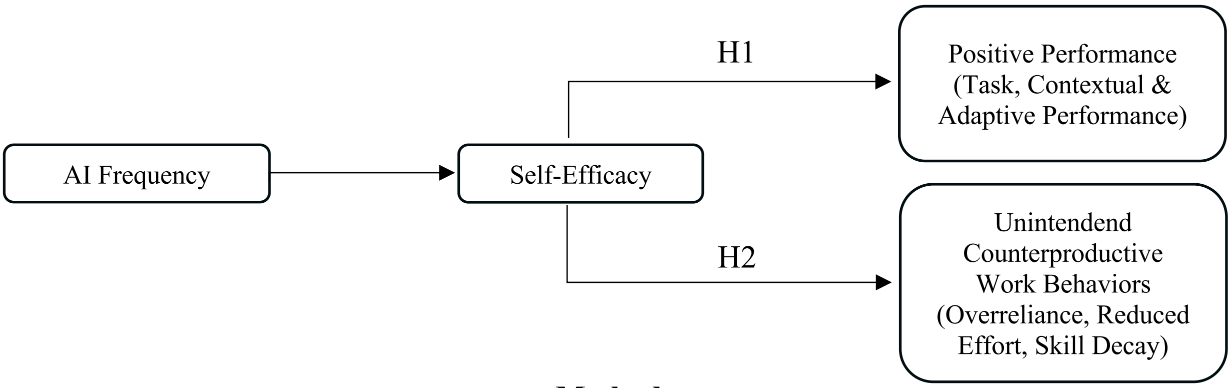
It is important to notice that this study assumes that AI frequency alone does not inherently lead to counterproductive work behaviors. Instead, it is driven by psychological mechanisms. It is assumed that especially employee confidence, which they have established by using AI technologies, can lead to over relying on AI outputs without adequately reviewing them (McLuhan 1977). In the same way, confidence in achieving one's goals may lead to employees reducing their efforts and losing their skills over time once manual involvement goes down (Vancouver et al., 2001; Morandini, 2023). Therefore, the frequency of using AI indirectly influences unintended counterproductive work behaviors by first increasing self-efficacy.

Therefore, this study finally assumes that:

H2: AI usage frequency has a positive relationship with employees' unintended counterproductive work behaviors, and this is mediated by self-efficacy.

Figure 1

Conceptual Model



Method

Study Design and Participants

This research is a quantitative survey aiming to explain the relationship between AI usage frequency and employee performance, including task, contextual, and adaptive performance as well as unintended counterproductive work behavior, with self-efficacy as a mediating factor. To investigate these relationships, a cross-sectional survey was chosen as it is efficient in capturing individual perceptions, behaviors, and beliefs over a single time period (Rindfleisch et al., 2008). The survey was designed as a 10–15-minute online questionnaire. Before its publication, it was approved by the Faculty of Behavioral, Management, and Social Sciences at the University of Twente.

Targeted sampling was used to select participants of any gender and who were employed in any role. This included individuals who are full-time, part-time, or self-employed. Students without a job, the unemployed, or retired were excluded. The ineligibility criteria further excluded minors and occupations focused on manual tasks, such as blue-collar workers. This was to include only those employees who could use AI at work. The respondents were chosen regardless of the industry or the type of AI technology they use.

This approach ensured capturing a variance of people who differ in the frequency of using AI tools in their work.

Procedure

Information was collected purely based on online invitations and promotional ads of the Qualtrics XM questionnaire. Participants were personally approached to ensure a considerable response rate and that adequate time was devoted to completing the survey. Additionally, a public post was shared via LinkedIn and WhatsApp group chats and distributed further by family and friends.

The consent page at the beginning of the survey provided information on the purpose of the study, expectations from the participant, and practical information, for example, the estimated time of completion. It also included ethical considerations, such as the explanation of anonymity and the right to withdraw at any time of the study. Data collection was done at the end of December 2024 and the beginning of January 2025, when employees are less busy and therefore able to complete the study thoroughly. All measurement scales were presented sequentially, and confidentiality was maintained throughout the study.

To collect the data, this study used a questionnaire divided into five sections. In the first section, demographic information was gathered, including participants' gender, age, educational degree, nationality, and industry. In the second section, AI Frequency was measured to delve into the extent of participants' AI use. This part also aimed to account for other factors that might influence the relationship between AI Frequency and Self-Efficacy, such as participants' qualitative experience with AI. In addition, participants also indicated which AI tools they use (e.g., Machine Learning Models, Generative AI Tools) and for what specific tasks (e.g., data analysis, writing, scheduling). These items are not part of any variable but were collected to provide more context and make findings more interpretable for readers. The third section was dedicated to measuring the Self-Efficacy construct. The fourth section measured the Positive Performance outcomes while the fifth focused on the Unintended Counterproductive Work Behaviors. The items used were drawn from validated behavioral studies to ensure validity and reliability, with adjustments to suit the context of AI use.

Materials

AI Frequency. To quantify the respondents' AI utilization, they were asked how often they use AI technologies in their work tasks on a five-point Likert scale, ranging from "*Never*" to "*Always*". The response options were as follows: "Never," indicates no usage of

AI. "Rarely," corresponds to usage once per week. "Sometimes," indicates usage two to three times a week. "Often," signifies usage four to five times per week, and "Always," represents daily or more frequent use. AI Frequency serves as the primary independent variable in this study.

Additionally, participants' positive or negative experiences with AI could add valuable insight into the development of self-efficacy in the work environment. If they found their interactions to be helpful, they may feel more confident in being able to deal with their tasks. Negative or frustrating experiences, on the other hand, may decrease this confidence. To account for these varying experiences, the variable AI Experience was added.

AI Experience. Participants rated their experiences on a five-point scale from "*Negative*" to "*Positive*". By capturing both, how often and how positively AI is integrated into daily tasks, it ensures that the study captures the depth and quality of AI usage in the workplace. However, this measure is not part of the core analysis but will be used for additional exploration to provide more context.

Self-Efficacy. In line with Bandura's (1997) original theory, the Self-Efficacy construct was operationalized to measure the possible impacts of AI on improving work-related self-efficacy. Bandura's self-efficacy theory emphasizes the importance of one's belief in their ability to influence behavior and accomplish one's goals (Bandura, 1997). Based on this definition, Zhang and Xu (2024) measured the construct in the context of AI usage using confidence and efficiency perceptions. This study adopts this approach and formulates five questions to measure the construct accordingly.

First, confidence perception about how AI affects their confidence in solving challenges was measured with the statement, "*Using AI has made me confident in solving work-related problems.*" Secondly, efficiency perception involves perceptions of increased efficiency in performing job duties expressed as "*Using AI has made me more efficient in completing work tasks*.". Thirdly, goal achievement perception measured whether the use of AI tools enhanced the confidence of an individual in reaching their professional objectives, reflected in the item "*Using AI has made me more confident in achieving the goals I have set for myself.*" Fourthly, the belief of whether AI tools support individuals in handling unexpected challenges effectively was assessed with the item "*Using AI has made me more confident in solving unexpected challenges in my work*." All questions used a five-point Likert scale, ranging from "*Strongly disagree*" to "*Strongly disagree*." Taken together, these items fully operationalize the Self-Efficacy construct by capturing confidence and efficiency in task completion, problem-solving, and goal achievement. With a Cronbach's alpha value of .81, the internal reliability of the variable is considered acceptable (George & Mallery, 2019).

Positive Performance. The Positive Performance construct was operationalized using the Individual Work Performance Questionnaire (IWPQ), developed by Koopmans et al. (2014). The IWPQ consists of the three subdimensions of Positive Performance, Task Performance, Contextual Performance, and Adaptive Performance. Each dimension was measured on a five-point Likert scale, ranging from "*Never*" to "*Always*", by using both general and AI-specific items. For the dimension Task Performance, three general items were used, assessing the core execution of the job tasks, for example, "*I manage to plan my work so that it is done on time.*" It also contained three AI-specific items like "*Since I started using AI in my work, I am better able to perform my work with minimal time and effort*," thereby assessing how AI influences task execution. Similarly, Contextual Performance was assessed with three general items related to extra-role behaviors, such as "*I take on extra responsibilities at my work*." In order to investigate the influence of AI on proactive behaviors, three items related to AI such as "*AI tools help me focus on higher-priority tasks*" were added. Finally, Adaptive Performance was measured using three general items to assess adaptability, such as "*I work at keeping my job knowledge up-to-date.*" The AI-specific items, such as "*Using AI helps me develop new skills relevant to my role*," therefore aimed to show how AI acts to enhance the capability of employees to adapt to changing work contexts. This integrated approach will offer a comprehensive measurement of Positive Performance, considering traditional performance indicators and the influence of AI integration in the workplace.

Additionally, the internal reliability of the variable is considered acceptable with a Cronbach's alpha value of .73. The alphas of the subscales are .71 for Task Performance, .57 for Contextual Performance, and .62 for Adaptive Performance. The reliability of the Contextual and Adaptive Performance dimensions falls below the accepted threshold of .70. However, since these dimensions are not the main variables of interest in this study, the findings related to these subscales can be regarded as exploratory and should be interpreted with caution (George & Mallery, 2019).

Unintended Counterproductive Work Behaviors. The original construct of Counterproductive Work Behavior by Koopmans et al. (2014) focuses on intentionally harmful behaviors that reduce organizational effectiveness. In this study, the framework will be extended to focus on unintended negative behaviors, which arise from AI use. Accordingly, Unintended Counterproductive Work Behaviors refer to actions that reduce organizational effectiveness without such being deliberate. Based on the literature review, the construct in this study was measured through three dimensions, Overreliance, Reduced Effort, and Skill Decay.

One way to measure Overreliance is to assess human errors made as a result of unchecked AI outputs (Buçinca et al., 2021), posed as "*I have made errors in my work because I didn't evaluate the output of an AI system.*" Moreover, decision delegation shows where users allow AI tools to fully control decision-making processes without personal evaluation (Chiang & Yin, 2021), measured by *"I let the AI make decisions for me without evaluating its recommendations".* To further account for automation bias, which can be seen in users giving higher credibility to AI outputs than to their own judgement (Mosier et al., 1997), the following item was included *"When presented with conflicting information, I tend to trust the AI output more than my own judgment".*

The Reduced Effort dimension addresses the extent to which workers decrease personal involvement and effort in performing tasks because there are AI tools available to perform them (Parasuraman & Riley, 1997). It reflects motivational disengagement whereby automation reduces the perceived need to put in a personal effort to execute the task (Moores & Chang, 2009). Accordingly, three items were formulated: *"I put less effort into a task because I assumed AI would handle the difficult parts", "I allowed tasks to pile up because I expected AI to streamline them later.", "I avoided learning new skills because I believed AI could perform the task better."* These items try to capture the motivational shift and reduce personal involvement when employees use AI tools.

The dimension Skill Decay refers to whether frequent AI use causes personal skills and poor retention of knowledge over time. This construct is based on the fact that with the continuous use of AI in performing tasks, the use of specific skills decreases, which can eventually lead to the degradation of task proficiency (Ackerman & Tatel, 2023). To capture this effect, three items were developed: "*My ability to perform tasks without AI has decreased over time*," which measures perceived skill loss directly related to AI "*I have stopped seeking new learning opportunities because I believe AI can replace the need for certain skills*," which reflects a stagnation in skill and knowledge, and "*I constantly need validation or feedback from AI systems to feel confident in my decisions*," which gauges dependency on AI for decision-making confidence rather than personal expertise. These statements were designed to capture both perceived skill degradation and reduced proactive learning behaviors as the two important factors indicating skill decay due to frequent AI use (Gerrie, 2008).

The Cronbach's alpha value was measured for the overall variable Unintended Counterproductive Work Behavior and is considered acceptable as it scored .84 The alphas of the subscales are .65 for Overreliance, .80 for Reduced Effort, and .74 for Skill Decay. The Overreliance subscale falls below the conventional threshold of .70. Accordingly, results involving this subscale should be interpreted with caution and regarded as exploratory. (George & Mallery, 2019).

In addition to Unintended Counterproductive Work Behaviors, trust in AI was measured as it might be an antecedent to overreliance on AI and therefore indicate hidden or unconscious behaviors (Klingbeil et al., 2024). Employees' attitudes and beliefs toward AI play a critical role in how effectively they use the technology and benefit from it (Marimon et al., 2024). Without trust, employees may be hesitant to engage with the tool and diminish its potential benefits for their productivity and performance (Chan et al., 2017). Therefore, the AI Trust measurement might give additional insights into both, AI's influence on positive performance and counterproductivity.

AI Trust. Generally, AI Trust reflects a user's perception of the reliability and credibility of the system, which in turn influences his or her likelihood of relying on AI tools (Kohn et al., 2021). Among trust questionnaires, the TPA scale is most frequently used in human-AI research and consists of 12 items (Jian et al., 2000). Three of those were taken over and adapted, for example, "*The AI is reliable*" was changed to "*I find AI systems to be reliable"*. The modified phrasing emphasizes the participant's personal perception rather than making a generalized statement about the AI system itself. The trust measurement provides added context to overreliance behaviors as an indirect indicator of the conditions where overreliance or reduced effort may occur but will be measured separately from the Unintended Counterproductive Work Behavior variable. With a Cronbach's alpha value of .73, the internal reliability of the variable is considered acceptable (George & Mallery, 2019).

To complement the survey items, open-ended questions that queried participants for richer, more detailed descriptions of their experiences with AI tools, were included. The question, "*Have you ever been negatively impacted or experienced any consequence as a result of the use of AI? If yes, please describe what happened*," attempts to capture personal experiences with unintended consequences that might not be captured well by the previously defined dimensions of overreliance, reduced effort, and skill decay. The more general overall reflections questions, "*What do you think are the biggest advantages and disadvantages of using AI tools in your work?"* and "*If you could change or improve anything about how AI tools are integrated into your work, what would it be?"* allowed participants to reflect more holistically on the benefits and challenges of usage on their work performance. These items help capture an in-depth view of AI's influence on performance and behaviors at work.

Pre-Test

Before the survey was published, a pre-test with five participants was conducted. The aim of this was to identify technical issues, ambiguities in the wording of the questions, or challenges that participants might have when answering the questions. According to the feedback from the pre-test, adjustments were made to improve the survey. For example, the survey did initially not exclude participants who responded that AI is not used in their organization. Accordingly, a filter was introduced to exclude those participants. This ensured that only suitable participants took part in the analysis. Additionally, the survey did not ask about participants' professional backgrounds. Therefore, work-related questions were included to make sure only participants who are full-time, part-time, or self-employed could take part in the survey. Furthermore, an option for student workers was added here, so that their responses could be included in the analysis as well. These changes ensured that the survey effectively reached the desired audience and minimized potential sources of unwanted information.

Data Analysis

For the analyses, the statistical software R version 4.4.2 was used. A power analysis was conducted to assess the smallest sample size needed to identify an effect (Erdfelder et al., 1996). The analysis showed a minimum of 296 participants to detect an average effect size ($f^2 = 0.46$) with a power level of 0.80, an alpha level of 0.05, and 6 predictors (AI Frequency, Self-Efficacy, AI Trust, Gender, Education, and Age). This study included a smaller sample of 185 due to time constraints. As a result, the study may be underpowered, which increases the risk of Type II error, and findings should be interpreted with caution.

First, descriptive statistics summarized key characteristics of the dataset (Table 1), including means and standard deviations. These help in gaining an initial understanding of the sample. The bivariate relationship between all of the variables was analyzed via Pearson correlations (Table 2). They provide measures of the strength and direction of the linear relationships (Lee Rodgers & Nicewander, 1988). Subsequently, hierarchical regressions were run to assess the direct effects of the variables AI Frequency, AI Trust and Self-Efficacy on Positive Performance, and Unintended Counterproductive Work Behaviors. Second, a mediation analysis was performed to determine whether Self-Efficacy acts as a mediator for the relationship between AI Frequency and the performance outcomes (H1, H2).

Furthermore, exploratory analyses were conducted to determine whether AI Experience and AI Trust are additional predictors of these relationships. Lastly, qualitative responses were analyzed to complement the quantitative results.

Results

Descriptive Statistics

A total of 185 employees started the questionnaire, while 134 completed it entirely. Those who completed at least 80% of the items of one variable, were included in the analysis for that variable. This led to varying sample sizes across different measures. If a variable with a lower sample size was included in one analysis, its overall sample size decreased. The participants had an average age of M = 31.0 years (SD = 9.4), ranging from 18 to 65 years. The sample was evenly distributed by gender (50% male, 50% female), and the majority of participants had a master's (41%) or bachelor's (37%) degree.

Table 1

Descriptive Statistics of Scales

Variable	N	Mean	Std. Dev.
Age	180	31	9.4
Gender	178		
... Female	89	50%	
... Male	89	50%	
Education	179		
... Bachelor's degree	66	37%	
... Master's degree	73	41%	
... Secondary education (High school)	31	17%	
... Doctorate (PhD)	3	2%	
... Secondary Vocational Education and Training	5	3%	
... Primary education (Elementary school)	1	1%	

The respondents represented various industries (N=180), with the largest group being from the Technology and IT sector (N=57). Other notable industries included Media and Marketing (N=21), Professional Services (N=20), and Finance and Banking (N=11). The Transportation and Logistics sector had the smallest representation with 4 participants.

Furthermore, AI Frequency (N=170) has a trend for frequent usage of AI tools. While only a few of the interviewed respondents never (6%) used AI or just once a week (18%), 23% utilized it occasionally (two to three times a week), and 26% in a regular fashion (four to five times weekly). The other 26% employed AI on a daily or more regular basis, which suggests that AI was widely employed by the respondents. The sample overall was well gender-balanced, mostly highly educated, and reflected high rates of AI use in working contexts.

Moreover, participants had the option to select multiple AI tools and the tasks they used them for. Most frequently mentioned (N=91) were Generative AI tools, such as ChatGPT and DALL·E. This was followed by machine learning models (N=43), natural language processing models (N=38), and deep learning applications (N=28). Respondents use AI mostly for communication tasks (N=63) followed by content creation (N=55), task automation (N=37), and data analysis (N=26). Less frequently cited tasks included problem-solving (N=6), and learning (N=4). For the purpose of this study, the focus was on analyzing the overall impact of AI use on employee performance, regardless of the specific type of AI technology used.

Table 2 displays the Pearson correlation coefficients between the demographic control variables, AI Frequency, Self-Efficacy, Positive Performance, and Unintended Counterproductive Work Behaviors (UCWBs) with its subdimensions, AI Experience, and AI Trust. The results show that AI Frequency is positively correlated with Self-Efficacy and Positive Performance, but has no significant correlations with UCWB overall or its dimensions. This indicates that higher AI usage is associated with enhanced self-confidence and performance outcomes. Self-Efficacy was positively correlated with Positive Performance and its dimensions, while not being correlated with UCWBs. This indicates that higher self-efficacy is only associated with better performance outcomes. Among the Positive Performance dimensions, Task Performance was most highly correlated with AI Frequency. Overall, the variables related to Positive Performance show higher correlations than those involving UCWBs. The correlations ranged from .21 to .61, which are considered moderate to strong correlations, according to Dancey's (2007) classification.

Table 2

Pearson Correlation Between Variables (N=134)

Variable	**M**	**SD**	**1**	**2**	**3**	**4**	**5**	**5a)**	**5b)**	**5c)**	**6**	**6a)**	**6b)**	**6c)**	**7**	**8**
1. Age	30.84	9.35	-													
2. Gender	0.50	0.50	**.26**													
3. Education	4.05	1.12	**.29**	-0.3												
4. AI Frequency	3.48	1.24	.05	.01	**.26**											
5. Self-Efficacy	3.55	0.75	-.08	-.02	.03	**.40**										
6. Positive Performance	3.62	0.35	-.00	-.01	**.21**	**.38**	**61**									
a. Task Performance	3.78	0.46	-.07	-.12	.15	**.44**	**.56**	**.75**								
b. Contextual Performance	3.49	0.48	.08	.01	**.18**	**.21**	**.31**	**.73**	**.23**							
c. Adaptive Performance	3.60	0.45	-.02	.10	.16	**.21**	**.54**	**.82**	**.49**	**.41**						
7. UCWB	2.39	0.70	**-.20**	-.07	-.08	-.01	**.24**	.03	-.12	**-.20**	-.03					
a. Overreliance	2.66	0.70	-.17	.03	.01	.04	.06	.02	-.09	-.12	.02	**-.59**				
b. Reduced Effort	2.35	0.86	-.10	-.09	-.09	-.06	**.21**	.02	-.07	**.19**	-.06	**-.89**	**.34**			
c. Skill Decay	2.33	0.85	**-.19**	-.04	-.07	.04	**.21**	.00	-.13	**.18**	-.05	**-.89**	**.39**	**.66**		
8. AI Experience	4.21	0.81	.10	-.02	.10	**.48**	**.37**	**.38**	**.45**	.13	**.29**	**.17**	**-.18**	-.12	**-.22**	
9. AI Trust	3.12	0.75	-.16	.02	-.08	.12	**.46**	**.36**	**.30**	**.22**	**.30**	**-.42**	.15	**.39**	**.32**	**.20**

p<0.05

Effects of AI Frequency on Positive Performance and UCWB

A hierarchical regression analysis was conducted to examine whether AI Frequency predicts Positive Performance with Age, Gender, and Education as control variables (Table 3). The study employed a four-step hierarchical approach, which introduced the predictors in the following order: demographic control variables (Age, Gender, Education), AI Frequency, AI Trust, and Self-Efficacy. The results show that the control variables did not significantly predict Positive Performance (adjusted R^2=.011, F (3, 130) = 1.506, p = .216). Step 2 improved the model fit (ΔF (1, 129) = 24.187, $p < .001$) with AI Frequency significantly predicting Positive Performance. This indicates that higher AI usage frequency is associated with better performance outcomes. AI Trust was included as an exploratory predictor in step 3 and also emerged as a significant contributor to Positive Performance. The addition of Self-Efficacy further improved the model significantly (ΔF (1, 127 = 37.088, $p < .001$) and emerged as the strongest predictor for Positive Performance. Additionally, AI Frequency and AI Trust were no longer significant in the final model, which suggests that the effect of AI Frequency on Positive Performance is mediated through Self-Efficacy.

Table 3

Hierarchical Regression Analysis for Positive Performance (n=134)

Step	Predictor	B	SE	t	p	95% CI
1	Age	-0.003	0.003	-0.796	.428	[-0.010, 0.004]
	Gender	0.025	0.061	0.403	.688	[-0.098, 0.148]
	Education	0.064	0.030	2.120	.036	[0.004, 0.124]
2	Age	-0.000	0.003	-0.046	.963	[-0.007, 0.007]
	Gender	0.018	0.058	0.315	.753	[-0.097, 0.134]
	Education	0.031	0.030	1.038	.301	[-0.027, 0.089]
	AI Frequency	0.105	0.026	4.088	<.001	[0.054, 0.156]
3	Age	0.002	0.004	0.512	.610	[-0.004, 0.008]
	Gender	0.004	0.055	0.079	.937	[-0.105, 0.114]
	Education	0.040	0.028	1.418	.159	[-0.014, 0.094]
	AI Frequency	0.094	0.024	3.847	<.001	[0.046, 0.141]
	AI Trust	0.152	0.036	4.197	<.001	[0.080, 0.224]
4	Age	0.002	0.003	0.547	.585	[-0.004, 0.008]
	Gender	0.003	0.049	0.065	.948	[-0.093, 0.099]
	Education	0.041	0.025	1.638	.104	[-0.007, 0.088]
	AI Frequency	0.038	0.023	1.615	.109	[-0.008, 0.084]
	AI Trust	0.055	0.036	1.550	.124	[-0.015, 0.126]
	Self-Efficacy	0.234	0.039	6.090	<.001	[0.159, 0.310]

Further additional analysis examined the relationship between the AI Frequency and the three Positive Performance dimensions Contextual Performance, Task Performance, and Adaptive Performance (See Appendix C, Table 9). Three multiple linear regression analyses were used with Age, Gender Education, AI Trust, and Self-Efficacy as Control variables. The results show that the AI Frequency significantly predicts Task Performance ($B = 0.101$, $SE = 0.032$, $p = .002$, 95% CI [0.037, 0.165]). This indicates that employees who use AI more frequently tend to specifically perform better on task-related aspects of their work.

In contrast, AI Frequency did not significantly predict Contextual Performance ($B = 0.031$, $SE = 0.037$, $p = .409$, 95% CI [-0.050, 0.112]) or Adaptive Performance ($B = –0.018$, $SE = 0.032$, $p = .570$, 95% CI [-0.080, 0.043]). Across all three models, Self-Efficacy emerged as the most robust and consistent predictor of performance outcomes ($ps < .05$). Trust did not significantly predict any performance outcomes. These results suggest that frequent AI use most strongly enhances task-related performance, while Self-efficacy seems to be a general driver of performance across all work behaviors. Therefore, these findings provide partial support for Hypothesis 1.

Next, a hierarchical regression analysis examined whether AI Frequency contributes to UCWBs with Age, Gender, and Education as control variables (Table 4). Predictors were entered in four steps, following the same logic as the model for Positive Performance. The control variables (Age, Gender, Education) did not significantly predict UCWBs (adjusted $R^2 = .026$, $F(3, 130) = 2.179$, $p = .094$). Only Age shows a significant effect, which indicates that older employees tended to report higher UCWB. Adding AI Frequency in step 2 did not significantly improve the model ($\Delta F(1, 129) = 0.100$, $p = .752$). However, in step 3 AI Trust significantly enhanced the model fit ($\Delta F(1, 128) = 23.636$, $p < .001$) and emerged as a strong positive predictor of UCWB. The inclusion of Self-Efficacy in the final step did not show a significant change in model fit ($\Delta F(1, 127) = 0.559$, $p = .456$). Additionally, neither Self-Efficacy nor AI Frequency were significant in the final model. These results highlight AI Trust as the only substantial predictor of higher UCWB.

Table 4

Hierarchical Regression Analysis for UCWB (n=134)

Step	Predictor	B	SE	t	p	95% CI
1	Age	-0.015	0.007	-2.021	.045	[-0.030, 0.000]
	Gender	-0.021	0.122	-0.176	.861	[-0.262, -0.219]
	Education	-0.037	0.060	-0.626	.532	[-0.155, -0.081]
2	Age	-0.015	0.007	-2.032	.044	[-0.029, -0.001]
	Gender	-0.021	0.123	-0.167	.868	[-0.263, 0.220]
	Education	-0.032	0.062	-0.520	.604	[-0.155, 0.080]
	AI Frequency	-0.016	0.054	-0.292	.770	[-0.123, 0.091]
3	Age	-0.011	0.007	-1.534	.127	[-0.024, 0.002]
	Gender	-0.054	0.113	-0.477	.634	[-0.263, 0.220]
	Education	-0.011	0.058	-0.193	.847	[-0.155, 0.080]
	AI Frequency	-0.043	0.050	-0.860	.392	[-0.123, 0.091]
	Trust	0.364	0.075	4.870	<.001	[0.216, 0.512]
4	Age	-0.011	0.007	-1.535	.127	[-0.024, 0.002]
	Gender	-0.054	0.114	-0.479	.633	[-0.263, 0.220]
	Education	-0.011	0.058	-0.193	.847	[-0.155, 0.080]
	AI Frequency	-0.060	0.055	-1.083	.281	[-0.123, 0.091]
	Trust	0.337	0.075	4.023	<.001	[0.216, 0.511]
	Self-Efficacy	0.067	0.090	0.748	.456	[-0.111, 0.245]

Additional regression analyses were conducted to examine whether AI Frequency predicts the three UCWB dimensions, Overreliance, Reduced Effort, and Skill Decay, with Age, Gender Education, Trust, and Self-Efficacy as Control variables (See Appendix C, Table 10). Neither of the relationships between AI Frequency and the UCWB dimensions are significant. However, AI Trust significantly predicted both Reduced Effort ($B = 0.403$, $SE = 0.103$, $p < .001$, 95% CI [0.199, 0.608]) and Skill Decay ($B = 0.403$, $SE = 0.103$, $p < .001$, 95% CI [0.199, 0.608]). Together, these results indicate that AI usage frequency does not meaningfully predict UCWB or its subdimensions. Yet, employees who trust AI are more likely to experience reduced effort and skill decay as unintended consequences of AI usage.

The Mediating Role of Self-Efficacy in the Relationship Between AI Frequency and Employee Performance

A mediation analysis tested whether the effect of AI Frequency on Positive Performance is mediated by Self-Efficacy with Age, Gender, Education, and Trust as control variables (Table 5). A nonparametric bootstrap confidence interval method (1000 simulations) was used as it provides a robust estimate of the mediation effect (Alfons et al., 2021). The mediation analysis revealed a significant indirect effect of AI Frequency on Positive Performance through Self-Efficacy. Specifically, AI Frequency positively predicted Self-Efficacy (B = 0.241, p<.001), and Self-Efficacy, in turn, positively predicted Positive Performance (B = 0.234, p<.001). The indirect effect accounted for 59.7% of the total effect. The direct effect was not significant, which indicates that the impact of AI usage frequency on work performance is primarily explained by Self-Efficacy and therefore an indirect-only mediation.

Table 5

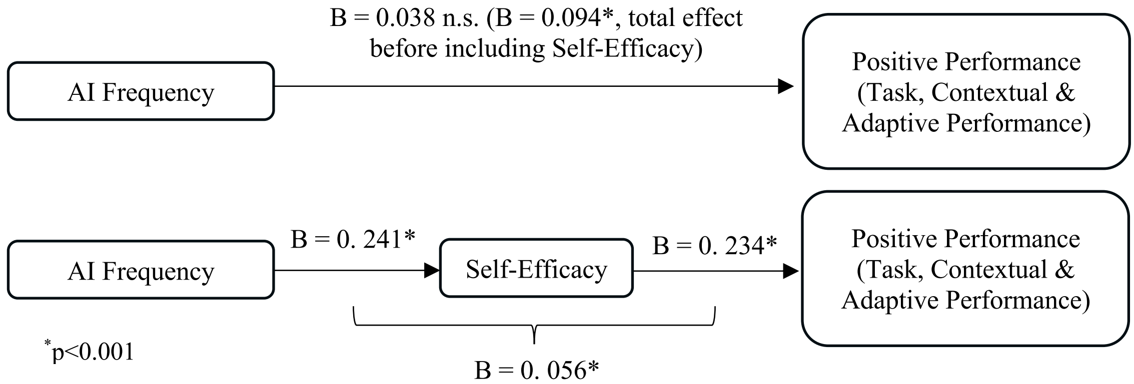
Mediation Analysis between AI Frequency and Positive Performance through Self-Efficacy

Effect	B	95% Confidence Interval	p-value
Indirect Effect	0.056	[0.027, 0.090]	<.001
Direct Effect	0.038	[-0.012, 0.090]	.134
Total Effect	0.094	[0.044, 0.140]	.002
Prop. Mediated	0.597	[0.264, 1.220]	.002

Sample Size Used: 134
Simulations: 1000

Figure 2

Mediation Analysis



The second mediation analysis examined whether the relationship between AI Frequency and UCWB is mediated by Self-Efficacy, with Age, Gender, Education, and Trust as control variables (Table 6). Here, the same procedure as for mediation analysis between AI Frequency and Positive Performance through Self-Efficacy was used. The results showed no significant indirect effect of AI Frequency on UCWB through Self-Efficacy. Similarly, the direct effect and the total effect remained non-significant. These results do not provide evidence for a meaningful mediating role of Self-Efficacy in the relationship between AI Frequency and UCWB.

Table 6

Mediation Analysis between AI Frequency and UCWB through Self-Efficacy

Effect	B	95% Confidence Interval	p-value
Indirect Effect	0.061	[-0.032, 0.060]	.460
Direct Effect	-0.059	[-0.153, 0.030]	.230
Total Effect	-0.043	[-0.136, 0.050]	.380
Prop. Mediated	-0.372	[-5.307, 5.570]	.740

Sample Size Used: 134
Simulations: 1000

The Role of AI Trust In Predicting Employee Performance

In addition to the primary focus of this study, AI Trust significantly improved the model fit of the hierarchical regression predicting Positive Performance (ΔF (1, 128) = 22.579, $p < .001$) and emerged as a significant positive predictor. However, when Self-Efficacy was added in the final step, the effect of AI Trust became non-significant. This suggests that Self-Efficacy may be explaining some of the variance in Positive Performance that was initially attributed to AI Trust. One explanation for this is that the effect of AI Trust on Positive Performance is mediated by Self-Efficacy.

This was confirmed by a mediation analysis examining whether the relationship between AI Trust and Positive Performance is mediated by Self-Efficacy (Table 7). It revealed a significant indirect effect of AI Trust on Positive Performance through Self-Efficacy. The direct effect after accounting for Self-Efficacy as a mediator was non-significant, which suggests that the relationship between Trust and Positive Performance is primarily mediated by Self-Efficacy.

Table 7

Mediation Analysis between AI Trust and Positive Performance through Self-Efficacy

Effect	B	95% Confidence Interval	p-value
Indirect Effect	0.097	[-0.056, 0.150]	<.001
Direct Effect	0.055	[-0.010, 0.130]	.120
Total Effect	0.152	[0.084, 0.220]	<.001
Prop. Mediated	0.636	[0.322, 1.120]	<.001

Sample Size Used: 134
Simulations: 1000

Furthermore, a mediation analysis examining whether the relationship between AI Trust in UCWB is mediated by Self-Efficacy (Table 8). The results revealed that the indirect effect through Self-Efficacy was not statistically significant. The analysis revealed a significant direct effect of Trust, which indicates that higher trust in AI is associated with more unintended counterproductive work behaviors. Therefore, Trust appears to influence UCWB directly, independent of individuals' confidence in using AI. These findings support the idea that Trust plays a meaningful role in explaining workplace outcomes in the context of AI, especially in enhancing negative behaviors.

Table 8

Mediation Analysis between AI Trust and UCWB through Self-Efficacy

Effect	B	95% Confidence Interval	p-value
Indirect Effect	0.028	[-0.045, 0.120]	.400
Direct Effect	0.336	[-0.158, 0.530]	<.001
Total Effect	0.364	[0.212, 0.530]	<.001
Prop. Mediated	0.076	[-0.129, 0.350]	.400

Sample Size Used: 134
Simulations: 1000

The Moderating Role of AI Experience in the Relationship Between AI Frequency and Self-Efficacy

As further exploratory insights, a moderation analysis was conducted to examine whether positive AI Experience moderates the relationship between AI Frequency and Self-Efficacy. This analysis was based on the assumption that frequent AI use may only enhance Self-Efficacy when those experiences are perceived as positive. A multiple linear regression was performed including the main effects of AI Frequency and AI Experience, as well as their interaction term (AI Frequency × AI Experience), along with Age, Gender, and Education as control variables. The interaction term was not statistically significant ($B = 0.05$, $SE = 0.05$, $t = 0.91$, $p = .364$), which indicates that AI Experience did not significantly moderate the relationship between AI Frequency and Self-Efficacy.

Qualitative Results

To complement the quantitative results, open-text responses were analyzed to identify common themes. While not analyzed through a full thematic approach, several common key insights were identified. Responses were reviewed and grouped into broad categories based on recurring topics. A main theme was concerns about AI accuracy and reliability. Several respondents (N=74) mentioned issues such as “wrong information”, “generating incorrect outputs” and “every type of information must be evaluated carefully”. These reflect a general caution around AI-generated content. Another main theme was participants reporting reduced cognitive engagement. A few respondents (N=38) noted becoming overly reliant on AI, indicating possible effects on critical thinking, for example of person explained “I used all the AI input, which was lazy.”

In terms of advantages, efficiency and time-saving occurred as a main theme. The most frequent advantage cited was time-saving on manual or repetitive tasks such as summarizing documents, drafting emails, or automating reports (N=63). Examples of respondents’ answers include “AI has helped me be more productive and accomplish more tasks as my to-do list continues to grow.” “Advantage: Accelerating manual tasks, research, and idea generation.” This suggests that AI's greatest benefits may lie in reducing cognitive load for routine work. Several responses (N=27) also suggested that AI is not suitable for every type of task, especially with increasing complexity. Some users reported that AI tools can generate errors or oversimplify complex problems and that outputs often require careful verification.

For recommendations for improvement, participants suggested clearer instructions, improved fact verification, and simplified outputs. They wish for instance for “Source tagging, option to weight different facts.” and “More instructions on how to optimize my workloads”. This qualitative input supports the observed duality in the quantitative findings, where AI use enhances performance, particularly task performance. However, it also highlights user negative experiences and a desire for more transparent and tailored AI interactions.

Discussion

The introduction of AI in organizations has significantly transformed how employees think, decide, and engage with their tasks (Wang et al., 2023). Accordingly, it influences how they perform at their work (Jutel, 2023). The use of AI technologies could enhance employee performance beyond enhancing efficiency, by improving decision making, extra-role engagement, and supporting skill development (Chen et al., 2024; Ameen et al., 2022; Cacicio

& Riggs, 2023). At the same time, it could impact employee performance by increasing mistakes due to overreliance, reduced effort, and skill degradation (Malik et al., 2021). This study aimed to explain this duality by investigating the psychological mechanisms at play, in particular self-efficacy. Specifically, the purpose of the present study was to investigate how frequent AI usage boosts self-efficacy and thereby simultaneously influences positive performance outcomes (task, contextual, and adaptive performance) as well as unforeseen counterproductivity (overreliance, reduced effort, and skill decay).

The results show that frequent AI use positively impacts employee positive performance through self-efficacy, particularly in task performance. However, the relationship between AI usage frequency and unintended counterproductive was not significant. These findings both confirm and challenge aspects of the current understanding of workplace technology integration. Throughout the following sections, these findings will be discussed in light of existing literature. Furthermore, organizational practical recommendations will be given and lastly, limitations and potential future research directions will be explored**.**

Effects on Positive Performance

The impact of AI usage on positive performance has been a significant area of research in recent years (Huang & Rust, 2018). The findings of this research support a positive association between the frequency of using AI and overall positive performance. However, the relationship is not entirely direct. As the analysis illustrates, the relationship between AI frequency and positive performance is mediated primarily through self-efficacy. This highlights the critical role of self-efficacy in bridging AI usage with enhanced performance levels and therefore, provides strong evidence for the psychological mechanism at play. It means that frequent AI use impacts employees' overall performance by enhancing their confidence in their own abilities.

When examining the different positive performance dimensions, the results showed that, without considering self-efficacy as a mediator, AI usage frequency directly influenced task performance, with no significant effects on contextual performance and adaptive performance. The influence of frequent AI use on task performance shows that the technology use is directly linked to facilitating employees in completing core work tasks. Several qualitative responses about the highest advantage of AI support this finding. Additionally, this was shown in studies across various sectors, such as manufacturing, healthcare, and agriculture (Chen et al., 2024).

The positive relationship between AI frequency and task performance is further justified by theoretical expectations based on the Technology Acceptance Model. According to Davis (1989), increased usage of a technology makes the technology appear easier to use and more helpful for tasks. This creates a virtuous cycle, in which repeated usage enhances understanding and useful application of AI tools, gradually building up their positive effects in the long term (Saadé, 2007). These results indicate that companies may be able to maximize AI returns by encouraging employees to use such technology more regularly. With users dealing with AI-enabled tools more often, they would most likely be more productive.

The lack of significant effects on contextual and adaptive performance may reflect the current strengths and limitations of AI in the workplace. Contradicting previous literature, AI may be only effective for executing work tasks, but its direct influence might not persist in subsequent tasks performed independently by humans. This was also shown by a recent study, which investigated the immediate and sustained effects of human-AI collaboration across four online experiments. Their results revealed that the technology enhanced immediate task performance, but the transition from working with AI tools to working alone led to a decrease in employees' intrinsic motivation and an increase in feelings of boredom (Wu et al., 2025). Contextual performance, the engagement in tasks beyond core responsibilities, requires intrinsic motivation (Lavelle, 2010). It is also a driver for adaptive performance as it influences employees to proactively learn new skills during organizational changes (Di Domenico & Ryan, 2017). Therefore, while AI boosts short-term productivity directly, its long-term impact on psychological engagement and adaptability remains unclear.

It is further important to recognize that employee's perceived benefits appear to be task-specific. While AI seems to enhance efficiency in structured and predictable tasks, some participants also expressed reservations about its limitations. In particular, concerns were raised about the lack of fit for tasks with higher complexity. These reflections align with recent literature, which emphasizes that AI agents often produce more errors when they have to take more steps to complete a task (Varanasi, 2025). The danger is that individuals find it challenging to detect mistakes made by AI systems in such complex tasks (Bansal, 2019). As a result, individuals might over-rely on AI systems and accept recommendations even if they are incorrect (Vasconcelos et al., 2023).

Recent studies have analyzed the role of task complexity in human-AI performance, such as Salimzadeh et al. (2024), who examined how task complexity influences human-AI decision-making. They conducted an experiment in a trip-planning task, where they manipulated task complexity. The results showed that with higher complexity, humans tend to shift from their own judgment to relying on AI systems. This could be due to heightened information overload in such activities (Chan et a., 2015). Furthermore, employees often perceive AI as more competent than humans in more difficult tasks because AI explanations simplify complex processes (Vasconcelos et al., 2023). Employee’s excessive reliance can ultimately have a negative impact on their performance by reducing appropriate reliance levels (Salimzadeh et al., 2024). Therefore, these findings suggest that organizations should focus on identifying task domains where AI is most effective.

Taken together, AI usage may directly improve task performance, but its influence on all positive performance dimensions is mediated by self-efficacy. This means that the self-confidence employees gain from using AI tools is what drives improvements in other areas of work and therefore, general work performance. This finding is in line with Bandura’s (2006) social cognitive theory, which posits that self-efficacy, the belief in one’s ability to execute actions necessary to achieve a goal, is a key determinant of motivation, perseverance, and ultimately performance. When employees use AI systems, they are often able to complete tasks better and more efficiently. These experiences serve as mastery experiences, which Bandura identifies as the most powerful source of self-efficacy (Bandura, 1982). For example, when AI tools assist in analyzing data, generating reports, or suggesting decisions, employees feel more competent in executing these as well as other responsibilities.

These results are also supported by more contemporary research by Lin (2023) in the educational context. They found that AI-assisted learning enhances the self-efficacy of students and, consequently, improves their learning performance. Similarly, Noy and Zhang's (2023) research demonstrated that AI tools can significantly enhance self-efficacy and performance in learning settings. The present study extrapolates these findings to the work setting, suggesting that AI use enhances workers' confidence in their capacity, which results in improved overall performance.

However, it has to be noted that although the relationship between AI frequency and positive performance through self-efficacy is statistically significant, the effect size is relatively small. This indicates that AI frequency does have an impact on employee performance, but the practical significance of this effect is minimal and may not be of substantial relevance in real-world applications.

Additionally, the pattern may change if another relevant mediator is accounted for. Another important mediator in this relationship could be perceived job autonomy. It is defined as the degree of freedom employees feel to determine the methods, processes, and timing of their tasks (Hackman & Oldham, 1975). AI technologies can take over repetitive tasks and enable greater self-management, which could impact the level of autonomy employees feel (Morgeson & Humphrey, 2006). This perception can in turn facilitate employee performance because it promotes positive attitudes and behaviors (Humphrey et al., 2007). Employees who perceive autonomy take an active interest in how their job is structured, guided by intrinsic motivation (Joo et al., 2010). For example, Kong et al. (2023) revealed in a recent study that employees who perceive AI-supported autonomy engender intrinsic work motivation, which leads to more exploratory activities and higher performance.

In addition to the primary focus of this study, exploratory analysis tested whether positive AI Experience would moderate the relationship between AI Frequency and Self-Efficacy. This assumption was based on the idea that AI usage may be more beneficial when accompanied by positive experiences. However, the interaction term was not statistically significant, which indicates that the strength of the relationship between AI use and self-efficacy did not depend on how positively the experience was rated.

A possible reason for this non-significant finding is that while positive experiences with AI can enhance self-efficacy, the effect may be more direct rather than interactive. That is, both frequency and quality of experience contribute independently to self-efficacy, but their interaction may not add explanatory power. Additionally, it is possible that the measurement of positive AI experience in this study captured only general satisfaction, rather than deeper aspects such as mastery or meaningful accomplishment, which are more closely tied to self-efficacy building according to Bandura's theory (Bandura, 1997).

Effects on Counterproductive Work Behaviors

The relationship between AI usage frequency and unintended counterproductive work behaviors presents a nuanced picture. The findings revealed that there were no direct significant relationships between AI usage frequency with unintended counterproductive work behaviors. This indicates that the interaction can be indirect and influenced by multiple psychological and organizational factors. However, the mediation analysis also identified no significant negative indirect effect of AI use on negative work behaviors through self-efficacy. This suggests that high usage of AI doesn't increase unintended counterproductive work behaviors through self-efficacy.

This finding challenges earlier assumptions made in the theoretical framework, which were based on the notion that increased self-efficacy from AI assistance might encourage overreliance, reduced effort, or skill decay (Klingbeil et al., 2024; Moores & Chang, 2009; Morandini, 2023) It was assumed that employees, who achieve work targets in collaboration with AI tools, may lower their awareness for verifying AI outcomes, and thus they might make errors (Klingbeil et al., 2024). This was assumed to make them "lazy" and unconsciously reduce their efforts (Moores & Chang, 2009). Similarly, more self-assured individuals would be less motivated to seek feedback because of thinking that AI technologies are sufficient to perform their work tasks (Morandini, 2023). This mindset was theorized to prevent them from detecting and counteracting areas in which their skills are declining (Arthur & Day, 2020). However, the actual data suggests that frequent AI use and greater self-efficacy don't lead to such unintended effects.

The absence of these effects raises questions about psychological and methodological factors that may obscure these effects. One factor could be social desirability bias, the tendency to report behaviors perceived as socially acceptable (Hebert et al., 1995). This could lead participants to understate overreliance on AI or overstate that they are verifying its outputs. For instance, employees might avoid admitting to reduced effort because to concerns in a work context competence is highly valued. This aligns with findings that self-reports of certain behaviors are systematically distorted by stigma or perceived norms (Latkin et al., 2017).

Additionally, common method bias may attenuate true relationships (Kreitchmann et al., 2019) This is because people might answer similar questions in the same way, even if the things being measured are actually different. For example, if participants conflate being faster at work because of AI with being more flexible, they might give high ratings for both. These biases suggest that unintended consequences could manifest in ways that defy conscious awareness or remain unreported due to measurement limitations. Future research could mitigate these issues through longitudinal designs with objective performance metrics (e.g., error rates in AI-verified vs. non-AI tasks).

A notable strength of this study lies in its novel extension of the traditional counterproductive work behavior concept to include unintended negative consequences of AI use. While the conventional construct typically focuses on deliberate harmful actions, this study broadens the construct to encompass inadvertent negative outcomes that may arise through technological interaction. This expansion acknowledges the evolving nature of workplace behaviors in increasingly AI-integrated environments.

Yet, this extended conceptualization may not capture the full range of negative effects that can arise from AI use. For example, the introduction of new technology can negatively impact employees' well-being and productivity by inducing job insecurity (Gallie et al., 2016). Job insecurity is a psychological state when fearing job loss through environmental cues, such as technological changes (Greenhalgh & Rosenblatt, 1984). If workers anticipate negative future impacts on their employment, they might develop anxiety (Patel et al., 2018). This anxiety can have negative effects on employees' performance, including avoiding tasks or absenteeism (Cullen et al., 2014). Research has shown the positive impacts of negative emotions on counterproductive work behaviors, such as being less productive (Liu et al., 2023; Xu & Lu, 2023).

Furthermore, in contrast to the hypothesized relationship in this study, some literature indicates that self-efficacy from the use of AI can actually reduce these types of counterproductive work behavior. For instance, Kim et al., 2024 found that self-efficacy at work actually mitigated counterproductive behaviors among employees, such as being less productive due to job insecurity (Kim et al., 2024). Liu et al. (2023) also carried out a study where it was found that self-efficacy could mitigate employee burnout due to technology stressors and that this could possibly minimize negative workplace behavior. Therefore, future research could refine the construct of unintended counterproductive work behaviors to better understand the nuanced effects of AI use in the workplace.

The Role of AI Trust

Further exploratory analyses revealed that trust in AI plays a significant role in shaping both positive and negative workplace outcomes. In terms of positive performance outcomes, AI trust positively influences it through self-efficacy, rather than directly. This could be explained by Gist and Mitchell (1992), who state that employees who have trust in their work environment, including its tools, believe they are more capable of performing their work tasks. In turn, employees with higher work self-efficacy are more likely to reach higher performance achievements (Bandura, 1997).

In terms of unintended counterproductive work behaviors, high trust in AI emerged as the strongest predictor, independent of self-efficacy levels. When considering the counterproductive behavior subdimensions, AI trust wasn't a significant predictor for overreliance, which contradicts prior research (Klingbeil et al., 2024). Yet, other studies have also shown that individuals may not necessarily increase their reliance on AI systems even if they trust them (Kirlik, 1993). Instead, they might rely more on their own judgments despite acknowledging the capabilities of the AI system. In this way, the trusting behavior of users can differ from their trusting beliefs (Miller et al., 2016).

However, AI trust emerged as a strong predictor for reduced effort and skill decay. This is in line with current literature, confirming that over-trusting AI systems might create a false sense of security, which leads employees to be more impatient and passive (Krakauer, 2016). Instead of improving their own abilities, employees use AI tools to solve problems, which, over time, can lead to a decline in motivation and skills (Farrow, 2022). This finding suggests that risks like skill atrophy are more closely tied to employees' trust in AI's capabilities than to how frequently they use the technology. Organizations must therefore evaluate not just adoption rates but also how employees psychologically engage with AI.

Overall, the findings of this study underscore the need for a more holistic strategy for AI integration that balances both performance enhancement and potential psychological impact on employees. Specific measures include intensive training programs to enhance AI literacy and critical thinking while responding to AI outputs (Stajkovic & Luthans, 2022). Open communication of AI integration goals and regular impact assessment are necessary (Botica, 2024). Additionally, mandating cross-checks of AI recommendations, which is already seen in legal firms using AI contract reviewers, mitigates performance declines by maintaining human expertise (Bansal et al., 2021). For instance, regular audits of AI's impact on workflows help identify emerging errors made in AI-human collaboration (Shollo et al., 2020). These measures can help organizations take advantage of the benefits of AI while minimizing the risk of unintended behavior.

Finally, questions about ethical responsibility and accountability become increasingly important as organizations rely on AI to make decisions (Khan & Vice, 2022). The literature highlights that accountability for AI errors is often diffused among organizations as well as developers (Bartsch et al., 2024). Therefore, it is critical that organizations establish clear governance structures, which guide the ethical use of AI technologies (Ligot, 2024). This includes taking responsibility for its outcomes, proactively informing how AI is being utilized, and providing avenues for redress for mistakes (Cheong, 2024).

Future research

While this study focused on self-efficacy as a mediator, future research could disentangle self-efficacy from overconfidence, which refers to more unwarranted certainty in one's own capabilities. Overconfidence, often linked to automation complacency, could explain unintended consequences like overreliance better. For example, employees who feel overly confident in their AI-aided abilities may neglect critical verification. Operationalizing these constructs separately and using scales like the Overconfidence Scale (Moore & Healy, 2008) alongside Bandura's self-efficacy measures could clarify their distinct roles in AI-driven performance.

The construct of AI usage frequency, so how often employees interact with AI, has limitations in capturing the nuanced relationship between AI and workplace outcomes. The findings of this study, specifically in terms of trust, suggest that how employees engage with

AI (e.g., depth, purpose, criticality) may better explain its effects on performance and unintended consequences.

Additionally, the study's cross-sectional design leaves open the question of whether long-term AI use mitigates negative effects. Longitudinal research could test if initial overreliance diminishes as users gain experience, refining their ability to balance AI assistance with independent judgment. For instance, employees might develop AI expertise over time, and learn to identify tasks where human oversight is critical. This aligns with the expertise reversal effect in educational psychology, where novices benefit more from AI guidance than experts (Kalyuga, 2007).

The relatively small sample size and homogeneity consisting of mostly highly educated and more regular user limits the generalizability of findings. Replication with larger, more diverse samples would strengthen external validity. For example, industries with stringent safety protocols (e.g., healthcare, manufacturing) may exhibit different patterns of AI trust and counterproductive behaviors. Additionally, addressing selection bias, where participants in AI studies tend to be tech-affine already, could involve recruiting through organizations with mandatory AI adoption policies to capture a broader range of behaviors.

Furthermore, it is important to note that the present study relies on self-reported measures of positive performance rather than objective performance data. This means that the results reflect participants' own perceptions of how well they performed at work, and not whether they truly performed better or worse. Self-reports are also subject to biases such as overestimation or social desirability. Especially, the items on this construct might be prone to social desirability bias, as participants could be reluctant to admit making mistakes since such behavior could be seen as unprofessional. Therefore, future research should incorporate objective performance metrics or supervisor ratings alongside self-reported data to provide a more comprehensive assessment of AI's effects in the workplace.

Finally, the objective of this study was to evaluate the general impact that AI as a whole has on employee performance, regardless of the type of technology used, such as machine learning, deep learning, and natural language processing. This approach was chosen because of the increasing prevalence of AI technologies in workplaces. Employees often interact with a combination of different AI tools in their daily tasks (Jarrahi, 2018). However, it is recognized that each type of AI technology has distinct characteristics and applications. In future studies, a more nuanced analysis that differentiates between specific AI technologies could provide deeper insights into the distinct impacts each technology has on various aspects of employee performance.

Conclusion

This study set out to explore the interplay between frequent AI use, self-efficacy, and employee performance, which included examining the potential for unintended negative consequences in the workplace. In this way, it attempted to contribute to a holistic approach to performance improvement by using AI. The findings suggest that frequent use of AI is positively associated with positive employee performance through the mediating effect of self-efficacy. This supports the idea that when employees feel more confident in their ability to perform work tasks, they are likely to perform better across different performance dimensions. However, a direct positive association, without considering self-efficacy as a mediator, was observed only for task performance and in less complex tasks.

Contrary to initial expectations, the study did not find a relationship between frequent AI use and unintended counterproductive work behaviors through self-efficacy. This may be due to the subtle and gradual nature of these negative effects, which can go unnoticed by employees themselves or be underreported due to social desirability bias. Interestingly, the results also highlight that trust in AI plays a double-edged role. While it boosts performance via self-efficacy, it is also the strongest predictor of reduced effort and skill decay, independent of self-efficacy. This underscores the importance of not only promoting AI adoption but also fostering critical engagement and calibrated trust among employees.

For the first time, AI isn't just automating hidden processes. It's sitting across from us and responds to our questions, helps with our decisions, and learns from our habits. Unlike other technologies, AI doesn't just serve us, but it imitates us. This makes us more likely to trust it and forget that beneath the human-like responses, it remains a fallible machine. Organizations, leaders, and employees must therefore learn how it works, how it affects us and our performance, and how to use it most effectively.

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Appendix

Appendix A: AI Statement

During the preparation of this work, I used ChatGPT in order to assist with the data analysis and improve readability and language of the thesis. After using this tool, I reviewed and edited the content as needed and take full responsibility for the content of the work.

Appendix B: Questionnaire

Control Variables.

How old are you?

What is your gender?

What is your nationality?

What is your highest educational degree?

What is your industry?

Does your company use any of the following Artificial Intelligence technologies?

- *Machine Learning Models (e.g., predictive modeling, recommendation engines, data classification).*
- *Deep Learning Applications (e.g., neural networks for image recognition or autonomous systems).*
- *Natural Language Processing (NLP) and Speech Tools (e.g., language translation, voice assistants like Siri, automated transcription).*
- *Generative AI Tools (e.g., text generation, creative AI like ChatGPT or DALL-E)*
- *Other ______________________*
- *AI is not being used in my company*

What kinds of tasks do you use AI for?

- *Data Analysis and Reporting (e.g., analyzing trends, creating dashboards, summarizing data)*
- *Content Generation (e.g., writing reports, creating text, image generation)*
- *Automation of Repetitive Tasks (e.g., scheduling, task automation, data entry)*
- *Communication and Collaboration (e.g., chatbots, email drafting, translation tools)*
- *Learning and Skill Development (e.g., personalized learning, training simulations)*
- *Problem-Solving and Decision-Making (e.g., analyzing complex situations, making recommendations)*

Is your experience with using AI more positive or negative?

AI Frequency.

AI1 How often do you use AI for work tasks on average per week?

- *Never*
- *Rarely (e.g., once a week)*
- *Sometimes (e.g., 2-3 times a week)*
- *Often (e.g., 4-5 times a week)*
- *Always (daily and more)*

Self-Efficacy

SE1 Using AI has made me confident in solving work-related problems.

SE2 Using AI has made me more efficient in completing work tasks.

SE3 Using AI has made me more confident in achieving the goals I have set for myself.

SE4 Using AI has made me more confident in solving unexpected challenges in my work.

SE5 Even without AI, I feel capable of achieving my work goals.

Positive Performance.

TP1 I manage to plan my work so that it was done on time.

TP2 I keep in mind the results that I have to achieve in my work.

TP3 I am able to perform my work well with minimal time and effort.

TP4 Using AI tools allow me to complete my tasks faster.

TP5 Since I started using AI in my work, I am better able to perform my work well with minimal time and effort.

TP6 Using AI help me handle tasks I previously found challenging.

CP1 I take on extra responsibilities at my work.

CP2 I start new tasks myself, when my old ones were finished.

CP3 I take on challenging work tasks, when I am available.

CP4 AI tools enable me to approach tasks more creatively.

CP5 I keep looking for new challenges in my job due to AI support.

CP6 AI tools help me focus on higher-priority tasks.

AP1 I work at keeping my job knowledge up-to-date.

AP2 I work at keeping my job skills up-to-date.

AP3 I am able to cope well with difficult situations and setbacks at work.

AP4 I demonstrate flexibility due to using AI.

AP5 I recover fast, after difficult situations or setbacks at work due to using AI.

AP6 Using AI helps me develop new skills relevant to my role.

Unintended Counterproductive Work Behaviors.

OR1 When presented with conflicting information, I tend to trust the AI output more than my own judgment.

OR2 I let the AI make decisions for me without evaluating its recommendations.

OR3 I have made errors in my work because I didn't evaluate the output of an AI system.

RE1 1 I put less effort into a task because I assumed AI would handle the difficult parts.

RE2 I allowed tasks to pile up because I expected AI to streamline them later.

RE3 I avoided learning new skills because I believed AI could perform the task better.

SD1 My ability to perform tasks without AI has decreased over time.

SD2 I have stopped seeking new learning opportunities because I believe AI can replace the need for certain skills.

SD3 I constantly need validation or feedback from AI systems to feel confident in my decisions.

Trust.

AIT1 I trust the recommendations provided by AI systems.

AIT2 I can depend on AI systems to function properly.

AIT3 I find AI systems to be reliable.

Open ended questions & overall reflections.

Have you ever experienced a negative impact or consequence due to the use of AI? If so, can you describe what happened?

What do you think are the biggest advantages and disadvantages of using AI tools in your work?

If you could change or improve anything about how AI tools are integrated into your work, what would it be?

Appendix C: Results

Table 9

Regression Models for Positive Performance Dimensions (n=128)

Outcome	Predictor	B	SE	t	p	95% CI
Task Performance	AI Frequency	0.1	0.03	3.18	0.002	[0.037, 0.165]
	Age	0.0	0.0	0.46	0.650	[-0.010, 0.010]
	Gender	-0.1	0.07	-1.56	0.122	[-0.240, 0.040]
	Education	0.04	0.03	1.1	0.274	[-0.033, 0.113]
	Self-Efficacy	0.25	0.05	4.83	<.001	[0.148, 0.354]
	Trust	0.07	0.05	1.38	0.172	[-0.029, 0.169]
	R^2					.0.39
	Adjusted R^2					0.369
	F Statistic					13.97 (6, 127), p < .001
Contextual Performance	AI Frequency	0.03	0.04	0.83	0.409	[-0.043, 0.106]
	Age	0.0	0.0	0.94	0.35	[-0.010, 0.010]
	Gender	-0.01	0.08	-0.13	0.895	[-0.150, 0.130]
	Education	0.02	0.04	0.5	0.619	[-0.060, 0.100]
	Self-Efficacy	0.15	0.06	2.48	0.015	[0.031, 0.274]
	Trust	0.05	0.06	0.92	0.358	[-0.060, 0.160]
	R^2					0.121
	Adjusted R^2					0.079
	F Statistic					2.91 (6, 127), p=.011
Adaptive Performance	AI Frequency	-0.02	0.03	-0.57	0.57	[-0.081, 0.044]
	Age	0.0	0.0	-0.37	0.715	[-0.010, 0.010]
	Gender	0.12	0.07	1.83	0.07	[-0.010, 0.254]
	Education	0.06	0.03	1.92	0.058	[-0.005, 0.134]
	Self-Efficacy	0.3	0.05	5.68	<.001	[0.195, 0.404]
	Trust	0.04	0.05	0.9	0.371	[-0.050, 0.130]
	R^2					0.323
	Adjusted R^2					0.291
	F Statistic					10.12 (6, 127), p < .001

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 10

Regression Models for Unintended Counterproductive Work Behavior Dimensions(n=123)

Outcome	Predictor	B	SE	t	p	95% CI
Overreliance	AI Frequency	0.005	0.062	0.082	0.935	[-0.120, 0.130]
	Age	-0.017	0.008	-2.034	0.044	[-0.033, 0.001]
	Gender	0.103	0.127	0.806	0.422	[-0.151, 0.357]
	Education	0.044	0.065	0.676	0.501	[-0.083, 0.171]
	Self-Efficacy	-0.032	0.103	-0.312	0.756	[-0.234, 0.170]
	Trust	0.153	0.099	1.55	0.124	[-0.040, 0.346]
	R^2					.059
	Adjusted R^2					.010
	F Statistic					1.20 **(**6, 116)**,** p **< .**312
Reduced Effort	AI Frequency	-0.106	0.069	-1.538	0.127	[-0.241, 0.030]
	Age	-0.002	0.009	-0.244	0.807	[-0.019, 0.016]
	Gender	-0.155	0.144	-1.073	0.285	[-0.439, 0.129]
	Education	-0.042	0.073	-0.571	0.569	[-0.183, 0.099]
	Self-Efficacy	0.093	0.114	0.818	0.415	[-0.130, 0.317]
	Trust	0.403	0.106	3.808	<.001	[0.199, 0.608]
	R^2					.175
	Adjusted R^2					.136
	F Statistic					4.48 (6, 127), p < .001
Skill Decay	AI Frequency	-0.036	0.07	-0.513	0.609	[-0.174, 0.102]
	Age	-0.015	0.009	-1.661	0.099	[-0.033, 0.003]
	Gender	-0.022	0.147	-0.148	0.882	[-0.310, 0.266]
	Education	-0.009	0.074	-0.118	0.907	[-0.160, 0.143]
	Self-Efficacy	0.09	0.116	0.778	0.438	[-0.136, 0.316]
	Trust	0.282	0.108	2.626	<.001	[0.072, 0.492]
	R^2					.124
	Adjusted R^2					.083
	F Statistic					2.98 (6, 126), p = .009

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$