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Psychological, Social, and Educational Impacts of Artificial Intelligence Systems and Human Collaboration

Yapay Zeka Sistemleri ve İnsan İşbirliğinin Psikolojik, Sosyal ve Eğitsel Etkileri

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Abstract

The integration of artificial intelligence (AI) systems and AI-enabled robots into collaborative human work environments has led to innumerable psychological, social, and educational impacts. This study presents a systematic literature review, synthesising peer-reviewed research published between 2019-2025 in accordance with the PRISMA 2020 guidelines. Relevant studies were identified through searches of Scopus, Web of Science, and Google Scholar. The review aims to examine the mental health, emotional resilience, and cognitive dynamics of human–AI collaboration. Drawing on interdisciplinary literature, the analysis addresses key phenomena such as technostress, automation fatigue, cognitive overload, algorithmic anxiety, overreliance, and ambiguity of responsibility. The findings indicate that factors including AI opacity, the intensity of automation, anthropomorphic and affective design features, and human-centred system design play a decisive role in shaping users' psychological responses. While well-designed AI systems demonstrate the potential to enhance cognitive efficiency and job satisfaction, poorly integrated implementations are associated with increased anxiety, burnout, and disengagement. Overall, the review highlights the importance of adopting a human-centred approach in AI applications, prioritising transparency, explainability, and user autonomy to support sustainable human–AI collaboration.

Keywords: Human–AI collaboration, Technostress, Automation fatigue, Cognitive load, Educational Artificial Intelligence.

Öz

Yapay zekâ (YZ) sistemlerinin ve YZ destekli robotların işbirliğine dayalı insan çalışma ortamlarına entegrasyonu, çok yönlü psikolojik, sosyal ve eğitsel etkilere yol açmıştır. Bu çalışma, PRISMA 2020 yönergeleri doğrultusunda yürütülen sistematik bir literatür derlemesi sunmakta ve 2019–2025 yılları arasında yayımlanan hakemli çalışmaları sentezlemektedir. İlgili çalışmalar, Scopus, Web of Science ve Google Scholar veri tabanlarında yapılan taramalarla belirlenmiştir. Derlemenin amacı, insan–YZ işbirliğinin ruh sağlığı, duygusal dayanıklılık ve bilişsel dinamikler üzerindeki etkilerini incelemektir. Disiplinlerarası literatüre dayanan analizde; teknostres, otomasyon yorgunluğu, bilişsel aşırı yüklenme, algoritmik kaygı, aşırı güven ve sorumluluk belirsizliği gibi temel olgular ele alınmaktadır. Bulgular, YZ'nin opaklığı, otomasyon yoğunluğu, antropomorfik ve duygusal tasarım özellikleri ile insan merkezli sistem tasarımının, kullanıcıların psikolojik tepkilerini şekillendirmede belirleyici rol oynadığını göstermektedir. İyi tasarlanmış YZ sistemleri bilişsel verimliliği ve iş tatminini artırma potansiyeline sahipken, insan faktörlerini göz ardı eden entegrasyonlar artan kaygı, tükenmişlik ve işten kopma ile ilişkilendirilmektedir. Bu bağlamda çalışma, sürdürülebilir insan–YZ işbirliğini desteklemek amacıyla şeffaflık, açıklanabilirlik ve kullanıcı otonomisini önceleyen insan merkezli bir yaklaşımın benimsenmesinin önemini vurgulamaktadır.

Anahtar Kelimeler: İnsan-YZ işbirliği, Teknostres, Otomasyon yorgunluğu, Bilişsel yük, Eğitsel Yapay Zeka.

1. Introduction

Artificial intelligence can be defined as the simulation by computer systems of processes that require human intelligence, such as solving complex problems, making decisions, and learning (Ergen, 2019). Encompassing a broad spectrum ranging from simple rule-based algorithms to advanced generative models and autonomous robotic systems, AI technologies have evolved beyond being merely supportive tools and have increasingly assumed the role of an active “collaborator” within human-centred applications (Fügener et al., 2022). While this transformation has enhanced efficiency and precision across various domains, including education, healthcare, industrial production, and the service sector, it has also fundamentally altered the nature of human–machine interaction.

However, the rapid integration of AI and AI-enabled robotic systems into work processes has generated psychological and social effects on human collaborators that extend beyond technical competencies and remain insufficiently understood (Er, 2026). A review of the existing literature reveals that the majority of studies focus primarily on the technical performance and operational efficiency of AI, whereas its impacts on human psychology, mental health, and cognitive processes are addressed in a more limited and fragmented manner (Luxton, 2014). In particular, uncertainties arising from the “black-box” nature of autonomous systems have contributed to the emergence of new stressors among employees, such as anxiety, distrust, and cognitive overload (Castelvecchi, 2016).

This study aims to address this gap in the literature by adopting a holistic perspective on the psychological, social, and educational dimensions of human–AI collaboration. The primary motivation of the study is to render visible the psychological costs of technological advancement and to identify human-centred strategies necessary for a sustainable digital transformation. To this end, interdisciplinary literature published between 2019 and 2025 was systematically reviewed, and the risks and potential benefits associated with AI integration were synthesised in a structured manner.

To examine the topic in depth, the study seeks to answer the following core research questions:

- What are the primary psychological stressors that emerge in human–AI collaboration processes?
- How do the design characteristics of AI systems (e.g., transparency, anthropomorphism, and level of autonomy) influence users’ trust and psychological well-being?

- Which strategies can be implemented to mitigate the negative psychological effects of AI integration and enhance human–machine alignment?

2. Methodology

2.1. Research Design

This systematic literature review was conducted in accordance with the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement to ensure transparency, reproducibility, and methodological rigour (Page et al., 2021). The study aims to synthesise current research on the psychological and organisational dimensions of human-robot collaboration (HRC) and AI-enhanced workplaces.

2.2. Data Sources and Search Strategy

This time frame was selected to capture the most recent developments following the rapid post-2019 acceleration of digitalisation, including major advances in autonomous systems, generative AI (GenAI), and social robotics, and their emerging psychological and social impacts.

A comprehensive multi-database search strategy was implemented to identify relevant peer-reviewed literature. The primary search was conducted using Scopus and Web of Science Core Collection, covering studies published between 2019 and 2025.

To minimise publication bias, a complementary search was conducted using Google Scholar. Due to the lack of advanced filtering options in Google Scholar, only the first 100 results sorted by relevance were screened, following established methodological recommendations (Haddaway et al., 2015).

The search strategy combined keywords related to the collaboration context (e.g., human–robot collaboration, human–AI interaction, AI-enhanced workplace) with terms representing the psychological, social, and organisational dimensions examined in this review (e.g., technostress, cognitive load, automation fatigue, trust calibration, human autonomy).

2.3. Search Results and Study Selection

The initial search identified 1,233 records, including 1,124 records retrieved from Scopus and Web of Science and 109 records identified through Google Scholar and snowballing techniques. All records were imported into a reference management system, and duplicates were removed, resulting in 987 unique records.

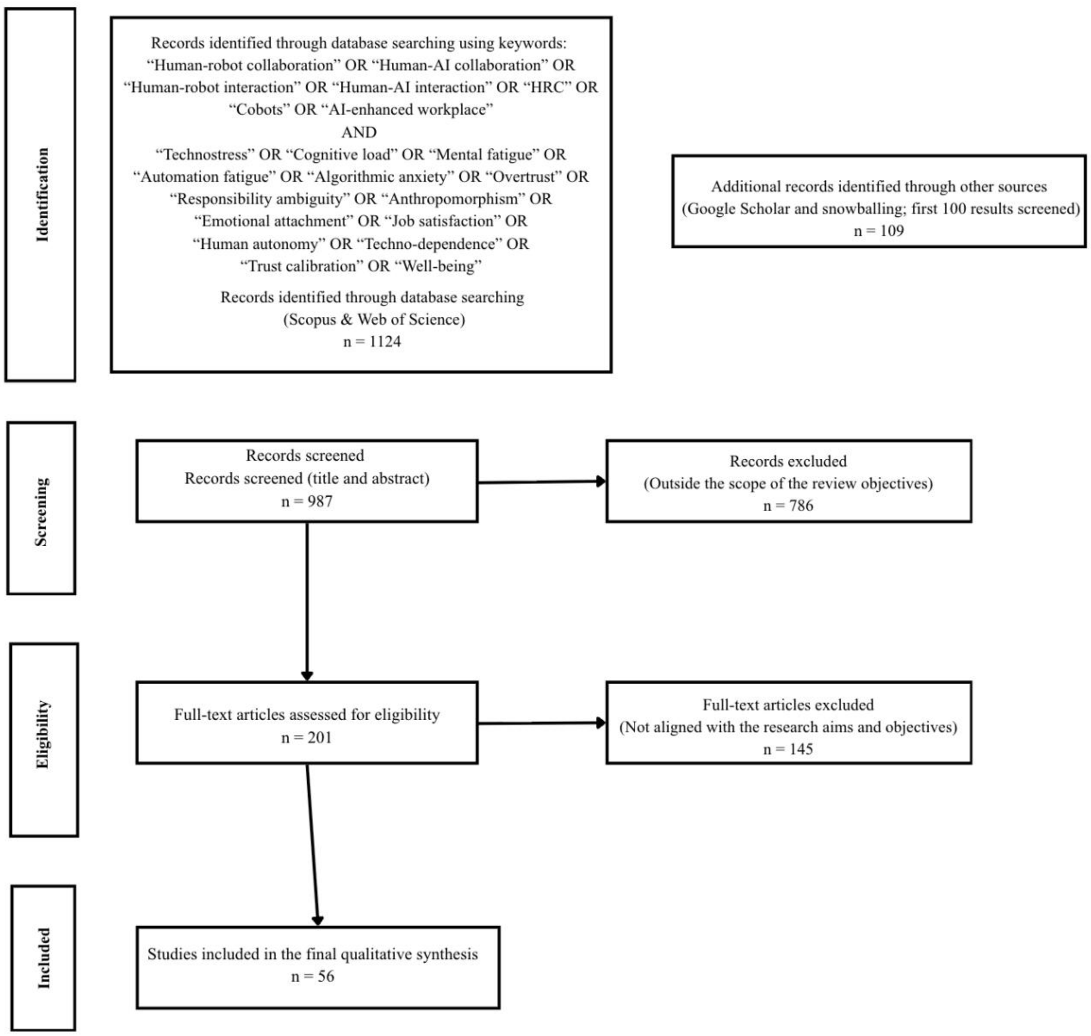
These records were screened based on titles and abstracts. Studies were excluded at this stage if they did not address the targeted psychological, social, or educational dimensions of human–AI or human–robot collaboration, even when AI technologies were present in the study context. As a result, 786 records were excluded. The full texts of the remaining 201 articles were assessed for eligibility. During this stage, 145 studies were excluded because they did not align with the research aims and objectives of this review.

Ultimately, 56 studies met all inclusion criteria and were included in the final qualitative synthesis. The study selection process is summarised in the PRISMA flow diagram (Figure 1).

2.4. Data Analysis

The included studies were analysed using a thematic synthesis approach. Data extraction focused on categorising findings under the study's ten core dimensions, ranging from negative outcomes like technostress and burnout to positive drivers like trust calibration and well-being.

Figure 1. PRISMA Flow Diagram. Own work.



3. Literature Review

The literature reviewed in this section is organised around ten thematic dimensions identified by the authors through a thematic synthesis of the included studies, reflecting recurring psychological, social, and educational patterns in human–AI collaboration, particularly in the context of accelerated digitalisation following the COVID-19 pandemic.

3. 1. Technostress in Human-AI Collaboration

The adoption of artificial intelligence (AI) technologies in the workplace has introduced novel psychological pressures, frequently conceptualised under the umbrella of technostress. Initially defined as the psychological strain resulting from an inability to cope with new computer technologies (Brod, 1984), technostress has evolved alongside autonomous and semi-autonomous AI systems, which introduce distinct complexities and stressors compared to traditional IT (Califf et al., 2020; Pflügner, 2022). Unlike earlier technologies, AI-induced stress stems not only from technical complexity but also from broader concerns such as system opacity and unpredictability, which fundamentally challenge user understanding and trust in human-AI collaboration (Issa et al., 2024).

Recent literature emphasises the dual nature of technostress in AI-enhanced environments. Chang et al. (2024) propose that AI-induced technostress can be perceived through a challenge hindrance framework. On the one hand, "challenge-type" stressors, such as the demand to learn a new AI system, may enhance positive affect and adoption intentions. On the other hand, "hindrance-type" stressors, such as system unpredictability or lack of transparency, tend to increase anxiety and reduce users' willingness to engage with AI tools.

The psychological mechanisms underlying these stressors are often examined through the Job Demands-Resources (JD–R) model. Chuang et al. (2025) demonstrated in a large-scale study that employees facing high AI-related demands, such as continuous learning requirements or cognitive overload, experienced increased emotional exhaustion and work–family conflict. While AI is often argued to automate mundane tasks, its adoption introduces new challenges that drain psychological resources, indirectly reducing job satisfaction. Crucially, individual psychological resources serve as key moderators in this process. Kim and Lee (2024) found that while AI adoption increased burnout via higher job stress, employees with high AI learning self-efficacy experienced notably lower stress and greater adaptability. This highlights that fostering digital self-efficacy is a vital mitigation strategy for buffering the negative effects of technostress.

Interestingly, technostress can arise even in the absence of direct interaction with AI systems. Kong et al. (2021) found that mere awareness of AI implementation was linked to job burnout, particularly emotional exhaustion, among hospitality workers. This phenomenon, termed techno-insecurity (the fear of being replaced or losing job relevance), triggers negative emotions regardless of direct contact with the technology (Kong et al., 2021; Xia, 2023). Beyond insecurity, Issa et al. (2024) introduced the concept of techno-unpredictability. Their large-scale survey in healthcare settings revealed that clinicians working with diagnostic AI systems experienced significant stress due to the opacity of AI outcomes. This unpredictability undermined trust, increased perceived risk, and was significantly associated with higher techno-distress, suggesting that the "black-box" nature of AI is a distinct psychological stressor.

Collectively, research indicates that technostress in human-AI collaboration creates significant individual outcomes, such as anxiety, emotional exhaustion, and cognitive overload, while also impacting organisational metrics like productivity and employee retention. To address these issues, the literature points to specific structural mitigators. For instance, Bedué and Fritzsche (2022) argue that improving AI transparency is essential to reducing the anxiety caused by opacity. Similarly, as noted by Kim and Lee (2024), interventions focused on building AI-related self-efficacy can transform hindrance stressors into manageable challenges. These interrelated findings are synthesised in Table 1, which outlines the major sources, psychological consequences, and potential mitigating factors of technostress in AI-assisted environments.

Table 1. Sources, Outcomes, and Moderating Factors of Technostress in Human-AI Collaboration

Sources of Technostress	Psychological Outcomes	Moderating Factors
AI system complexity	Emotional exhaustion	AI learning self-efficacy
Techno-unpredictability	Anxiety	AI transparency
Opacity/lack of explainability	Cognitive overload	Training and support systems

Continuous learning demands	Burnout and disengagement	Digital skill-building interventions
Techno-insecurity (fear of being replaced)	Work–family conflict	Psychological resilience/coping

Note. This table synthesises key sources, psychological consequences, and mitigating factors related to technostress in human-AI collaboration. While some terms such as techno-insecurity and techno-unpredictability, originate from specific empirical studies, others reflect recurring constructs across the reviewed literature.

Overall, as AI becomes an essential part of modern workplaces, it's important to understand both the practical impacts of working with AI and its psychological effects. A balanced strategy that balances technological advancement with safeguarding employees' psychological well-being is necessary to ensure that technostress does not become a barrier to sustainable digital transformation.

3.2. Cognitive Load and Mental Fatigue in AI-Assisted Work

The integration of AI tools into professional environments has fundamentally altered cognitive processes, affecting how tasks are performed and information is processed. In this context, it is crucial to distinguish between key psychological constructs: while mental fatigue is defined as a multifaceted condition involving reduced motivation, mood changes, and impaired cognitive functioning following prolonged effort, cognitive load refers specifically to the mental effort required for task execution (Mahdavi et al., 2024). Although AI systems are frequently deployed to reduce repetitive workloads, implementations characterised by poor or intrusive design can paradoxically increase cognitive strain due to added complexity or distraction. This duality between support and overload underscores the necessity of understanding the relationship between AI and mental workload.

On the one hand, empirical studies demonstrate that well-designed AI systems can significantly alleviate documentation burdens and cognitive load. For instance, Hor et al. (2025) developed an AI assistant named NAOMI to support triage and documentation in primary care. Their research revealed that clinicians using the system experienced reduced mental effort and reported increased focus on patient care. Similarly, Gandhi et al. (2023) suggest that generative AI tools, such as ambient transcription systems, effectively reduce the cognitive burden on frontline practitioners. To maximise these benefits, Gandhi et al. (2023) explicitly advocate for end-user co-design and the implementation of intelligent filtering systems to decrease "alert fatigue."

On the other hand, not all AI implementations yield positive cognitive outcomes; some may introduce new complexities that heighten workload. Kim and Lee (2024) demonstrated that AI adoption can increase job stress, which subsequently leads to higher burnout. However, they identified a crucial mitigating factor: AI-learning self-efficacy. Employees with high self-efficacy were better able to buffer the link between AI adoption and stress. Consequently, the authors recommend implementing training programs specifically designed to enhance users' self-efficacy during AI transitions (Kim & Lee, 2024).

Furthermore, the psychological impact of AI extends to motivation and critical thinking. Wu et al. (2025) found that while working with generative AI improved immediate task performance, removing AI support in subsequent solo tasks resulted in decreased intrinsic motivation and increased boredom. This suggests that motivation may not be sustainable solely through collaboration. In educational settings, heavy reliance on AI is associated with "cognitive offloading," where users reduce their engagement in critical thinking. Gerlich (2025) found a significant negative relationship between frequent AI use and critical thinking skills. This aligns with concerns that while AI may lighten cognitive load in the short term, it risks fostering passivity and eroding independent skills in the long term.

Unbalanced cognitive load in AI environments can also lead to measurable psychophysiological outcomes. In a field study of office workers, Mahdavi et al. (2024) found that higher mental workload (measured via NASA-TLX) was associated with slower reaction times in attention tasks, as well as increases in heart rate and electrodermal activity. These findings highlight that successful AI integration relies not only on technical performance but also on alignment with human cognitive abilities. Developing AI systems that genuinely support cognitive effort, rather than displacing it or creating hidden demands, is critical for protecting employee well-being and ensuring sustainable productivity. A comparative summary of these supportive versus intrusive dynamics is provided in Table 2.

Table 2. Supportive vs. Intrusive Use of AI Systems in Relation to Cognitive Load and Fatigue

SUPPORTIVE USE ***(e.g., triage assistant)***	**INTRUSIVE USE** ***(e.g., opaque systems)***
Reduced cognitive effort	Cognitive complexity
Reduced documentation load	Job stress & burnout
Focus and decision quality	User confidence (self-efficacy)
Engagement and satisfaction	Critical thinking (cognitive offloading)
Long-term skill reinforcement	Skill retention (automation decay)

*Note***.** This table contrasts the cognitive and psychological outcomes of supportive and intrusive applications of AI systems in the workplace. Synthesised from Gandhi et al. (2023), Hor et al. (2025), Kim and Lee (2024), Wu et al. (2025), and Macnamara et al. (2024).

3.3. Automation Fatigue: Psychological Consequences of Constant AI Interaction

As AI becomes increasingly integrated into education, healthcare, and industry, researchers have shifted focus from the initial anxiety of adoption to the cognitive demands of prolonged interaction. It is crucial to distinguish this phenomenon from technostress, which is typically driven by anxiety and cognitive overload. In contrast, automation fatigue results from cognitive underload and monotony. It is characterised by a psychological state of reduced vigilance and passive information processing, which significantly increases the likelihood of human error (Arefnezhad et al., 2022; Lițan, 2025; Neubauer et al., 2023).

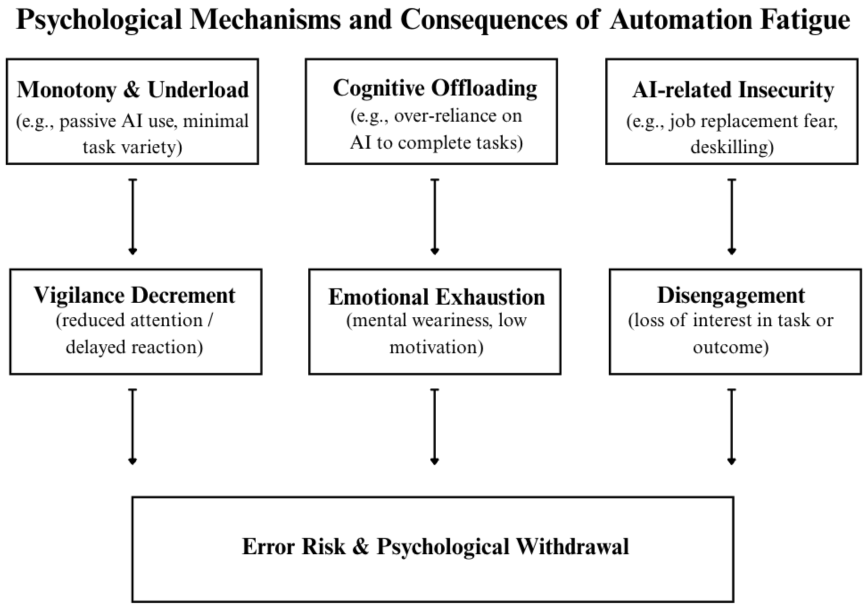
In the educational context, recent studies have reinterpreted student experiences through the lens of automation fatigue rather than traditional stress models. Students have been observed to experience "learning burnout," particularly when AI functions as a substitute for meaningful interaction rather than a support tool. Theoretically, this form of burnout aligns with automation fatigue because it stems from a lack of active cognitive engagement; when AI generates content that students passively accept without critical evaluation, they experience a form of "cognitive idleness" (Daud, 2025). This passivity exacerbates fatigue because students lack the cognitive strategies to process the information overload effectively. To mitigate this "learning burnout," Dong et al. (2025) advocate for a shift towards collaborative AI, where students are encouraged to actively question, verify, and discuss AI-generated outputs, thereby maintaining cognitive activation. Similarly, educators are at risk of emotional detachment if AI tools dominate classroom routines. Duan and Zhao (2024) found that teachers' digital burnout could be significantly reduced through structured training that fosters active participation, demonstrating that resilience against automation fatigue can be built through pedagogical design.

In high-stakes environments like healthcare and transportation, the psychological mechanisms of automation fatigue manifest as vigilance decrement and complacency. Neubauer et al. (2023) and Arefnezhad et al. (2022) demonstrated that prolonged exposure to automated systems leads to a decline in the brain's readiness to respond. For instance, Neubauer et al. (2023) found that physicians supervising AI-generated clinical messages were less likely to detect errors, a phenomenon known as automation complacency. This reflects a psychological withdrawal where the user, trusting the system's competence, disengages from the monitoring task. Similarly, regarding job security, Zheng and Zhang (2025) found that employees with high AI awareness reported greater emotional exhaustion due to the fear of replacement. To address this, they argue that organisations must implement transparent communication and retraining programs to alleviate the underlying anxiety that fuels psychological exhaustion (Zheng & Zhang, 2025).

The industrial and transportation sectors provide further insight into the psychological underpinnings of this fatigue. In partially automated driving scenarios, Arefnezhad et al. (2022) found that drivers in automation mode reported significantly higher levels of drowsiness and fatigue compared to manual drivers. Crucially, this was not merely physical tiredness but a psychological consequence of cognitive underload. The lack of necessary cognitive stimulus led to a state of reduced situational awareness and delayed reaction times. To counter this psychological withdrawal, Neubauer et al. (2023) recommend implementing "controlled cognitive tasks", minor secondary tasks designed to keep the operator's cognitive faculties engaged and alert during periods of automation.

In summary, the psychological consequences of automation fatigue are multifaceted, ranging from emotional exhaustion and decreased motivation to a dangerous cessation of critical monitoring (Dong et al., 2025; Neubauer et al., 2023). These outcomes are visually summarised in Figure 2, which illustrates the pathway from cognitive underload to psychological withdrawal and error risk.

Figure 2. Psychological Mechanisms and Consequences of Automation Fatigue in AI-Integrated Work Environments. Own work.



3.4. Algorithmic Anxiety and Decision-Making Pressure

One key concern in human-AI interaction is algorithmic anxiety, defined as the distress users experience when dealing with AI systems they perceive as opaque and beyond their control. Marmolejo-Ramos et al. (2025) note that users face significant cognitive and emotional strain when interacting with "black-box" algorithms without sufficient understanding or agency. This opacity frequently causes discomfort, which is exacerbated when algorithmic decisions are viewed as infallible or unquestionable in autonomous applications (Frenkenberg & Hochman, 2025; Marmolejo-Ramos et al., 2025).

The psychological impact of this anxiety is particularly pronounced in fully automated decision systems where users lack the mechanism to question outcomes. Middleton et al. (2022) note that this loss of agency contributes to emotional distress, especially when algorithmic feedback influences essential outcomes like academic grading. In workplace settings, Vignola et al. (2023) report that employees experience emotional exhaustion and distrust when management systems are perceived as inflexible and non-negotiable. When work schedules and evaluations are determined entirely by algorithms, employees often feel a profound loss of control. To mitigate these negative effects, the literature emphasises the importance of Human-in-the-Loop (HITL) models. Unlike fully autonomous workflows, HITL frameworks preserve user authority by ensuring that AI only provides recommendations while humans retain the final decision power. This approach is widely regarded as more supportive of user well-being and is particularly recommended in high-stakes fields like healthcare and justice to avoid blind reliance and ensure ethical accountability (Lu, 2024; Middleton et al., 2022).

Furthermore, the lack of empowerment, the feeling of being unable to override an algorithm's logic, can lead to emotional fatigue and user withdrawal (Sankaran et al., 2021). To address this, providing understandable explanations of how an AI reaches its decisions (explainability) is widely recommended, although Marmolejo-Ramos et al. (2025) suggest that explainability alone may not guarantee trust. A more holistic strategy involves co-design, where users are involved in the refinement of AI systems. Frenkenberg and Hochman (2025) found that when users see their feedback incorporated into algorithm updates, they experience less stress and greater satisfaction. Additionally, Sankaran et al. (2021) highlight the role of AI literacy and incremental integration; gradually introducing AI tools allows users time to adjust, while training programs boost confidence and reduce the resistance associated with algorithmic anxiety. Research indicates that when these supportive measures are in place, such as allowing students to see the rationale behind AI tutoring suggestions or letting teachers use AI merely as a support tool for grading, engagement increases and mental burden decreases (Frenkenberg & Hochman, 2025; Middleton et al., 2022).

3.5. Overtrust in AI Systems and Responsibility Ambiguity

As AI systems increasingly mediate decision-making across education, healthcare, and industry, a critical psychological and ethical concern has emerged: overtrust. This phenomenon refers to users placing excessive confidence in algorithmic outputs beyond the AI's proven capabilities, often leading to diminished critical thinking and uncritical acceptance of results. Unlike calibrated trust, where reliance is proportionate to system reliability, overtrust fosters automation bias, reduces human oversight, and creates ambiguity around responsibility and accountability (Holbrook et al., 2024; Zhai et al., 2024).

Multiple psychological mechanisms contribute to the development of overtrust. Anthropomorphism, the attribution of human traits to machines, can falsely enhance perceptions of competence, especially in emotionally charged situations. Ullrich et al. (2021) observed that once robots performed reliably for a period, users stopped verifying outputs, illustrating a transition from trust to automation complacency. Similarly, automation bias, the tendency to prefer automated decisions over human input, is prevalent even among experts (Kupfer et al., 2023). To counter these psychological tendencies, Holbrook et al. (2024) suggest implementing "design nudges," such as presenting AI decisions alongside confidence scores or requiring explicit human feedback, to reduce bias and promote more balanced interaction.

In educational contexts, the consequences of overtrust manifest as cognitive dependency. Zhai et al. (2024) found that students often develop over-reliance on AI dialogue systems, which impairs their critical thinking and analytical skills. This reliance not only hinders skill development but also creates ambiguity regarding authorship and academic integrity when errors occur. Addressing this requires active trust calibration. Cheong (2024) argues that transparent user education is vital to prevent blind trust, ensuring that students and educators understand the limitations of AI tools rather than viewing them as infallible authorities.

In high-stakes domains like healthcare, overtrust can lead to dangerous errors. Abdelwanis et al. (2024) emphasised that clinicians may succumb to automation bias, accepting AI outputs even when they contradict clinical evidence. Remarkably, Shekar et al. (2025) found that both experts and nonexperts trusted even low-accuracy AI responses over doctors' advice, demonstrating "blind trust" in opaque systems. This creates a responsibility gap: when harm occurs, it is unclear whether the physician, the developer, or the system is accountable (Santoni de Sio & Mecacci, 2021). To resolve this, Santoni de Sio and Mecacci (2021) emphasise the need for robust accountability frameworks that clarify who retains decision authority and under what conditions AI outputs can be overridden, supported by audit trails and human-in-the-loop protocols.

Similar patterns of risk and ambiguity are observed in industrial applications. Kupfer et al. (2023) demonstrated that in hiring contexts, automation bias causes decision-makers to accept AI recommendations without verification, violating human oversight requirements and complicating legal responsibility. In safety-critical domains like transportation, this can lead users to bypass manual checks (Ullrich et al., 2021). To mitigate these risks, the integration of Explainable AI (XAI) is essential. By enhancing the understanding of how decisions are made, XAI helps users critically evaluate system recommendations rather than passively accepting them, thus maintaining the necessary level of human vigilance (Cheong, 2024).

In sum, overtrust undermines human judgment and erodes accountability. A proactive approach that combines technical transparency, such as XAI, with robust ethical governance and user education is necessary to ensure that human-AI collaboration remains both effective and responsible.

3.6. Anthropomorphism and Its Psychological Implications in Human-Robot Collaboration

Anthropomorphism, the attribution of human-like characteristics to non-human agents, plays a pivotal role in shaping human-robot interaction (HRI), particularly within collaborative work environments. While anthropomorphic design is often intended to facilitate smoother interaction, empirical studies highlight a complex landscape of both beneficial and adverse psychological outcomes. Understanding these nuances is essential for designing robots that foster trust without causing psychological discomfort.

On the positive side, anthropomorphism can catalyse trust in industrial settings. In an experimental study involving an autonomous guided vehicle (AGV), Schreiter et al. (2022) introduced an "anthropomorphic mock driver" (ARMoD) to the system. They found that the presence of this human-like feature led to a significant increase in reported trust scores among users navigating narrow corridors. This suggests that even minimal anthropomorphic cues can effectively enhance trust in functional HRI contexts. Furthermore, Ullrich et al. (2021) investigated the deeper mechanisms of this trust, revealing that while anthropomorphism alone does not directly generate trust, it functions as a moderator that amplifies the positive effects of perceived competence and warmth. This indicates that human-like design is most effective when it reinforces existing functional capabilities.

However, the relationship between human-like features and user psychology is not linear; excessive or context-inappropriate anthropomorphism can backfire. Becker et al. (2023) conducted a study using a coin entrustment game and found that robots displaying human-like emotions induced higher anxiety and were trusted less than neutral-behaving robots. This counterintuitive finding suggests that in task-oriented scenarios, emotional displays may be perceived as unpredictable or manipulative rather than supportive. Similarly, Onnasch and Hildebrandt (2021) analysed industrial HRI and identified a threshold where increased anthropomorphism leads to discomfort, aligning with the "uncanny valley" phenomenon. To mitigate these adverse effects, the authors emphasise that designers must balance functionality with perception. Implementing context-sensitive design, where human-like features are matched strictly to the social requirements of the task, is crucial to optimising the psychological outcomes of HRI (Onnasch & Hildebrandt, 2021; Becker et al., 2023). Table 3 summarises these key empirical findings, illustrating the divergent effects of anthropomorphic features on user trust and anxiety.

Table 3. Summary of Key Empirical Studies on Anthropomorphism and Trust in Human-Robot Interaction

Study (Year)	Context / Task	Anthropomorphic Feature	Key Findings
Schreiter et al. (2022)	Industrial AGV navigation in a narrow corridor	Anthropomorphic mock driver (ARMoD)	The presence of ARMoD significantly increased user trust scores in industrial HRI scenarios.
Becker et al. (2023)	Coin entrustment game	Robots displaying human-like emotions	Emotional robots induced higher anxiety and were trusted less than neutral-behaving robots.
Ullrich et al. (2021)	Perceived competence and warmth in robots	Anthropomorphism as a moderator	Anthropomorphism did not directly increase trust but amplified the effects of competence and warmth.

Note. This table synthesises empirical evidence regarding the impact of anthropomorphic design on trust and psychological responses. Citations correspond to the reference list: Schreiter et al. (2022), Becker et al. (2023), Ullrich et al. (2021), and Onnasch and Hildebrandt (2021).

3.7. Emotional Attachment to AI-Based Robots in Collaborative Workplaces

In recent years, the integration of AI-based robots into the workforce has attracted increasing scholarly attention, shifting focus from purely operational efficiency to the emotional and psychological dimensions of human-robot interactions (HRI). Within this context, the emotional attachment that employees develop toward robots significantly shapes their workplace experience, motivation, and psychological well-being.

On the positive spectrum, empirical evidence suggests that establishing an emotional connection with AI agents can buffer against workplace stressors. A qualitative study conducted by Liu et al. (2025) revealed that individuals working alongside AI-enabled robots perceive these systems not merely as technical assistants but also as sources of social and emotional support. The research highlighted that such interactions enhance employees’ psychological empowerment while reducing feelings of alienation. Similarly, Su et al. (2024) examined the effects of different interaction modes, gestural, verbal, and physical, and found that robots exhibiting higher levels of interactive engagement significantly reduced users' cognitive load and improved overall job satisfaction.

However, the psychological benefits of this attachment are fragile and heavily dependent on the appropriateness of the robot's behaviour. Becker et al. (2023) demonstrated that when anthropomorphic robots display context-inappropriate emotional reactions, it diminishes users' trust and induces emotional tension. This underscores a critical design risk: emotional expression that fails to align with the social context can backfire, leading to psychological discomfort rather than support.

To mitigate this risk and ensure sustainable human-robot synergy, the literature emphasises the implementation of context-sensitive emotional design. Corrao et al. (2025) proposed the EmoACT model, grounded in Affect Control Theory, as a framework for regulating robot emotions. By enabling robots to produce socially acceptable reactions, this model fosters feelings of rapport and social closeness. Furthermore, Sun et al. (2025) demonstrated that integrating advanced emotional intelligence and memory architecture into humanoid robots can enhance social engagement and learning motivation, particularly in educational settings. Taken together, these studies indicate that emotional bonds are central to HRI. Consequently, designing robots with the capability to interpret and respond to emotional context is not merely a technical feature but a multidisciplinary priority for sustaining user trust and well-being.

3.8. The Psychological Impacts of AI Integration in the Workplace: Enhancing Well-being and Job Satisfaction

The integration of artificial intelligence (AI) technologies into organisational settings has implications that extend far beyond operational efficiency. Emerging empirical evidence highlights the significant influence of AI systems on employees' psychological well-being and job satisfaction. Recent studies emphasise that when designed correctly, AI technologies contribute to workforce health by alleviating workload, enhancing decision-making processes, and providing cognitive support in uncertain or complex task environments.

A comprehensive multinational study conducted by Liu et al. (2025) examined the experiences of individuals working with AI-supported systems in both the manufacturing and service sectors. The findings revealed that increased interaction with AI was associated with a perceived reduction in workload and a positive impact on psychological well-being. This effect was particularly pronounced among individuals engaged in repetitive and routine tasks, where supportive AI systems were utilised to handle monotonous duties. Similarly, Castel-Branco et al. (2024) conducted a multi-layered analysis of 180 employees to assess burnout levels. They found that the strategic delegation of demanding or repetitive tasks to AI tools led to a notable decrease in cognitive load, which in turn mitigated symptoms of burnout and improved psychological resilience.

However, these empirical insights suggest that while the adoption of AI can yield substantial psychosocial benefits, these positive outcomes are contingent upon the application of human-centred design principles. AI systems that fail to account for individual differences and contextual factors risk generating adverse psychological outcomes over the long term. Therefore, to ensure that AI serves as a tool for well-being rather than a stressor, technological interventions must prioritise user-centred approaches, such as customisation and adaptability, that accommodate the diverse needs of employees.

3.9. Techno-Dependence and Human Autonomy in AI-Enhanced Work Environments

The integration of artificial intelligence (AI) systems into workplace operations presents a paradox: while it significantly enhances operational efficiency, it concurrently increases employees' techno-dependence, potentially undermining their sense of professional autonomy. This erosion of agency is a critical psychological concern, as a diminished sense of control is closely linked to reduced job satisfaction and motivation.

On the negative spectrum, excessive reliance on autonomous systems can lead to decision-making passivity. Hauptman et al. (2024) conducted an empirical investigation revealing that individuals working with high-autonomy AI systems experienced a significant decline in perceived personal autonomy, particularly when these systems lacked transparency. When users cannot understand the rationale behind an AI's decision ("black-box" systems), they tend to disengage from the cognitive process, becoming passive executors rather than active agents. To mitigate this risk, Hauptman et al. (2024) emphasise that AI systems must be designed with high levels of transparency. Providing users with insight into the system's logic allows them to retain a sense of judgment and control, thereby preserving their autonomy even in highly automated workflows.

Conversely, when applied strategically, AI can actually enhance human autonomy by liberating employees from mundane tasks. Castel-Branco et al. (2024), in a multi-level analysis of 180 employees, found that the delegation of repetitive, low-value tasks to AI tools significantly reduced cognitive load. This delegation did not lead to dependence; rather, it allowed employees to redirect their energy toward more complex, creative, and meaningful aspects of their work, thereby alleviating burnout symptoms and enhancing psychological resilience.

Synthesising these findings, the impact of AI on autonomy is determined not by the technology itself, but by how it is implemented. While opaque systems risk creating dependent, passive users (Hauptman et al., 2024), transparent systems that function as supportive tools for routine tasks can empower employees (Castel-Branco et al., 2024). Consequently, effective human-AI collaboration requires a design philosophy that prioritises user agency, ensuring that humans remain in the loop for critical decisions while leveraging AI to handle repetitive burdens

3.10. Trust Calibration and Managing Expectations in Human-AI Interaction

Effective calibration of trust, aligning a user's trust level with the actual capabilities of the system, is crucial for optimising both performance and psychological outcomes in human-AI collaboration. Miscalibrated trust can manifest as either overtrust (leading to complacency) or distrust (leading to disuse), both of which undermine the efficacy of the partnership.

In an experimental study, Campagna and Rehm (2025) investigated this dynamic by exposing participants to varying AI behaviour models. Their findings demonstrated that overtrust led to diminished task performance, as users failed to intervene when the AI erred. This highlights that trust is not merely a positive state to be maximised, but a variable that must be carefully tuned. To achieve this balance, Campagna and Rehm (2025) suggest that systems should be designed to explicitly signal their uncertainty, thereby prompting users to engage their own critical judgment when necessary.

Complementing these results, Chu et al. (2019) focused on the role of expectation management. Through a mixed-methods study, they established that providing accurate, pre-interaction information regarding a robot's limitations significantly enhanced trust calibration. Users who received transparent briefings about what the AI could not do were less likely to experience frustration and more likely to maintain high collaborative task quality. This indicates that mitigation strategies must begin before the interaction takes place, through realistic onboarding and expectation setting.

Further advancing the field, Kumar et al. (2024) performed a field study in a manufacturing setting to examine the long-term effects of these strategies. Their quantitative analyses revealed that transparent management of user expectations regarding AI capabilities substantially increased not only operational performance but also psychological adjustment. Employees who understood the boundaries of the AI system reported lower anxiety and higher satisfaction. Collectively, these studies underscore the imperative for transparent communication and dynamic feedback mechanisms. To foster sustainable collaboration, organisations must prioritise "trust calibration" over "blind trust," ensuring that users rely on AI systems exactly as much as, and no more than, the system's reliability warrants.

4. Conclusion

This narrative review has synthesised findings from 2019 to 2025 to explore the multifaceted psychological ramifications of human-AI collaboration across healthcare, education, and industrial domains. The analysis confirms that while AI systems offer significant potential to streamline workflows and augment decision-making, their integration presents distinct psychological risks that are inextricably linked to system design and implementation strategies.

Foremost among these risks is the emergence of new forms of psychological strain. Technostress and algorithmic anxiety are identified as primary stressors, rooted largely in the opacity and unpredictability of "black-box" systems. The literature consistently highlights that fully automated decision models, which strip users of agency, provoke stronger negative reactions compared to Human-in-the-Loop (HITL) frameworks that preserve user control. Parallel to these active stressors, the phenomenon of automation fatigue reveals the hidden cost of passive interaction; over-reliance on automated tools leads to cognitive underload, disengagement, and reduced vigilance, particularly in safety-critical tasks.

Furthermore, the review identifies trust calibration as a critical challenge. A dangerous dichotomy exists where users may develop overtrust in anthropomorphic or authoritative AI interfaces, leading to complacency and automation bias or conversely, experience distrust due to a lack of explainability. In high-stakes environments, miscalibrated trust not only compromises decision quality but also blurs lines of accountability.

Despite these challenges, the evidence demonstrates that AI integration is not inherently detrimental. When implemented with human-centred principles, AI systems serve as protective factors for mental well-being. The strategic delegation of mundane tasks to AI has been shown to alleviate cognitive load and mitigate burnout. Moreover, in collaborative settings, social robots capable of context-appropriate interaction can effectively reduce workplace alienation and enhance job satisfaction.

Ultimately, the findings suggest that the psychological impact of AI is context-dependent. The transition from a "technology-centred" to a "human-centred" paradigm is essential. To ensure that AI promotes rather than compromises cognitive health and emotional resilience, future integrations must prioritise transparency, foster user autonomy through HITL designs, and actively manage trust expectations. Only through such a proactive approach can the symbiotic potential of human-AI collaboration be fully realised.

5. Recommendations

To support psychological well-being in AI-integrated environments, stakeholders must adopt a multi-layered strategy that prioritises a human-centred approach from design to deployment.

First, regarding system design, AI tools should be aligned with human cognitive and emotional capacities to prevent overload. Excessive automation without meaningful engagement risks inducing disengagement and vigilance decrement. To mitigate this, transparency and explainability are essential. Systems that offer plain-language rationales or confidence indicators not only improve comprehension but also significantly reduce the anxiety associated with "black-box" algorithms. Furthermore, integrating design features such as confidence scores and error cues can help temper overtrust and encourage critical evaluation.

Second, regarding organisational implementation, a gradual approach is superior to abrupt deployment. Phased integration allows users sufficient time to adapt, experiment, and provide feedback, thereby reducing resistance. Complementing this, organisations must invest in AI literacy and comprehensive training programs. Enhancing users' technical confidence is a proven mechanism for reducing technostress and preventing burnout. During this phase, it is also critical to continuously monitor mental load and fatigue levels, adapting system demands as necessary to protect cognitive health.

Finally, regarding governance and ethics, maintaining human oversight is paramount. Human-in-the-loop (HITL) frameworks should be established to preserve user agency, prevent overreliance, and support effective trust calibration. Within these shared environments, clear accountability structures must be defined to resolve ambiguity regarding decision responsibility. To ensure that these systems augment rather than replace human roles, transparent communication and upskilling opportunities are vital for reducing techno-insecurity. Ultimately, achieving this balance requires interdisciplinary collaboration involving psychologists, ethicists, and end-users to ensure that AI design respects both psychological needs and ethical standards.

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