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It's Scary to Use It, It's Scary to Refuse It: The Psychological Dimensions of AI Adoption—Anxiety, Motives, and Dependency

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Abstract: The current study examines the psychological factors shaping AI adoption, focusing on anxiety, motivation, and dependency. It identifies two dimensions of AI anxiety: anticipatory anxiety, driven by fears of future disruptions, and annihilation anxiety, reflecting existential concerns about human identity and autonomy. We demonstrate a U-shaped relationship between AI anxiety and usage, where moderate engagement reduces anxiety, and high or low levels increase it. Perceived utility, interest, and attainment significantly correlate with AI engagement, while frequent AI usage is linked to high dependency but not to anxiety. These findings highlight the dual role of psychological factors in hindering and alleviating AI usage. This study enriches the understanding of emotional and motivational drivers in AI adoption and highlights the importance of balanced implementation strategies to foster sustainable and effective AI integration while mitigating the risks of over-reliance.

Keywords: digital transformation; AI anxiety; anticipatory anxiety; annihilation anxiety; AI usage; motivational factors; problematic use; technology adoption; AI dependency

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1. Introduction

Artificial intelligence (AI) has rapidly become a transformative force, shaping industries and societies alike. Its adoption has sparked significant debate, with some tools facing regulatory bans, such as temporary restrictions in Italy and ongoing prohibitions in China [1]. AI is predicted to contribute $15.7 trillion to the global economy by 2030—surpassing the current output of China and India combined [2]. While offering immense opportunities, AI also raises critical concerns, including distinguishing real from artificial content, addressing ethical issues like bias and transparency, managing uncontrolled growth, and mitigating job displacement risks [3]. Moreover, there is growing recognition that algorithms, in specific contexts, may improve decision-making accuracy compared to human judgment. These complexities highlight the need for a deeper understanding of the psychological and societal dimensions of AI adoption.

AI has been widely recognized as the current technological revolution, provoking both interest and debate. Over 73% of U.S. companies have adopted or plan to adopt AI technologies by 2024 [4], and 75 to 375 million workers—3–14% of the global workforce—may need to change occupations or upgrade their skills by 2030, depending on the pace of AI adoption [5]. PwC's 2024 Global CEO Survey provides similar indications, with 69% of global CEOs expecting AI to necessitate workforce reskilling [6]. These projections reflect the profound impact of AI on both industries and the global workforce.

The benefits of AI, e.g., enhanced efficiency, effectiveness, and decision-making accuracy, are well-documented [7–10]. Still, many individuals and organizations remain

hesitant to adopt AI tools despite their advantages. For instance, a 2024 U.S. survey found that 37% of respondents had never used AI tools, and 20% were unsure if they had [11]. Cautious (54%), concerned (49%), and skeptical (40%) attitudes toward AI are prevalent [11], particularly among small and medium-sized enterprises, with half reporting no plans to implement AI [12]. This reluctance reflects "algorithm aversion," [13] where individuals resist relying on AI for decision-making, even when it could improve outcomes, such as in healthcare [14,15]. Addressing this hesitation is crucial for realizing AI's potential benefits.

As AI continues to advance, its constraints and ethical considerations are becoming increasingly critical in shaping adoption and integration. AI's reliance on massive amounts of human data raises significant concerns about data privacy [16] and questions of ownership over AI-generated outputs [17]. A major barrier to adoption is the lack of trust in AI-driven systems, which is essential for both managers and employees as trust directly influences acceptance and usage [18]. One source of distrust is the perception that AI systems, trained on vast datasets of human behaviors, often inherit and amplify human biases. For instance, machine learning algorithms trained on historical hiring data have been shown to perpetuate gender and racial biases, creating ethical and operational challenges for organizations striving for fairness [19]. AI has also been found to produce biased decisions based on individuals' dialects and even fabricate fake references, further eroding trust in its outputs [20,21]. Such issues contribute to perceptions of AI as opaque, unreliable, and unfair, especially for those negatively impacted by its biases [22].

Ethical concerns surrounding AI extend beyond bias to include transparency, control, accuracy, and accountability [23,24]. Many view AI systems as "black boxes," leading to confusion and anxiety about their outputs [25]. Employees may distrust these systems, fearing errors or a lack of clear accountability pathways [26]. Concerns about data misuse or exposure also amplify resistance to adoption, especially regarding data privacy and surveillance [27]. To address these challenges, organizations are increasingly implementing ethical guidelines for AI. Initiatives like the Organization for Economic Co-operation and Development's "Principles for AI" and the European Commission's "Ethical Guidelines for Trustworthy AI" aim to promote responsible AI usage, reduce public anxieties, and foster trust [28,29]. These measures emphasize transparency, fairness, and ethical governance to enable sustainable AI adoption.

Although several concerns about AI may seem unique to the current technological landscape, they resonate with historical patterns of anxiety accompanying disruptive technologies. From the Industrial Revolution to the rise of digital technologies, these anxieties often stem from fears of displacement, erosion of social norms, or loss of control, which mirror contemporary apprehensions about AI systems. This phenomenon, termed "technology anxiety," increases cognitive load and impedes adoption [30]. Over time, various forms of technology anxiety have been conceptualized, like "Technophobia" [31], reflecting a fear of new technology; "Computer Anxiety" [32], describing apprehension toward human–computer interaction; and "Technostress" [33], characterized by an inability to cope with technological change, often leading to mental health issues [34]. The important effect of these anxieties on education [35,36] and consumer behavior [37,38] was demonstrated in earlier technological transitions. This historical context highlights the importance of understanding how user perceptions and anxieties affect the adoption of novel technologies.

Wach et al. [39] provide a thorough examination of the factors shaping perceptions of AI systems. They categorize these barriers into seven critical domains, including regulatory shortcomings, algorithmic biases, and technostress. These barriers emphasize the intricate interplay between ethical, social, and psychological concerns in fostering or hindering AI adoption. For instance, the absence of robust regulations exacerbates trust

issues, while algorithmic biases erode perceptions of fairness and equity. Furthermore, the psychological condition stemming from difficulties in adapting to new technologies [33] underscores the mental toll that AI integration can impose on individuals and organizations. Together, these dimensions frame the complex environment within which AI adoption must be understood.

The current study addresses these multifaceted challenges by focusing on the psychological dimensions of adopting AI conversational agents (e.g., ChatGPT), decision-support systems, and productivity tools. These systems, widely used by individuals and organizations, directly engage users in decision-making and cognitive tasks. Drawing from existing literature, we explore how AI adoption is shaped by two distinct AI-anxiety constructs. Anticipatory anxiety, which is conceptualized as a forward-looking apprehension about the potential disruptions AI might bring, particularly concerning job displacement and ethical dilemmas, and annihilation anxiety, which reflects existential fears about the erosion of human identity and autonomy in the face of increasingly advanced AI systems. The study hypothesizes distinct patterns of interaction between these anxieties and AI usage, emphasizing both immediate apprehensions and deeper existential concerns that influence adoption behaviors (see Figure 1).

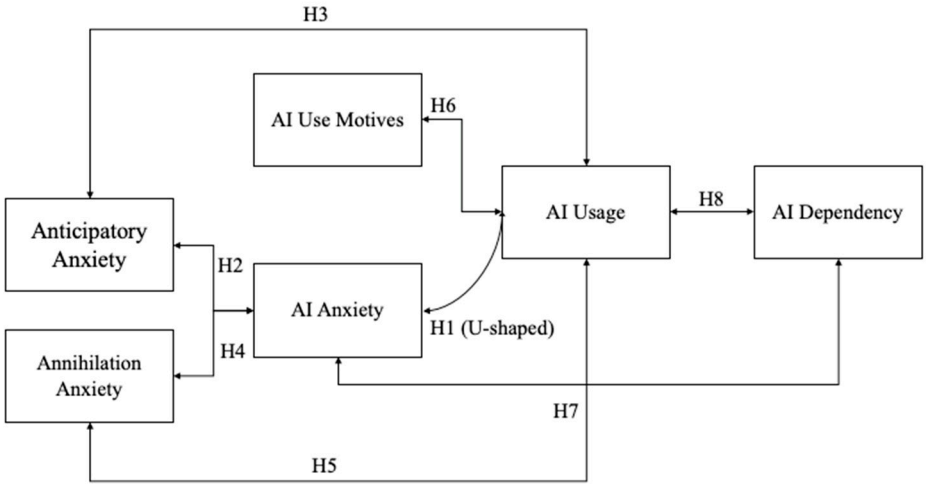


Figure 1. An illustration of the proposed theoretical model and hypotheses.

Building on cognitive-behavioral theories, we posit that the relationship between AI usage and anxiety follows a U-shaped trajectory due to distinct psychological processes. Initially, exposure to AI can alleviate anxiety by fostering familiarity and competence, consistent with the principles of exposure therapy, where repeated interactions with a perceived threat diminish fear over time [40]. Studies on technology adoption and human–computer interaction show that increased usage correlates with reduced anxiety and improved confidence in digital tools [41,42]. This suggests that familiarity can reduce uncertainty and build trust in AI systems.

However, as engagement with AI deepens, users may encounter unforeseen complexities, ethical dilemmas, or dependencies that reignite anxiety. Research shows that overexposure to technology can amplify concerns about trust, autonomy, and reliability [43,44]. For instance, studies indicate that high reliance on AI systems can lead to perceptions of diminished control and increased vulnerability to system failures [18]. Ethical concerns, such as bias or opacity in decision-making processes, may exacerbate anxieties among users who feel over-reliant on AI for critical tasks [45,46]. These dynamics illustrate the dual effects of AI adoption: while moderate engagement reduces anxiety through

familiarity, excessive reliance can heighten anxiety due to dependency and trust-related concerns. Accordingly, we hypothesize the following:

Hypothesis 1. *There is a U-shaped relationship between AI usage and AI anxiety, with a turning point at which increased usage is associated with an increase in AI anxiety.*

This hypothesis provides a nuanced perspective on how engagement with AI influences user reactions. Understanding this relationship will offer critical insights for organizations striving to balance usage and familiarity-building initiatives with strategies to address emergent concerns as AI integration deepens.

1.1. The Dual Nature of AI Anxiety

AI anxiety can lead to a myriad of cognitive and emotional responses to AI adoption, reflecting both its potential benefits and inherent risks. Another aim of the current work is to show that two important dimensions of AI anxiety are anticipatory anxiety, which arises from fears of future disruptions or challenges, and annihilation anxiety, which reflects deeper existential concerns about human identity and autonomy. These dimensions provide a framework for understanding the dual nature of AI anxiety, where moderate engagement may alleviate fears while deeper reliance could amplify them.

In recent years, researchers have focused on understanding the dimensions of AI anxiety [3,47,48]. Studies highlight concerns such as fear of being superseded, anxiety about AI integration into the workplace, and inadequate preparation for the AI era [3]. Wang and Wang [47] developed the AI Anxiety Scale (AIA) to measure the fear or anxiety that inhibits individuals from engaging with it. They identify four key dimensions: job replacement anxiety, anxiety over human dependency on AI, anxiety toward humanoid AI, and anxiety about acquiring AI-related skills. These dimensions reflect both anticipatory and annihilation anxieties: anticipatory anxiety is evident in fears about job replacement and inadequate preparation, while annihilation anxiety manifests in concerns about sociotechnical dependency and the erosion of human autonomy. A critical implication of these anxieties is their potential to hinder technology adoption. For instance, Chang et al. [49] found a significant negative relationship between AI anxiety and AI adoption intention, underscoring the importance of addressing these fears to foster broader acceptance and effective integration of AI into organizational and societal contexts.

Barlow, Chorpita, and Turovsky [50] describe anticipatory anxiety as the inclination to anticipate or predict a possible future threat, danger, or negative event, leading to anxiety in response to that expectation. Anticipatory anxiety, the shadow side of AI anxiety, reflects a future-oriented unease about what AI might disrupt or replace. This fear, much like past technology-related anxieties, often stems from uncertainty about the implications of AI adoption [3,51]. Anticipatory anxiety introduces unease, just like earlier instances of computer anxiety, where concerns about dehumanization were prominent [52]. This type of anxiety presents significant challenges for AI adoption by influencing individual decisions and shaping organizational and governance strategies. Thus, understanding the relationship between the shadow side of AI anxiety and technology acceptance is crucial to informing policymakers and designing strategies to facilitate effective AI system implementation [51].

The current study posits that anticipatory anxiety may serve as a foundational driver of AI anxiety, particularly during the early adoption phase when users have limited or no direct experience with these systems. According to the fear extinction model [53], avoidance behaviors can reinforce these anxieties, preventing individuals from challenging unrealistic beliefs about AI. This perpetuates mistrust, hinders adoption, and underscores the need for strategies to address anticipatory fears during initial interactions with AI.

When linked to AI, anticipatory anxiety reflects a cognitive state focused on future uncertainties rather than immediate realities. Research on AI anxiety [47,49] highlights primary fears, including job loss, unemployment, and AI surpassing human intelligence. While valid, these concerns often remain abstract, influencing users' perceptions more than their everyday experiences. This aligns with findings that anticipatory anxiety frequently exacerbates concerns about potential rather than current threats [51]. As a result, anticipatory anxiety represents a psychological barrier that influences both individual and organizational decision-making processes.

Given the growing implementation of AI tools in our daily and organizational lives, understanding the intersection of AI and anticipatory anxieties can inform strategies to reduce psychological barriers to AI adoption. For example, addressing anticipatory anxiety could mitigate avoidance behaviors, foster public confidence, and promote adoption, which are key factors for leveraging AI systems effectively in organizational and decision-making contexts. Furthermore, reducing anticipatory anxiety could improve trust in AI-driven decision-making, mitigate user resistance, and facilitate ethical and effective system design. By addressing this anxiety, organizations can create a pathway for broader acceptance and more sustainable implementation of AI technologies.

Hypothesis 2. *Anticipatory anxiety is positively correlated with AI anxiety.*

The hypothesized positive correlation between AI anxiety and anticipatory anxiety is grounded in theories that connect anticipatory emotions with domain-specific anxieties. Cognitive-behavioral frameworks suggest that anticipatory anxiety reflects heightened emotional arousal triggered by perceived threats, even when those threats remain hypothetical [54,55]. This theoretical perspective aligns closely with the psychological mechanisms underlying AI anxiety, where individuals experience fear related to potential future disruptions caused by AI technologies. These disruptions often include concerns about the loss of human agency or autonomy, further amplifying anticipatory anxiety in contexts where AI systems are perceived as unpredictable or overly autonomous [3].

Based on the role that anticipatory anxiety plays in shaping technology adoption, it is crucial to understand the connection between anticipatory anxiety and digital tools usage. Digital transformation initiatives often rely on managers' ability to evaluate engagement levels and identify resistance among employees and stakeholders. Proactively addressing this question allows for a more effective allocation of resources, mitigates barriers, and refines implementation strategies. Thus, it maximizes the efficiency and impact of these initiatives [56]. A pivotal aspect of this process is addressing anticipatory anxiety, which often arises from unfamiliarity with new technologies. When individuals lack exposure to emerging digital tools, they tend to overestimate risks and complexity, exacerbating their unease [51]. In the current work, we argue that experience plays a critical role in mitigating such anxieties. This is based on the premise that as individuals interact more frequently with digital tools, they become less intimidated by their perceived complexity [57]. Familiarity reduces both cognitive and emotional uncertainty, fostering confidence and diminishing avoidance behaviors. In line with this claim, research consistently shows that repeated exposure to technology reduces uncertainty, builds confidence, and decreases emotional resistance [53,54]. These findings align with findings that familiarity fosters competence and control, thereby alleviating domain-specific anxieties [55]. Accordingly, we hypothesize the following:

Hypothesis 3. *Increased usage of AI is associated with decreased anticipatory anxiety.*

While anticipatory anxiety focuses on the immediate uncertainties and risks of AI adoption, a deeper layer of concern emerges as AI becomes increasingly integrated into daily life. This deeper layer, referred to as annihilation anxiety, shifts the focus to the abyss side of AI anxiety, which represents more profound psychological concerns. The shadow and abyss sides form a spectrum of anxieties, ranging from fears about adoption and adaptation to existential threats. On the surface, anticipatory anxiety reflects individuals' apprehension about the uncertainties and potential disruptions caused by AI. On the other side, annihilation anxiety delves into fears about the erosion of human identity, autonomy, and the boundaries that have traditionally distinguished humans from machines. As AI continues to reshape human interaction and even foster dependency, these existential fears underscore the psychological depth of AI anxiety.

Annihilation anxiety reflects a fear for the survival of the self or ego [58], encompassing the dread of mental, physical, or symbolic destruction and extinction [59]. Richardson [60] explored this concept in the context of AI and machines, proposing that annihilation anxiety is triggered when humans and nonhumans become comparable. This comparison threatens to "erase the difference between humans and nonhumans" (p. 6), symbolically undermining what makes humans unique. The rapid advancements in AI systems that mimic or surpass specific aspects of human cognition intensify this psychological unease. As AI is increasingly perceived not only as a tool but also as a potential rival, it fosters a profound sense of vulnerability and existential threat [61,62].

This existential fear is not merely theoretical. The rapid development of AI challenges traditional visions of harmonious human–machine collaboration, raising concerns about whether synergy and mutual enhancement can be achieved [63]. Instead, there is growing apprehension that AI might dominate or undermine human roles, fueling a broader narrative of technological displacement. This narrative exacerbates annihilation anxiety, as individuals fear not only the loss of jobs or societal roles but also the erosion of what it means to be human in the face of increasingly intelligent and autonomous machines.

To fully grasp the complexities of AI anxiety, it is crucial to address both its immediate (shadow) and existential (abyss) dimensions. Annihilation anxiety delves into deeper, more abstract concerns about the erosion of human identity, autonomy, and the uniqueness of human intelligence. Together, these dimensions offer a comprehensive framework for examining AI anxiety, underscoring its dual nature—rooted both in present-day interactions and in long-term existential threats.

Hypothesis 4. *Annihilation anxiety is positively correlated with AI anxiety.*

This hypothesis highlights the interplay between existential fears and broader concerns about AI adoption. Annihilation anxiety, rooted in apprehensions about the erosion of human identity and autonomy, amplifies general AI anxiety by framing AI systems as both a technological tool and a potential existential threat. Individuals experiencing heightened annihilation anxiety may perceive AI as challenging fundamental human distinctions, which intensifies their overall sense of unease. These findings emphasize the importance of understanding how existential dimensions of anxiety shape attitudes toward AI, offering critical insights for designing interventions that address these deeper concerns.

Hypothesis 5. *Increased usage of AI is associated with an increase in annihilation anxiety.*

This hypothesis suggests that deeper engagement with AI may intensify existential concerns by challenging the perceived boundaries between human and machine capabilities. As individuals interact with systems that mimic or surpass human skills, fears of obsolescence and the erosion of human distinctiveness may heighten [60]. Such anxieties

often stem from a perceived loss of autonomy and control as AI systems increasingly perform tasks traditionally associated with human expertise [18,45]. This dynamic reflects the broader psychological impact of advanced technologies, where the blurring of human–machine boundaries can evoke a sense of vulnerability and existential threat [61,62]. Understanding the interplay between annihilation anxiety and AI usage provides valuable insights into how individuals and organizations navigate these psychological barriers. Such insights are crucial for developing governance frameworks that optimize AI's benefits while mitigating its psychological and existential risks.

1.2. From Barriers to Drivers: Motivational Factors in AI Adoption

While addressing anticipatory and annihilation anxieties is crucial, focusing solely on these barriers provides an incomplete perspective on AI adoption. Equally important is the understanding of the motivations that drive the use of AI tools. As organizations increasingly integrate AI into their operations, recognizing both the hindrances and enablers of adoption becomes essential. Strategies to mitigate user concerns must be complemented by initiatives that foster positive engagement and sustain motivation, thereby facilitating smoother digital transformation efforts.

To this end, Yurt and Kasarci [64] developed the Questionnaire of AI Use Motives (QAIUM), which identifies five key motivational dimensions influencing AI adoption. These dimensions include (1) Expectancy, reflecting self-efficacy and the perceived ability to effectively use AI; (2) Attainment, representing the value placed on mastering and enhancing AI-related skills; (3) Utility Value, highlighting the practical benefits of AI for personal and professional growth; (4) Intrinsic/Interest Value, capturing the enjoyment and satisfaction derived from interacting with AI; and (5) Cost, which accounts for the effort, time, and sacrifices required to adopt and use AI tools. Together, these dimensions provide a robust framework for understanding the factors that motivate user engagement with AI technologies.

The importance of these motivational dimensions is further supported by research identifying specific drivers of AI adoption. Competitive advantages and performance improvement have been highlighted as powerful motivators, particularly in professional contexts [65]. Similarly, digital competence, which encompasses the skills and confidence needed to use AI effectively [66], and hedonic motivation, the enjoyment derived from using AI tools [67], underscore the role of positive reinforcement in driving adoption. These motivators align with Self-Determination Theory (SDT) [68], which emphasizes the significance of perceived autonomy, competence, and relatedness in fostering intrinsic motivation [69]. Studies show that intrinsic motivation often yields greater engagement and sustained effort than extrinsic factors, providing critical insights for organizations aiming to enhance AI integration.

Building on this foundation, we propose that increased usage of AI is positively associated with heightened AI use motives. As individuals engage more frequently with AI tools, they may develop stronger intrinsic motivations, such as a sense of competence and enjoyment, alongside extrinsic motivations, such as perceived utility and professional benefits. This dynamic interaction creates a positive feedback loop, where motivation reinforces engagement and fosters deeper, more sustained interactions with AI technologies. These findings highlight the importance of addressing not only the barriers to AI adoption but also the motivational factors that encourage its effective and responsible use.

Hypothesis 6. *Increased usage of AI is associated with an increase in AI Use Motives.*

1.3. AI Dependency: A New Behavioral Addiction

Building on the critical understanding of the psychological and motivational factors that influence AI usage, it is essential to examine how the use of AI technologies evolves, particularly as initial anxieties give way to dependency. Historically, technological advancements have followed a trajectory marked by early apprehension and eventual reliance, a process well described by the Diffusion of Innovations theory [70]. For example, when personal computers were first introduced, concerns about dehumanization and the potential loss of control were widespread [52]. Similarly, the early adoption of mobile phones was met with fears about their societal impact, including associations with crime, social anxiety, and uncertainty [71,72]. Over time, however, these technologies became indispensable tools for communication, work, and personal organization, transforming initial skepticism into deep-seated dependency [73–76]. The goal of this study is to identify the factors driving this progression, thereby informing strategies that promote healthy engagement with AI while mitigating the risks of maladaptive reliance.

Examining the transition from AI anxiety and motivators to dependency through the lens of historical patterns offers valuable insights into the lifecycle of AI adoption. As discussed earlier, AI systems, like their technological predecessors, are often met with skepticism and apprehension [3,45]. However, their integration into daily and organizational life suggests the potential for a parallel trajectory, where increased usage alleviates initial fears but also fosters dependency. This shift has profound implications for understanding how users interact with AI over time. As familiarity with AI tools grows, initial anxieties may diminish, driven by enhanced competence and perceived utility, as highlighted in earlier sections. Nevertheless, this familiarity can increase reliance as users turn to AI for decision-making, task execution, and productivity improvements. This dual dynamic, where usage reduces barriers while simultaneously creating risks of over-reliance, represents a critical area for exploration. Understanding how these transitions occur will illuminate the psychological and organizational factors contributing to dependency and guide developing governance frameworks and ethical strategies that balance the benefits of AI adoption with its inherent challenges.

As individuals and organizations increasingly adopt AI, understanding this evolution is essential to anticipate its broader impacts. If initial fears are gradually replaced by dependency, the ethical and operational challenges surrounding AI will likely shift. For instance, increased reliance on AI systems may exacerbate concerns about accountability, transparency, and the unequal distribution of technological benefits. Dependency on AI also raises critical questions about human agency in decision-making and the risks associated with over-reliance on automated systems. By examining whether AI follows a trajectory from initial anxiety to dependency, the current work aims to provide a deeper understanding of the psychological and governance challenges posed by AI tools. These insights are crucial for informing policies and practices that foster responsible AI adoption, balancing innovation's benefits with the need to address its risks and uncertainties.

With the increasing prevalence of AI in daily life, a distinct behavioral pattern known as AI Dependency is emerging. While earlier research often used terms like "overreliance", "addiction", and "dependency" interchangeably [77–79], AI dependency is now being recognized as a specific form of behavioral addiction. Behavioral addictions are defined by excessive engagement in activities that are generally acceptable when practiced in moderation. However, individuals experiencing such addictions often struggle to regulate their behavior, even when it leads to significant personal distress, impaired academic or occupational functioning, or strained relationships [80].

In the context of AI, problematic usage can manifest as compulsive engagement with tools like ChatGPT, where excessive reliance impairs various aspects of an individual's

life [81]. The Problematic ChatGPT Use Scale (PCUS) identifies key predictors of such behaviors, including increased weekly usage time and elevated levels of depression, illustrating the broader psychological toll of excessive AI use. This highlights the need to understand how certain patterns of interaction with AI evolve into maladaptive behaviors. However, AI dependency extends beyond general problematic use by reflecting a deeper, compulsive reliance on AI systems to perform everyday tasks, often at the expense of personal well-being and autonomy. For example, Zhang et al. [82] found that AI dependency in academic contexts is strongly linked to performance expectancy—the belief that using a specific system will enhance one's job performance [42]. This suggests that individuals who perceive AI as indispensable for achieving success are more likely to develop dependency, especially in high-pressure environments where efficiency and outcomes are emphasized. AI dependency has significant consequences. Laestadius et al. [83] highlighted that excessive reliance on AI, especially in social media and digital technology, is associated with adverse mental health outcomes, including heightened anxiety and depression. These findings align with broader research on behavioral addictions, where dependency exacerbates underlying psychological vulnerabilities [79]. Consequently, AI dependency may create a feedback loop: increased usage leads to dependency, which, in turn, amplifies anxiety and reinforces reliance on AI systems as a coping mechanism.

In the context of the current work, prior studies indicate that AI anxiety may play a pivotal role in driving compulsive behaviors, such as excessive reliance on AI tools. For instance, findings from digital addiction research suggest that anxiety often exacerbates problematic usage patterns [84]. Users with heightened AI anxiety may over-engage with these tools, either as an ineffective coping strategy to manage their fears or due to heightened concerns about staying competent in an increasingly AI-driven world. While problematic usage patterns are often regarded as detrimental, they may also signal greater engagement and adaptability in certain contexts, such as digital transformation initiatives. For example, Qiao et al. [85] observed that problematic usage behaviors among digital leaders implementing AI adoption strategies could reflect proactive efforts to integrate emerging technologies effectively. This dual perspective highlights the nuanced nature of "problematic" use in professional environments, suggesting it can sometimes indicate a high level of commitment and adaptability rather than purely maladaptive behavior. This complexity points to the importance of examining how psychological factors like anxiety influence AI usage. By exploring the interplay between AI anxiety and dependency, we aim to provide a deeper understanding of this relationship, contributing to the broader discourse on AI adoption and its implications for organizational and individual behavior. Based on the theoretical rationale outlined above, we hypothesize the following:

Hypothesis 7. *AI dependency is positively correlated with AI anxiety.*

Finally, the frequency and intensity of AI usage might also play a key role in driving the development of dependency. As individuals increasingly interact with AI tools, the line between productive use and compulsive engagement can become blurred. The accessibility and perceived utility of these tools, particularly for professional or personal tasks, may encourage habitual reliance, creating opportunities for dependency to emerge. At the global level, overuse of AI tools may lead to negative environmental consequences (e.g., energy use and dissipation of thermal energy into the atmosphere). This phenomenon aligns with findings from prior research, which highlight how repeated exposure can foster problematic usage patterns [81]. Building on these foundations, the current work also examines the role of AI usage in shaping dependency. As reliance on AI tools grows, individuals may become increasingly dependent on them to perform everyday tasks, particularly in contexts emphasizing efficiency, performance, and outcomes. This dynamic underscores the need to

understand how the frequency and intensity of AI interactions contribute to dependency and its broader implications for users' well-being and autonomy.

Hypothesis 8. *Increased usage of AI is associated with increased AI dependency.*

Building on behavioral addiction frameworks, we expect increased frequency and intensity of AI usage to contribute to the development of dependency as individuals increasingly perceive these systems as indispensable [86]. This dynamic may escalate from habitual reliance to compulsive behaviors, blurring the line between productive engagement and problematic use [87]. Understanding the interplay between AI usage, dependency, and anxiety is essential for addressing the psychological and organizational challenges posed by the widespread adoption of AI tools. By identifying these dynamics, this work aims to inform policymakers and design interventions that promote healthier relationships with AI, particularly in high-pressure environments where efficiency and performance demands may amplify the risks of over-reliance.

2. Materials and Methods

2.1. Participants

A total of 242 participants completed the study. The sample comprised individuals aged 18 to 73 years old (M = 34.08, SD = 11.36), with a balanced representation of gender identities: 48% female and 52% male. Participants were geographically diverse, representing multiple countries, with most residing in English-speaking regions. Participants were recruited through the Prolific platform. To ensure data integrity, only individuals with a prior approval rating of 95% or higher on the platform were invited to participate, adhering to established best practices in online research [45]. Data collection took place in October 2024. All participants provided informed consent and completed the study questionnaire in its entirety.

Ethical approval was obtained from the authors' institutional review board. Participation was entirely voluntary, and the study complied with GDPR and other relevant data protection laws. The survey was administered anonymously, with no personal identifying information collected beyond what was managed by Prolific for payment purposes. This approach ensured participant privacy and confidentiality. The sampling strategy was guided by the current focus on organizational implications. While the general population was targeted, additional efforts were made to include participants employed in organizational contexts where AI tools are increasingly relevant. Recruitment was not restricted by occupational background, ensuring a diverse range of professional experiences with AI tools. This approach aligns with our aim to generalize findings to organizational adoption of AI tools.

2.2. Design and Procedure

The study utilized a cross-sectional survey design to explore the psychological dimensions of AI adoption, including anxiety, motivational factors, and dependency. Data were collected through an online survey administered via the Qualtrics platform. The survey included five validated scales measuring distinct constructs related to AI adoption. To maintain consistency and minimize potential biases, the scales were presented in the same order to all participants. Clear instructions were provided at the beginning of each section to ensure comprehension.

After providing informed consent, participants completed the survey, which was designed to take approximately 15–20 min. Participants who indicated familiarity with AI tools completed all sections of the survey, while those unfamiliar with AI were directed to

the end of the survey. This approach ensured that only relevant data were collected for the study hypotheses.

The first part of the questionnaire was the AI Anxiety Scale (AIA) [47]. This scale measured participants' general anxiety about interacting with AI. Sample items included statements such as, "Taking a class about the development of AI techniques/products makes me anxious", and "I am afraid that AI techniques/products will replace someone's job". Participants responded using a 7-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree). This scale demonstrated high reliability, with a Cronbach's alpha of 0.94.

The second part of the survey included the Anticipatory Anxiety Inventory (AAI) [88], which evaluated anxiety experienced in anticipation of anxiety-provoking events. Sample items included, "As the time for the anxiety-provoking event approaches, I feel more panicky than I would feel earlier", and "Before an anxiety-provoking event, I am under a lot of pressure". Responses were recorded on a 4-point Likert scale (1 = Not True to 4 = Totally True), with a Cronbach's alpha of 0.95.

The third and fourth parts of the survey were the Annihilation Anxiety Scale (ANAS) and the AI Dependency Scale (ADS), respectively. The ANAS [89] assessed existential threats and fears, such as the loss of identity or group extermination. Sample items included, "I sometimes worry that I will lose my sense of self" and "I feel personally threatened by extreme inequalities in society". Responses were captured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). This scale demonstrated a Cronbach's alpha of 0.78. The ADS [90] measured reliance on AI tools in daily life. Sample items included "I feel unprotected without AI tools" and "I rely heavily on AI for my tasks". Responses were recorded on a 5-point Likert scale (1 = Completely False to 5 = Completely True), with a Cronbach's alpha of 0.75.

The final part of the survey utilized the Questionnaire of AI Use Motives (QAIUM) [64], which explored motives for AI usage across five dimensions: Expectancy, Attainment, Utility Value, Intrinsic/Interest Value, and Cost. Sample items included, "I can learn the skills that enable effective use of artificial intelligence applications" (Expectancy) and "I take pleasure in using artificial intelligence applications" (Intrinsic/Interest Value). Participants responded using a 5-point Likert scale (1 = Completely False to 5 = Completely True). This scale demonstrated a high reliability, with a Cronbach's alpha of 0.96 across motives.

2.3. Data Analysis

The data were analyzed using SPSS software (version 29). Descriptive statistics were calculated to summarize participant demographics and responses on the study scales. To test the first research hypothesis, a quadratic regression analysis was conducted to examine the U-shaped relationship between AI Usage and AI Anxiety. For subsequent hypotheses, Pearson correlation analyses were employed to investigate the relationships between AI Usage and anxiety-related variables, including Dependency and Motivation. In cases where linear correlations were not significant, quadratic regression models were applied to explore potential non-linear relationships. The criterion for statistical significance was set at an alpha level of 0.05 ($\alpha = 0.05$). These analytical approaches enabled a comprehensive examination of both linear and non-linear associations across the study variables.

3. Results

3.1. Descriptive Statistics

Table 1 presents the descriptive statistics for all study variables, including means, standard deviations (SD), and observed ranges. AI Usage exhibited the highest mean score (M = 4.42, SD = 0.93), reflecting frequent engagement with AI technologies within the

sample. AI Anxiety (M = 3.61, SD = 1.10) and AI Use Motives (M = 3.62, SD = 0.75) were also moderately high, suggesting that both concerns about AI and motivations for using AI were prevalent among participants. In contrast, the measures of Anticipatory Anxiety (M = 2.38, SD = 1.07), Annihilation Anxiety (M = 2.42, SD = 0.80), and AI Dependency (M = 2.29, SD = 0.87) indicated more moderate levels of these psychological dimensions. These trends suggest that while participants frequently engaged with AI and demonstrated significant motivational factors, concerns such as dependency and extreme anxieties were less pronounced.

Table 1. Mean, SDs, Minimum, and Maximum for study variables.

Variable	M	SD	Min	Max
AI Usage	4.42	0.93	1.00	5.00
AI Anxiety	3.61	1.10	1.05	6.19
Anticipatory Anxiety	2.38	1.07	1.00	4.00
Annihilation Anxiety	2.42	0.80	1.00	5.00
AI Dependency	2.29	0.87	1.00	5.00
AI Use Motives	3.62	0.75	1.29	5.00

3.2. Hypothesis Tests

Hypothesis 1. *There is a U-shaped relationship between AI usage and AI anxiety, with a turning point at which increased usage is associated with an increase in AI anxiety.*

To test the U-shaped relationship between AI Usage and AI Anxiety, we conducted a quadratic regression analysis. The results confirmed the significance of the quadratic term, indicating a U-shaped relationship (Figure 2). Specifically, the linear coefficient ($b_1 = -0.69$, SE = 0.29, $p = 0.047$) and the quadratic coefficient ($b_2 = 0.94$, SE = 0.04, $p = 0.007$) were both statistically significant. The model accounted for 8.6% of the variance in AI Anxiety ($R^2 = 0.086$) and was statistically significant ($F(2,229) = 10.83$, $p < 0.001$). These results suggest that AI Anxiety initially decreases as AI Usage increases, consistent with the notion that moderate engagement fosters familiarity and reduces fear. However, at higher levels of usage, AI Anxiety begins to rise again, potentially reflecting heightened concerns about dependency, control, or ethical implications. This finding emphasizes the complexity of AI adoption processes, highlighting the dual effects of usage on anxiety. Thus, organizations should encourage balanced AI engagement, where users are supported in their adoption journey to avoid over-reliance or heightened concerns at extreme usage levels.

To explore the associations among all study variables and specifically address the research hypotheses, we conducted a Pearson correlation matrix analysis (Table 2). This method enabled us to assess the direction, strength, and significance of the relationships between the variables, providing valuable insights into their connections.

Table 2. Pearson correlation matrix for study variables (N = 242).

Variable	2	3	4	5	6
AI Usage	−0.24 ***	−0.15 *	−0.06	0.27 ***	0.38 ***
AI Anxiety	---	0.45 ***	0.51 ***	−0.02	−0.40 ***
Anticipatory Anxiety		---	0.36 ***	0.01	−0.18 **
Annihilation Anxiety			---	0.17 **	−0.05

Table 2. *Cont.*

Variable	2	3	4	5	6
AI Dependency				---	0.55 ***
AI Use Motives					---

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

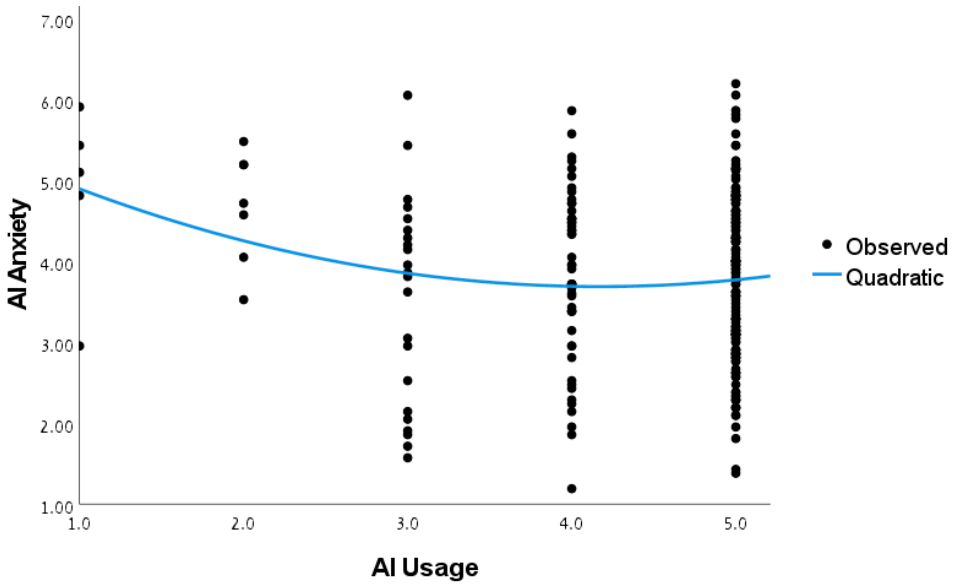


Figure 2. U-shaped quadratic relationship between AI usage and AI anxiety.

Hypothesis 2. *Anticipatory anxiety is positively correlated with AI anxiety.*

A strong positive correlation was observed between Anticipatory and AI Anxieties (r = 0.45, $p < 0.001$). This supports the hypothesis that individuals experiencing greater anticipatory fears about potential disruptions caused by AI also report higher overall AI Anxiety. This finding aligns with theoretical frameworks suggesting that anticipatory anxiety amplifies broader anxieties when individuals perceive future threats as unpredictable or significant.

Hypothesis 3. *Increased usage of AI is associated with decreased anticipatory anxiety.*

A statistically significant negative correlation was found between AI Usage and Anticipatory Anxiety (r = –0.15, $p = 0.028$), indicating that higher levels of AI engagement are associated with reduced anticipatory fears. This finding suggests that familiarity with AI tools may alleviate unease about their perceived complexity or disruptive potential, consistent with the principles of exposure therapy. These results emphasize the role of early exposure and training in reducing psychological barriers to AI adoption.

Hypothesis 4. *Annihilation anxiety is positively correlated with AI anxiety.*

Annihilation and AI Anxieties exhibited a strong positive correlation (r = 0.51, $p < 0.001$), supporting the hypothesis that existential concerns about the erosion of human identity and autonomy intensify broader anxieties about AI. This finding highlights the role of deeper psychological fears in shaping attitudes toward AI technologies, particularly as they challenge traditional human–machine distinctions.

Hypothesis 5. *Increased usage of AI is associated with an increase in annihilation anxiety.*

Hypothesis 5 was not supported, as no significant linear relationship was found between AI Usage and Annihilation Anxiety (r = −0.06, p = 0.364). However, a quadratic relationship was identified (Figure 3). Regression analysis revealed an inverted U-shaped curve, with the linear coefficient (b_1 = 0.82, SE = 0.45, p = 0.038) and quadratic coefficient (b_2 = −0.89, SE = 0.06, p = 0.024) both contributing to the model. The model accounted for 2.6% of the variance in Annihilation Anxiety (R^2 = 0.026) and was statistically significant (F(2,229) = 3.00, p = 0.050).

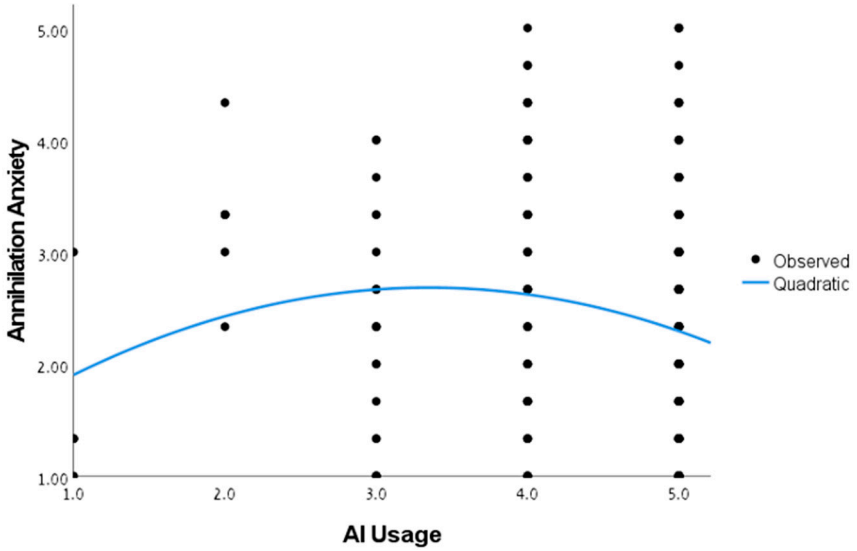


Figure 3. Quadratic relationship between AI usage and annihilation anxiety.

These results suggest that initial increases in AI usage are associated with heightened Annihilation Anxiety, potentially due to exposure to new and unfamiliar systems that challenge human distinctiveness. However, at higher levels of usage, these anxieties decrease, possibly reflecting users' adaptation and acceptance of AI as a complement to human capabilities. This finding highlights the nuanced relationship between usage intensity and existential fears.

Hypothesis 6. *Increased usage of AI is associated with an increase in AI Use Motives.*

A positive correlation was observed between AI usage and AI Use Motives (r = 0.27, p < 0.001), supporting the hypothesis that greater engagement with AI tools enhances users' motivations for their adoption. This finding aligns with motivational frameworks suggesting that frequent interaction with AI fosters both intrinsic and extrinsic motivators, such as perceived utility, enjoyment, and skill attainment. These results emphasize the dynamic feedback loop between AI usage and user motivation, where increased exposure strengthens users' perceived benefits and enjoyment of AI tools. This insight is particularly relevant for organizations aiming for sustained engagement by leveraging motivational strategies during onboarding and implementation processes.

Hypothesis 7. *AI dependency is positively correlated with AI anxiety.*

Hypothesis 8. *Increased usage of AI is associated with increased AI dependency.*

No significant relationship was found between AI dependency and AI anxiety (r = −0.02, p = 0.701), failing to support Hypothesis 7. This result does not align with findings that link dependency and anxiety [83], suggesting that these constructs may operate independently in the context of AI adoption. One possible explanation is that while

dependency may reflect a behavioral reliance on AI tools, it does not inherently evoke the emotional distress or existential concerns captured by AI Anxiety. This finding illustrates the complexity of AI-related psychological factors and highlights the need for further investigation into how dependency interacts with other dimensions of AI use, such as motivation or perceived utility.

Lastly, Hypothesis 8 was supported by a positive correlation between AI usage and AI dependency ($r = 0.27$, $p < 0.001$). This indicates that greater engagement with AI tools is associated with higher reliance on these technologies. These findings suggest that as individuals use AI more frequently, they may view these tools as indispensable, particularly for tasks requiring efficiency or accuracy. While this dependency might be beneficial in terms of productivity, it also raises concerns about over-reliance. Organizations should aim to foster healthy engagement by ensuring AI tools are positioned as supportive aids rather than replacements for human skills. Training programs emphasizing balanced use may help mitigate the risks associated with excessive reliance.

Table 3 provides a comprehensive summary of the results for each hypothesis, detailing the associated variables, correlation coefficients (R and R^2), type of correlation observed, significance levels, and the acceptance status of each hypothesis.

Table 3. Results of Hypotheses testing (H1 to H8).

Hypothesis	Variables	R	R^2	Correlation Type	Sig	Hypotheses Acceptance
H1	AI usage and AI anxiety	0.29	0.086	U-shape	<0.001	Accepted
H2	Anticipatory and AI anxiety	0.45	0.202	Linear	<0.001	Accepted
H3	AI usage and anticipatory anxiety	−0.15	0.022	Linear	0.028	Accepted
H4	Annihilation anxiety and AI anxiety	0.51	0.260	Linear	<0.001	Accepted
H5	Annihilation anxiety and AI usage	0.16	0.026	Reversed U-shape	0.050	Declined (Post Hoc Analysis)
H6	AI usage and AI Use motives	0.38	0.144	Linear	<0.001	Accepted
H7	AI dependency and AI anxiety	−0.02	<0.001	Linear	0.710	Declined
H8	AI usage and AI dependency	0.27	0.073	Linear	<0.001	Accepted

3.3. Additional Findings

The correlation matrix presented in Table 2 highlights several noteworthy relationships. Notably, there were strong positive correlations between Anticipatory Anxiety and Annihilation Anxiety ($r = 0.36$, $p < 0.001$), as well as between AI dependency and AI Use Motives ($r = 0.55$, $p < 0.001$). Conversely, a strong negative correlation was observed between AI anxiety and AI Use Motives ($r = -0.40$, $p < 0.001$), suggesting that higher levels of anxiety toward AI are associated with reduced motivational factors for its use. These findings emphasize the intricate interplay between anxiety, dependency, and usage motives within the context of AI-related behaviors.

4. Discussion

In a world where AI increasingly integrates into our lives, the current study examines the dual role of Use AI motives and AI anxiety—encompassing both anticipatory and annihilation dimensions—in successfully adopting conversational AI agents, decision-support systems, and productivity tools. While AI can enhance efficiency [91] and support strategic decision-making [92], our findings highlight significant emotional and motivational challenges that must be addressed to ensure smooth and sustainable digital transformation. These challenges are particularly pronounced in the U-shaped relationship observed between AI usage and anxiety, which is in line with our first hypothesis. This dual relationship demonstrates that moderate engagement reduces anxiety, but both low and high

levels of usage amplify it. Such insights are crucial for organizations seeking to mitigate psychological barriers while maximizing the benefits of AI.

One significant finding of the current study is the strong association between anticipatory and AI anxiety, which signifies the shadow side of AI anxiety and supports Hypothesis 2. Anticipatory anxiety often stems from perceived risks, such as job displacement, loss of autonomy, or ethical concerns surrounding AI's expanding role in decision-making [93]. This emotional response is not unique to AI but reflects broader anxiety patterns observed during technological disruption. Historical parallels, such as the mechanization anxieties of the Industrial Revolution [31], illustrate that such fears are deeply rooted in human responses to change. These findings align with prior research indicating that anticipatory emotions significantly influence technology adoption behaviors [94].

To address anticipatory anxiety, organizations should design interventions that reduce uncertainty, dissolve irrational fears, and set clear expectations. Transparent communication in the organization about the transition can reduce ambiguity and foster trust by providing regular updates about the purpose, scope, and impact of AI implementation [95]. Equally important can be targeted training programs, which offer employees hands-on experience and tailored support to demystify AI systems, enhance confidence, and reduce fear [96]. Additionally, establishing ongoing support systems, such as channels for feedback and dialogue, ensures that employees feel heard and supported throughout the transformation process [97]. Together, these interventions not only alleviate immediate concerns but also create an environment where employees are psychologically prepared to engage with AI systems.

The shadow side of AI anxiety highlights a critical gap in traditional technology adoption models. These models (e.g., the Unified Theory of Acceptance and Use of Technology—UTAUT [42]) prioritize rational factors like performance expectancy, effort expectancy, social influence, and facilitating conditions as primary determinants of user intentions. While valuable, such frameworks often fail to account for emotional and psychological factors influencing technology adoption. The current work emphasizes the need for a comprehensive approach that integrates strategies to overcome both cognitive and emotional barriers, ensuring the successful and sustainable incorporation of AI in the workplace or at home. This can be obtained, for example, with human-centric AI designs [98], which emphasize the development of transparent, user-friendly, and explainable systems. By clearly demonstrating how AI systems function and how decisions are made, this approach helps alleviate feelings of intimidation and uncertainty [99]. Transparency fosters trust in AI systems [100], while intuitive, user-friendly designs empower employees to interact confidently with AI, reducing the sense of being overwhelmed by technical complexities [101].

An essential component of this holistic approach is effective change management, which involves recognizing and addressing the emotional responses employees may experience during transitions to AI systems. Applying Kotter's change management principles [102], managers can implement practical steps to support employees through the change process. This could include forming a guiding coalition to lead the change, identifying short-term goals that demonstrate early wins with AI deployment, and empowering employees through active participation. Ensuring employees' voices are heard fosters a sense of ownership and psychological safety, making them more receptive to change and actively engaged in the transformation process. By addressing both the rational and emotional dimensions of AI adoption, organizations can create a balanced and inclusive approach that maximizes the benefits of AI while minimizing its psychological costs. This holistic approach enhances the effectiveness of AI integration and ensures employees feel supported and valued throughout the transition process.

The weak but significant negative correlation between the shadow side of AI anxiety and adoption supports Hypothesis 3, indicating that heightened uncertainty about AI discourages individuals from engaging with it. While anticipatory anxiety may not be a primary determinant of AI adoption, its influence is notable. Individuals with higher levels of shadow-side anxiety are less likely to use AI tools, potentially due to the discomfort and hesitation arising from uncertainties inherent in emerging technologies. This finding demonstrates the critical need to address emotional uncertainty as part of a comprehensive digital adoption strategy. By mitigating anticipatory anxiety, organizations can foster an environment of confidence and openness, ultimately encouraging more widespread and effective AI engagement [103].

Another key finding is the strong association between annihilation and AI anxiety, which signifies the abyss side of AI anxiety. Supporting Hypothesis 4, this finding suggests that individuals who experience existential fears, such as concerns about losing personal identity or autonomy due to AI technologies, are more likely to experience heightened AI anxiety. The abyss side of AI anxiety highlights the profound psychological impact that AI technologies can evoke, extending beyond practical concerns to deeply ingrained existential fears [104]. The perception that AI threatens qualities unique to humans—such as autonomy, decision-making, and personal identity—intensifies anxiety. For managers, this finding indicates the importance of addressing not only the functional and procedural implications of AI adoption but also the existential concerns (abyss side) employees may harbor. Strategies to support employees could include fostering transparency and explainability through clear communication, promoting ethical self-governance with well-defined policies and procedures, and implementing continuous monitoring across the system lifecycle [105].

While Hypothesis 5 was not supported, a significant inverted U-shaped relationship was found between the abyss side of AI anxiety and AI adoption. Initially, individuals experience heightened existential fears as their use of AI increases. This may be attributed to a growing awareness of the potential existential threats posed by AI systems among those with low to moderate levels of familiarity and usage [104,106]. However, as users become more familiar with AI technology, existential anxieties tend to diminish [104]. In an organizational context, this relationship highlights the importance of framing AI as a supportive tool. Managers should emphasize that AI complements, rather than replaces, human work. By highlighting how AI can support employees' existing roles and enhance efficiency rather than threatening their professional relevance or value, organizations can alleviate fears of obsolescence and foster a more productive and collaborative relationship with technology.

While the shadow and abyss sides of AI anxiety were found to be strong factors that hinder adoption, the current work also focused on identifying use motives. In line with Hypothesis 6, we found a significant positive correlation between AI usage and AI use motives [64]. These motives encompass expectancy, attainment, utility value, intrinsic/interest value, and cost. This finding suggests that individuals' beliefs about their ability to successfully use AI tools, particularly to achieve personal or professional goals, are critical factors in AI adoption. Additionally, adoption is influenced by the perceived practical benefits of AI, such as increased efficiency or problem-solving capabilities, and by the inherent enjoyment or curiosity associated with engaging with AI systems.

This relationship suggests that as individuals' motives to use AI across these dimensions increase, their engagement with AI tools also increases. For organizations aiming to enhance AI adoption, fostering these motivational components is crucial. For instance, they can improve expectancy by providing comprehensive training and support, emphasize attainment by aligning AI tools with employee goals, and promote utility value by

showcasing the tangible benefits of AI in real-world tasks. Cultivating intrinsic value might encourage exploration and innovation with technologies while mitigating perceived costs through accessible and user-friendly designs. By addressing these motivational factors, organizations can drive sustained engagement with AI, ultimately boosting employee motivation, satisfaction, and productivity [107].

The third and final goal of the current study was to provide an initial understanding of the factors contributing to AI dependency. Two key findings emerged. First, in contrast to Hypothesis 7 and previous research [108], no correlation was found between AI dependency and AI anxiety. This lack of a significant correlation suggests that while anxiety may influence the decision to adopt AI, it does not necessarily translate into dependency among users. This aligns with research indicating that ChatGPT reduces technostress [109], potentially buffering against anxiety-related misuse. Instead, problematic use appears more closely tied to high levels of AI engagement, where over-reliance and excessive interaction may emerge as primary drivers of maladaptive behaviors.

Second, a significant positive correlation was found between AI usage and dependency, suggesting that frequent interaction with AI tools may foster reliance, which can escalate into maladaptive use. This demonstrates the danger of habitual use in cultivating dependency. If left unchecked, this habitual use could hinder critical thinking and reduce interpersonal engagement [78,110]. These findings highlight the dual-edged nature of AI adoption. While increased usage can enhance productivity [111] and innovation [112], it also poses risks, such as over-reliance, diminished social interaction, and uncritical acceptance of AI outputs. For organizations aiming to maximize the benefits of AI while minimizing its drawbacks, it is crucial to implement strategies that promote balanced and mindful adoption. This includes fostering a healthy relationship with AI by providing clear guidelines, monitoring usage patterns, and addressing the emotional and behavioral factors that shape engagement. Managers should remain vigilant in mitigating dependency risks, ensuring that AI is a tool to complement, rather than replace, essential human skills like critical thinking and collaboration. By adopting these strategies, organizations can harness the potential of AI while safeguarding employee well-being and performance.

4.1. Limitation

It is important to recognize several limitations of this study that may influence the interpretation and generalizability of the findings. First, the research was conducted during the early stages of AI adoption. Widely accessible AI tools have only recently entered mainstream use, and as these technologies become more integrated and familiar in daily life, anxiety levels may naturally decline over time. This limits our ability to fully capture the long-term psychological and behavioral dynamics associated with AI usage. Furthermore, concepts such as AI dependency, currently framed as emerging challenges, may shift over time as they become normalized aspects of human–AI interactions.

Second, our cross-sectional design limited our ability to capture the dynamic and longitudinal nature of psychological responses to AI. Factors such as anxiety, dependency, and acceptance are likely to evolve as individuals gain more experience with AI technologies and as these tools become more ubiquitous in organizational and personal contexts. Longitudinal studies are essential for understanding these temporal changes, offering a clearer picture of how psychological responses develop parallel to AI integration. For example, longitudinal data could illuminate whether anxieties in early adoption stages diminish into confidence or intensify with usage due to dependency.

Third, we used a sample from Prolific, which is likely to have higher baseline technological familiarity and experience compared to the general population. This sample could lead to an underestimation of AI anxiety and dependency levels and an overestimation of

usage. Thus, results might be limited to organizations where digital literacy is prominent. Additionally, many AI applications operate seamlessly within everyday platforms without explicit labeling, making it difficult for users to recognize when using AI-powered tools. This lack of transparency introduces potential biases in participants' responses, which can be added to the biases that may stem from the reliance on self-reported data (e.g., social desirability effects and recall inaccuracies).

Lastly, as noted earlier, we did not calculate effect sizes a priori, which could have enhanced the study's methodological rigor. While post hoc effect size estimates confirmed the findings' statistical significance, incorporating power analyses during the planning phase would have ensured more precise sample size determinations. Future studies should prioritize these methodological considerations to bolster transparency and reproducibility. By addressing these limitations in future research, we can build a more comprehensive understanding of the complex relationships between AI usage, psychological well-being, and organizational outcomes.

4.2. Future Work

Future research can adopt a longitudinal approach to better understand how AI-related anxiety and dependency evolve over time. Such studies would provide valuable insights into the long-term psychological effects of increased familiarity with AI and its progressive integration into everyday life. For instance, longitudinal designs could explore whether the normalization of AI tools reduces anticipatory anxiety or, conversely, intensifies dependency concerns. These findings would enhance our understanding of whether societal perceptions of AI dependency and problematic use shift over time as these behaviors become more ingrained in daily routines. Moreover, future studies should investigate demographic factors such as age, education, and cultural context and differentiate between different types of uses. This can help uncover variations in how different populations experience AI adoption. For example, generational differences in technology familiarity or cultural attitudes toward innovation may significantly influence levels of anxiety or dependency. Examining these factors would provide a more nuanced understanding of how diverse groups adapt to the challenges and opportunities presented by AI.

Research within organizational contexts, where AI adoption is often mandatory, represents another promising avenue for exploration. Understanding how employees respond to AI integration under structured, professional conditions could reveal whether psychological responses differ from voluntary or personal adoption scenarios. Such studies could examine the effectiveness of tailored interventions, such as customized training programs, skill-building initiatives, and transparent communication strategies, in mitigating AI anxiety and enhancing adaptability. By focusing on organizational contexts, future research could also provide managers with practical tools to empower employees to engage confidently with AI technologies. Strategies such as phased implementation, clear articulation of AI's role and benefits, and fostering psychological safety would support smoother transitions and greater acceptance. These efforts are critical for fostering an inclusive and productive environment where the potential of AI can be fully realized without compromising employee well-being.

Finally, future research could employ more complex analytical approaches, such as PLS-Structural Equation Modeling, to capture potential feedback loops and reciprocal relationships between anticipatory anxiety, existential fears, and technological adaptation. While our current study established directional relationships between these constructs, the dynamic nature of human–AI interaction suggests that these relationships may also be more intricate, with possible bidirectional influences and recursive patterns. For instance, heightened abyss side of AI anxiety might not only result from existential fears but

could potentially reinforce them over time, creating self-reinforcing cycles that influence technological adaptation.

4.3. Conclusions

The findings in the current work emphasize the importance of adopting a phased, strategic approach to AI integration within organizations. Gradual implementation minimizes disruption and anxiety among employees [113]. This phased approach ensures that employees first adapt to simpler digital tools before transitioning to complex AI systems [114]. Incremental exposure enables individuals to build confidence and familiarity, reducing cognitive and emotional resistance to change [115]. A phased implementation strategy also aligns with recent research emphasizing the value of transparent communication and hands-on training during technological transitions. For example, Phillips and Klein [116] highlight that training programs and open communication alleviate uncertainty and foster trust. Furthermore, providing opportunities for feedback ensures that employees feel supported throughout the transition process, mitigating the shadow side of AI anxiety [100]. Managers can foster psychological safety and trust by maintaining transparency about the potential benefits and challenges of AI adoption [117]. Clear communication about AI's role in enhancing workflows, rather than replacing employees, reduces anticipatory fears of job displacement or obsolescence. Incorporating ethical guidelines and governance frameworks, such as those emphasized in global AI ethics initiatives, further bolsters trust [43].

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References

1. Forbes. Available online: https://www.forbes.com/sites/siladityaray/2023/02/22/chatgpt-reportedly-blocked-on-chinese-social-media-apps-as-beijing-claims-ai-is-used-to-spread-propaganda/ (accessed on 16 October 2024).
2. PwC. Available online: https://www.pwc.com/gx/en/issues/artificial-intelligence/publications/artificial-intelligence-study.html (accessed on 2 November 2024).
3. Kim, J.; Kadkol, S.; Solomon, I.; Yeh, H.; Soh, J.Y.; Nguyen, T.M.; Ajilore, O.A. AI anxiety: A comprehensive analysis of psychological factors and interventions. *SSRN* **2023**, 4573394. [CrossRef]
4. PwC. Available online: https://www.pwc.com/us/en/tech-effect/ai-analytics/responsible-ai-survey.html (accessed on 2 November 2024).
5. Manyika, J.; Lund, S.; Chui, M.; Bughin, J.; Woetzel, L.; Batra, P.; Ko, R.; Sanghvi, S. Jobs Lost, Jobs Gained: What the Future of Work Will Mean for Jobs, Skills, and Wages. Available online: https://www.mckinsey.com/featured-insights/future-of-work/jobs-lost-jobs-gained-what-the-future-of-work-will-mean-for-jobs-skills-and-wages (accessed on 2 November 2024).
6. PwC. Available online: https://www.pwc.com/bs/en/press-releases/pwc-2024-global-ai-jobs-barometer.html (accessed on 2 November 2024).
7. Blair, A.; Saffidine, A. AI surpasses humans at six-player poker. *Science* **2019**, *365*, 864–865. [CrossRef] [PubMed]
8. Wamba-Taguimdje, S.L.; Wamba, S.F.; Kamdjoug, J.R.K.; Wanko, C.E.T. Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. *Bus. Process Manag. J.* **2020**, *26*, 1893–1924. [CrossRef]
9. Grewal, D.; Guha, A.; Satornino, C.B.; Schweiger, E.B. Artificial intelligence: The light and the darkness. *J. Bus. Res.* **2021**, *136*, 229–236. [CrossRef]

10. Hubert, K.F.; Awa, K.N.; Zabelina, D.L. The current state of artificial intelligence generative language models is more creative than humans on divergent thinking tasks. *Sci. Rep.* **2024**, *14*, 3440. [CrossRef]
11. YouGov. Available online: https://today.yougov.com/technology/articles/49099-americans-2024-poll-ai-top-feeling-caution (accessed on 24 October 2024).
12. eco—Association of the Internet Industry. Available online: https://international.eco.de/presse/eco-yougov-survey-shows-that-small-and-medium-sized-enterprises-in-particular-are-reluctant-to-use-ai/ (accessed on 24 October 2024).
13. Mahmud, H.; Islam, A.N.; Ahmed, S.I.; Smolander, K. What influences algorithmic decision-making? A systematic literature review on algorithm aversion. *Technol. Forecast. Soc. Chang.* **2022**, *175*, 121390. [CrossRef]
14. Longoni, C.; Bonezzi, A.; Morewedge, C.K. Resistance to medical artificial intelligence. *J. Consum. Res.* **2019**, *46*, 629–650. [CrossRef]
15. Gaczek, P.; Pozharliev, R.; Leszczyński, G.; Zieliński, M. Overcoming consumer resistance to AI in general health care. *J. Interact. Mark.* **2023**, *58*, 321–338. [CrossRef]
16. Yanamala, A.K.Y.; Suryadevara, S.; Kalli, V.D.R. Evaluating the impact of data protection regulations on AI development and deployment. *Int. J. Adv. Eng. Technol. Innov.* **2023**, *1*, 319–353.
17. Draxler, F.; Werner, A.; Lehmann, F.; Hoppe, M.; Schmidt, A.; Buschek, D.; Welsch, R. The AI ghostwriter effect: When users do not perceive ownership of AI-generated text but self-declare as authors. *ACM Trans. Comput.-Hum. Interact.* **2024**, *31*, 1–40. [CrossRef]
18. Siau, K.; Wang, W. Building trust in artificial intelligence, machine learning, and robotics. *Cut. Bus. Technol. J.* **2018**, *31*, 47–53.
19. Fügener, A.; Grahl, J.; Gupta, A.; Ketter, W. Cognitive challenges in human–artificial intelligence collaboration: Investigating the path toward productive delegation. *Inf. Syst. Res.* **2022**, *33*, 678–696. [CrossRef]
20. Hofmann, V.; Kalluri, P.R.; Jurafsky, D.; King, S. AI generates covertly racist decisions about people based on their dialect. *Nature* **2024**, *633*, 147–154. [CrossRef] [PubMed]
21. Christensen, J.; Hansen, J.M.; Wilson, P. Understanding the role and impact of Generative Artificial Intelligence (AI) hallucination within consumers' tourism decision-making processes. *Curr. Issues Tour.* **2024**, 1–16. [CrossRef]
22. Mittelstadt, B.D.; Allo, P.; Taddeo, M.; Wachter, S.; Floridi, L. The ethics of algorithms: Mapping the debate. *Big Data Soc.* **2016**, *3*, 2053951716679679. [CrossRef]
23. Puntoni, S.; Reczek, R.W.; Giesler, M.; Botti, S. Consumers and artificial intelligence: An experiential perspective. *J. Mark.* **2021**, *85*, 131–151. [CrossRef]
24. Stahl, B.C.; Andreou, A.; Brey, P.; Hatzakis, T.; Kirichenko, A.; Macnish, K.; Wright, D. Artificial intelligence for human flourishing—Beyond principles for machine learning. *J. Bus. Res.* **2021**, *124*, 374–388. [CrossRef]
25. Burrell, J. How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data Soc.* **2016**, *3*, 1–12. [CrossRef]
26. Binns, R. Fairness in machine learning: Lessons from political philosophy. In Proceedings of the 2018 Conference on Fairness, Accountability, and Transparency, New York, NY, USA, 23–24 February 2018.
27. Zuboff, S. *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*; PublicAffairs: New York, NY, USA, 2019.
28. OECD. Available online: https://www.oecd.org/en/topics/sub-issues/ai-principles.html (accessed on 4 November 2024).
29. European Parliament. Available online: https://www.europarl.europa.eu/cmsdata/196378/AI%20HLEG_Policy%20and%20Investment%20Recommendations.pdf (accessed on 4 November 2024).
30. Steelman, K.S.; Tislar, K.L. Measurement of tech anxiety in older and younger adults. In Proceedings of the 21st International Conference on Human-Computer Interaction (HCI International 2019), Orlando, FL, USA, 26–31 July 2019.
31. Bloch, H.S. Review of *La France devant la reconstruction économique*, by R. Mossé. J. *Political Econ.* **1947**, *55*, 383–385. [CrossRef]
32. Rohner, D.J.; Simonson, M.R. Development of an art index of computer anxiety. In Proceedings of the Association for Educational Communications and Technology, Philadelphia, PA, USA, 6–10 April 1981.
33. Brod, C. *Technostress: The Human Cost of Computer Revolution*; Addison-Wesley: Reading, MA, USA, 1984.
34. Bondanini, G.; Giorgi, G.; Ariza-Montes, A.; Vega-Muñoz, A.; Andreucci-Annunziata, P. Technostress dark side of technology in the workplace: A scientometric analysis. *Int. J. Environ. Res. Public Health* **2020**, *17*, 8013. [CrossRef]
35. Alkhawaja, M.I.; Halim, M.S.A.; Afthanorhan, A. Technology Anxiety and Its Impact on E-Learning System Actual Use in Jordan Public Universities during the Coronavirus Disease Pandemic. *Eur. J. Educ. Res.* **2021**, *10*, 1639–1647. [CrossRef]
36. Huang, X.; Zou, D.; Cheng, G.; Chen, X.; Xie, H. Trends, research issues, and applications of artificial intelligence in language education. *Educ. Technol. Soc.* **2023**, *26*, 112–131.
37. Yang, K.; Forney, J.C. The moderating role of consumer technology anxiety in mobile shopping adoption: Differential effects of facilitating conditions and social influences. *J. Electron. Commer. Res.* **2013**, *14*, 334.
38. Aziz, S.A.; Jusoh, M.S.; Amlus, M.H. The moderating role of technology anxiety on brand service quality, brand image, and their relation to brand loyalty. *Int. J. Internet Mark. Advert.* **2018**, *12*, 270–289. [CrossRef]

39. Wach, K.; Duong, C.D.; Ejdys, J.; Kazlauskaitė, R.; Korzynski, P.; Mazurek, G.; Ziemba, E. The dark side of generative artificial intelligence: A critical analysis of controversies and risks of ChatGPT. *Entrep. Bus. Econ. Rev.* **2023**, *11*, 7–30. [CrossRef]
40. Wolpe, J. Psychotherapy by reciprocal inhibition. *Cond. Reflex Pavlov. J. Res. Ther.* **1968**, *3*, 234–240. [CrossRef] [PubMed]
41. Davis, F.D. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Q.* **1989**, *13*, 319–340. [CrossRef]
42. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. User acceptance of information technology: Toward a unified view. *MIS Q.* **2003**, *27*, 425–478. [CrossRef]
43. Afroogh, S.; Akbari, A.; Malone, E.; Kargar, M.; Alambeigi, H. Trust in AI: Progress, challenges, and future directions. *Humanit. Soc. Sci. Commun. 2024 11*, 1568.
44. Fan, M.; Huang, Y.; Qalati, S.A.; Shah, S.M.M.; Ostic, D.; Pu, Z. Effects of information overload, communication overload, and inequality on digital distrust: A cyber-violence behavior mechanism. *Front. Psychol.* **2021**, *12*, 643981. [CrossRef]
45. Shin, D. The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *Int. J. Hum.-Comput. Stud.* **2021**, *146*, 102551. [CrossRef]
46. Whittaker, M.; Crawford, K.; Dobbe, R.; Fried, G.; Kaziunas, E.; Mathur, V.; Myers West, S.; Richardson, R.; Schultz, J.; Schwartz, O. AI Now Report 2018. AI Now Institute. 2018. Available online: https://ainowinstitute.org/AI_Now_2018_Report.pdf (accessed on 10 November 2024).
47. Wang, Y.Y.; Wang, Y.S. Development and validation of an artificial intelligence anxiety scale: An initial application in predicting motivated learning behavior. *Interact. Learn. Environ.* **2019**, *30*, 619–634. [CrossRef]
48. Lemay, D.J.; Basnet, R.B.; Doleck, T. Fearing the Robot Apocalypse: Correlates of AI Anxiety. *Int. J. Learn. Anal. Artif. Intell. Educ. (iJAI) 2020 2*, 24–33. [CrossRef]
49. Chang, P.C.; Zhang, W.; Cai, Q.; Guo, H. Does AI-Driven technostress promote or hinder employees' artificial intelligence adoption intention? A moderated mediation model of affective reactions and technical self-efficacy. *Psychol. Res. Behav. Manag.* **2024**, *17*, 413–427. [CrossRef] [PubMed]
50. Barlow, D.H.; Chorpita, B.F.; Turovsky, J. Fear, panic, anxiety, and disorders of emotion. In *Nebraska Symposium on Motivation, 1995: Perspectives on Anxiety, Panic, and Fear*; Hope, D.A., Ed.; University of Nebraska Press: Lincoln, Nebraska, 1996; pp. 251–328.
51. Huang, C.L.; Haried, P. An evaluation of uncertainty and anticipatory anxiety impacts on technology use. *Int. J. Hum.–Comput. Interact.* **2020**, *36*, 641–649. [CrossRef]
52. Beckers, J.J.; Schmidt, H.G. The structure of computer anxiety: A six-factor model. *Comput. Hum. Behav.* **2001**, *17*, 35–49. [CrossRef]
53. Graham, B.M.; Milad, M.R. The study of fear extinction: Implications for anxiety disorders. *Am. J. Psychiatry* **2011**, *168*, 1255–1265. [CrossRef]
54. Grillon, C.; Lissek, S.; Rabin, S.; McDowell, D.; Dvir, S.; Pine, D.S. Increased anxiety during anticipation of unpredictable but not predictable aversive stimuli as a psychophysiologic marker of panic disorder. *Am. J. Psychiatry* **2008**, *165*, 898–904. [CrossRef] [PubMed]
55. Nitschke, J.B.; Sarinopoulos, I.; Oathes, D.J.; Johnstone, T.; Whalen, P.J.; Davidson, R.J.; Kalin, N.H. Anticipatory activation in the amygdala and anterior cingulate in generalized anxiety disorder and prediction of treatment response. *Am. J. Psychiatry* **2009**, *166*, 302–310. [CrossRef]
56. Marwaha, J.S.; Landman, A.B.; Brat, G.A.; Dunn, T.; Gordon, W.J. Deploying digital health tools within large, complex health systems: Key considerations for adoption and implementation. *NPJ Digit. Med.* **2022**, *5*, 13. [CrossRef]
57. Taylor, S.; Todd, P.A. Understanding information technology usage: A test of competing models. *Inf. Syst. Res.* **1995**, *6*, 144–176. [CrossRef]
58. Freedman, N.; Geller, J.D.; Hoffenberg, J.; Hurvich, M.; Ward, R. *Another Kind of Evidence: Studies on Internalization, Annihilation Anxiety, and Progressive Symbolization in the Psychoanalytic Process*; Routledge: London, UK, 2018.
59. Hurvich, M. The place of annihilation anxieties in psychoanalytic theory. *J. Am. Psychoanal. Assoc.* **2003**, *51*, 579–616. [CrossRef] [PubMed]
60. Richardson, K. *An Anthropology of Robots and AI: Annihilation Anxiety and Machines*; Routledge: London, UK, 2015.
61. Galanos, V. Exploring expanding expertise: Artificial intelligence as an existential threat and the role of prestigious commentators, 2014–2018. *Technol. Anal. Strateg. Manag.* **2019**, *31*, 421–432. [CrossRef]
62. Federspiel, F.; Mitchell, R.; Asokan, A.; Umana, C.; McCoy, D. Threats by artificial intelligence to human health and human existence. *BMJ Glob. Health* **2023**, *8*, e010435. [CrossRef] [PubMed]
63. Noble, S.M.; Mende, M.; Grewal, D.; Parasuraman, A. The Fifth Industrial Revolution: How harmonious human–machine collaboration is triggering a retail and service [r]evolution. *J. Retail.* **2022**, *98*, 199–208. [CrossRef]
64. Yurt, E.; Kasarci, I. A Questionnaire of Artificial Intelligence Use Motives: A Contribution to Investigating the Connection between AI and Motivation. *Int. J. Technol. Educ.* **2024**, *7*, 308–325. [CrossRef]

65. Krakowski, A.; Greenwald, E.; Hurt, T.; Nonnecke, B.; Cannady, M. Authentic integration of ethics and AI through sociotechnical, problem-based learning. In Proceedings of the AAAI Conference on Artificial Intelligence, Virtual Event, USA, 22 February–1 March 2022.
66. Okuonghae, N.; Tunmibi, S. Digital competence as predictor for the motivation to use artificial intelligence technologies among librarians in Edo and Delta States, Nigeria. *J. Technol. Innov. Energy* **2024**, *3*, 1–11. [CrossRef]
67. Qu, K.; Wu, X. ChatGPT as a CALL tool in language education: A study of hedonic motivation adoption models in English learning environments. *Educ. Inf. Technol.* **2024**, *29*, 19471–19503. [CrossRef]
68. Deci, E.L.; Ryan, R.M. The general causality orientations scale: Self-determination in personality. *J. Res. Personal.* **1985**, *19*, 109–134. [CrossRef]
69. Ryan, R.M.; Deci, E.L. Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemp. Educ. Psychol.* **2000**, *25*, 54–67. [CrossRef]
70. Rogers, E.M. *Diffusion of Innovations*; Free Press: New York, NY, USA, 2003.
71. Addo, A. The adoption of mobile phone: How has it changed us socially. *Issues Bus. Manag. Econ.* **2013**, *1*, 47–60.
72. Miller-Ott, A.E.; Kelly, L.; Duran, R.L. The effects of cell phone usage rules on satisfaction in romantic relationships. *Commun. Q.* **2012**, *60*, 17–34. [CrossRef]
73. Billieux, J. Problematic use of the mobile phone: A literature review and a pathways model. *Curr. Psychiatry Rev.* **2012**, *8*, 299–307. [CrossRef]
74. MacCormick, J.S.; Dery, K.; Kolb, D.G. Engaged or just connected? Smartphones and employee engagement. *Organ. Dyn.* **2012**, *41*, 194–201. [CrossRef]
75. King, A.C.; Hekler, E.B.; Grieco, L.A.; Winter, S.J.; Sheats, J.L.; Buman, M.P.; Cirimele, J. Harnessing different motivational frames via mobile phones to promote daily physical activity and reduce sedentary behavior in aging adults. *PLoS ONE* **2013**, *8*, e62613. [CrossRef] [PubMed]
76. CBS News. Available online: http://web.archive.org/web/20080412042610/http://www.wsbt.com/news/health/17263604.html. (accessed on 10 November 2024).
77. Adegbesan, A.; Akingbola, A.; Aremu, O.; Adewole, O.; Amamdikwa, J.C.; Shagaya, U. From Scalpels to Algorithms: The Risk of Dependence on Artificial Intelligence in Surgery. *J. Med. Surg. Public Health* **2024**, *3*, 100140. [CrossRef]
78. Zhai, C.; Wibowo, S.; Li, L.D. The effects of over-reliance on AI dialogue systems on students' cognitive abilities: A systematic review. *Smart Learn. Environ.* **2024**, *11*, 28. [CrossRef]
79. Zhou, T.; Zhang, C. Examining generative AI user addiction from a CAC perspective. *Technol. Soc.* **2024**, *78*, 102653. [CrossRef]
80. Yates, J.R. *Determinants of Addiction: Neurobiological, Behavioral, Cognitive, and Sociocultural Factors*; Elsevier: Amsterdam, The Netherlands, 2023.
81. Yu, S.C.; Chen, H.R.; Yang, Y.W. Development and validation of the Problematic ChatGPT Use Scale: A preliminary report. *Curr. Psychol.* **2024**, *43*, 26080–26092. [CrossRef]
82. Zhang, S.; Zhao, X.; Zhou, T.; Kim, J.H. Do you have AI dependency? The roles of academic self-efficacy, academic stress, and performance expectations on problematic AI usage behavior. *Int. J. Educ. Technol. High. Educ.* **2024**, *21*, 34. [CrossRef]
83. Laestadius, L.; Bishop, A.; Gonzalez, M.; Illenčík, D.; Campos-Castillo, C. Too human and not human enough: A grounded theory analysis of mental health harms from emotional dependence on the social chatbot Replika. *New Media Soc.* **2024**, *26*, 5923–5941. [CrossRef]
84. Hu, B.; Mao, Y.; Kim, K.J. How social anxiety leads to problematic use of conversational AI: The roles of loneliness, rumination, and mind perception. *Comput. Hum. Behav.* **2023**, *145*, 107760. [CrossRef]
85. Qiao, R.; Liu, C.; Xu, J. Making algorithmic app use a virtuous cycle: Influence of user gratification and fatigue on algorithmic app dependence. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 775. [CrossRef]
86. Xie, T.; Pentina, I.; Hancock, T. Friend, mentor, lover: Does chatbot engagement lead to psychological dependence? *J. Serv. Manag.* **2023**, *34*, 806–828. [CrossRef]
87. Yankouskaya, A.; Liebherr, M.; Ali, R. ChatGPT Addiction: From Support to Dependence in AI Large Language Models. *SSRN* **2024**, 4972612. [CrossRef]
88. Vural, S.; Ferreira, N. Development and psychometric properties of the Anticipatory Anxiety Inventory. *Cogn. Brain Behav.* **2021**, *25*, 261–288. [CrossRef]
89. Kira, I.; Templin, T.; Lewandowski, L.; Ramaswamy, V.; Ozkan, B.; Mohanesh, J.; Hussam, A. Collective and Personal Annihilation Anxiety: Measuring Annihilation Anxiety AA. *Psychology* **2012**, *3*, 90–99. [CrossRef]
90. Morales-García, W.C.; Sairitupa-Sanchez, L.Z.; Morales-García, S.B.; Morales-García, M. Development and validation of a scale for dependence on artificial intelligence in university students. *Front. Educ.* **2024**, *9*, 1323898. [CrossRef]
91. Deep, S.; Athimoolam, K.; Enoch, T. Optimizing Administrative Efficiency and Student Engagement in Education: The Impact of AI. *Int. J. Curr. Sci. Res. Rev.* **2024**, *7*, 7792–7804. [CrossRef]

92. Pérez-Campuzano, D.; Ortega, P.M.; Andrada, L.R.; López-Lázaro, A. Artificial Intelligence potential within airlines: A review on how AI can enhance strategic decision-making in times of COVID-19. *J. Airl. Airpt. Manag.* **2021**, *11*, 53–72. [CrossRef]
93. de Sio, F.S. Artificial Intelligence and the Future of Work: Mapping the Ethical Issues. *J. Ethics* **2024**, *28*, 407–427. [CrossRef]
94. Beaudry, A.; Pinsonneault, A. The other side of acceptance: Studying the direct and indirect effects of emotions on information technology use. *MIS Q.* **2010**, *34*, 689–710. [CrossRef]
95. Vössing, M.; Kühl, N.; Lind, M.; Satzger, G. Designing transparency for effective human-AI collaboration. *Inf. Syst. Front.* **2022**, *24*, 877–895. [CrossRef]
96. Dingel, J.; Kleine, A.K.; Cecil, J.; Sigl, A.L.; Lermer, E.; Gaube, S. Predictors of Health Care Practitioners' Intention to Use AI-Enabled Clinical Decision Support Systems: Meta-Analysis Based on the Unified Theory of Acceptance and Use of Technology. *J. Med. Internet Res.* **2024**, *26*, e57224. [CrossRef] [PubMed]
97. Mishra, K.; Boynton, L.; Mishra, A. Driving employee engagement: The expanded role of internal communications. *Int. J. Bus. Commun.* **2014**, *51*, 183–202. [CrossRef]
98. Rožanec, J.M.; Novalija, I.; Zajec, P.; Kenda, K.; Tavakoli Ghinani, H.; Suh, S.; Soldatos, J. Human-centric artificial intelligence architecture for industry 5.0 applications. *Int. J. Prod. Res.* **2023**, *61*, 6847–6872. [CrossRef]
99. Horvatić, D.; Lipic, T. Human-centric AI: The symbiosis of human and artificial intelligence. *Entropy* **2021**, *23*, 332. [CrossRef]
100. Gkinko, L.; Elbanna, A. Designing trust: The formation of employees' trust in conversational AI in the digital workplace. *J. Bus. Res.* **2023**, *158*, 113707. [CrossRef]
101. Kore, A. *Designing Human Centric AI Experiences*; Apress: Berkeley, CA, USA, 2022.
102. Kotter, J.P. *Leading Change*; Harvard Business School Press: Boston, MA, USA, 1996.
103. Matsunaga, M. Uncertainty in the Age of Digital Transformation. In *Employee Uncertainty Over Digital Transformation: Mechanisms and Solutions*; Springer Nature: Singapore, 2024; pp. 11–84.
104. Alkhalifah, J.M.; Bedaiwi, A.M.; Shaikh, N.; Seddiq, W.; Meo, S.A. Existential anxiety about artificial intelligence (AI)—Is it the end of humanity era or a new chapter in the human revolution: Questionnaire-based observational study. *Front. Psychiatry* **2024**, *15*, 1368122. [CrossRef]
105. Hilliard, A.; Kazim, E.; Ledain, S. Are the robots taking over? On AI and perceived existential risk. *AI Ethics* **2024**, 1–14. [CrossRef]
106. RealClearScience. Available online: https://www.realclearscience.com/articles/2023/07/06/ai_is_an_existential_threat__just_not_the_way_you_think_964205.html (accessed on 15 November 2024).
107. Pratt, M.; Boudhane, M.; Taskin, N.; Cakula, S. Use of AI for Improving Employee Motivation and Satisfaction. In Proceedings of the 23rd International Conference on Interactive Collaborative Learning (ICL2020), Tallinn, Estonia, 23–25 September 2020.
108. Spatola, N. The efficiency-accountability tradeoff in AI integration: Effects on human performance and over-reliance. *Comput. Hum. Behav. Artif. Hum.* **2024**, *2*, 100099. [CrossRef]
109. Duong, C.D.; Ngo, T.V.N.; Khuc, T.A.; Tran, N.M.; Nguyen, T.P.T. Unraveling the dark side of ChatGPT: A moderated mediation model of technology anxiety and technostress. *Inf. Technol. People* **2024**. [CrossRef]
110. Shaikh, S.J.; Cruz, I.F. AI in human teams: Effects on technology use, members' interactions, and creative performance under time scarcity. *AI Soc.* **2023**, *38*, 1587–1600. [CrossRef]
111. Al Naqbi, H.; Bahroun, Z.; Ahmed, V. Enhancing work productivity through generative artificial intelligence: A comprehensive literature review. *Sustainability* **2024**, *16*, 1166. [CrossRef]
112. Truong, Y.; Papagiannidis, S. Artificial intelligence as an enabler for innovation: A review and future research agenda. *Technol. Forecast. Soc. Chang.* **2022**, *183*, 121852. [CrossRef]
113. Verhoef, P.C.; Broekhuizen, T.; Bart, Y.; Bhattacharya, A.; Dong, J.Q.; Fabian, N.; Haenlein, M. Digital transformation: A multidisciplinary reflection and research agenda. *J. Bus. Res.* **2021**, *122*, 889–901. [CrossRef]
114. Mukherjee, D.; D'Souza, D. Think phased implementation for successful data warehousing. *Inf. Syst. Manag.* **2003**, *20*, 82–90. [CrossRef]
115. Tarafdar, M.; Roy, R.K. Analyzing the adoption of enterprise resource planning systems in Indian organizations: A process framework. *J. Glob. Inf. Technol. Manag.* **2003**, *6*, 21–51. [CrossRef]

116. Phillips, J.; Klein, J.D. Change Management: From Theory to Practice. *TechTrends* **2023**, *67*, 189–197. [CrossRef]
117. Edmondson, A. Psychological safety and learning behavior in work teams. *Adm. Sci. Q.* **1999**, *44*, 350–383. [CrossRef]

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