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PREDICTORS OF EMPLOYEE PSYCHOLOGICAL ADAPTATION TO AI SYSTEMS IN IT ORGANIZATIONS

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ABSTRACT
The integration of artificial intelligence (AI) into IT organizations has reshaped workplace dynamics, requiring employees to adjust both technically and psychologically. This study explores the main factors influencing employees' psychological adaptation to AI systems in IT environments. Drawing on technology acceptance, organizational behavior, and cognitive psychology, it develops a conceptual model based on perceived usefulness, trust in AI, psychological readiness, perceived job security, and organizational support. The study uses an integrative narrative review of recent literature on AI adoption and employee adaptation. It is not a systematic review or meta-analysis and does not follow PRISMA 2020 procedures, such as protocol registration, exhaustive search documentation, or formal quality scoring. The reviewed literature suggests that trust in AI and organizational support are among the most important factors supporting successful adaptation, while psychological readiness and perceived usefulness also contribute to positive outcomes. Perceived job security is proposed as a moderating factor that may influence these relationships when employees view AI as a threat to employment stability. The model offers practical guidance for IT managers and HR professionals seeking to reduce resistance, uncertainty, and workplace stress during AI implementation. It also provides testable propositions for future longitudinal, cross-cultural, and industry-specific research.

Keywords: *Artificial Intelligence, Psychological Adaptation, IT Organizations, Employee Behavior, Technology Adoption, Organizational Management, Trust, Job Security*

1. INTRODUCTION

The rapid development of artificial intelligence has significantly changed the structure and operation of IT organizations worldwide. AI is increasingly used for automation, decision support, predictive analytics, natural language processing, and process optimization. Recent estimates indicate that organizational AI adoption increased from below 20% in 2017 to more than 70% by the mid-2020s (AIPRM, 2026). Although AI can improve efficiency and productivity, it may also create psychological pressures for employees, including job insecurity, fear of displacement, cognitive overload, and the continuous need to update professional skills (Brynjolfsson & Mitchell, 2017).

Unlike earlier technologies, AI systems can generate recommendations, assess performance, support decisions, and operate with a certain level of autonomy. Employees therefore interact with AI not only as a tool but increasingly as a workplace collaborator. This development may require them to reconsider their professional roles, competencies, identity, and contribution to the organization (Davenport & Ronanki, 2018).

Employee adaptation to AI is therefore more than a technical adjustment. It involves cognitive, emotional, and behavioral changes. Cognitive adaptation concerns how employees understand AI and reinterpret their own roles (Nassanbekova et al., 2026). Emotional adaptation includes managing anxiety, uncertainty, distrust, and ambivalence. Behavioral adaptation refers to changes in work routines, decision-making practices, and willingness to rely on AI-generated outputs.

In this review, psychological adaptation is defined as an ongoing process through which employees revise their understanding of work, regulate emotional responses, and modify their behavior to function effectively alongside AI systems. This concept is broader than technology acceptance, intention to use, or actual system use. It is also distinct from well-being, resistance, and job performance, although it may influence each of these outcomes. Psychological adaptation is thus treated as an underlying process that may lead to acceptance, resistance, changes in well-being, or improved or reduced performance.

Organizations often focus primarily on technical implementation, system performance, and expected returns while paying insufficient attention to employees' psychological responses. However, limited adaptation may result in underuse of AI systems, passive resistance, reduced data quality, and rejection of organizational change, thereby weakening the expected benefits of AI adoption (Jarrahi, 2018).

The IT sector provides an especially relevant context for examining these issues. Although IT professionals are generally familiar with rapid technological change, technical expertise does not necessarily protect them from anxiety related to automation and role transformation. Their greater awareness of AI capabilities may even intensify concerns about professional relevance and future employment (Kellogg, Valentine, & Christin, 2020). Nevertheless, much of the available evidence comes from general employee and knowledge-worker samples (Alsharaideh et al., 2026). Therefore, its application to IT professionals should be viewed as an informed interpretation rather than direct IT-specific evidence.

This study identifies and discusses potential predictors of employees' psychological adaptation to AI in IT organizations. It adopts an integrative narrative review rather than a PRISMA-based systematic review. The analysis is guided by three research questions: which individual and organizational factors are most frequently associated with psychological adaptation to AI; how these factors may interact as predictors, mediators, or moderators; and what the reviewed evidence implies for organizational practice and future empirical testing. The proposed conceptual model is presented as a set of testable propositions rather than as a confirmed causal framework.

2. LITERATURE REVIEW

2.1. THEORETICAL FOUNDATIONS OF TECHNOLOGY ACCEPTANCE

Research on technology adoption has a long tradition in information systems and organizational psychology. The Technology Acceptance Model developed by Davis (1989) identifies perceived usefulness and perceived ease of use as the main factors influencing technology adoption. The Unified Theory of Acceptance and Use of Technology extends this approach by including performance expectancy, effort expectancy, social influence, and facilitating conditions as predictors of behavioral intention (Venkatesh et al., 2003). These frameworks remain important for understanding AI adoption in organizations.

Nevertheless, traditional acceptance models may not fully capture the distinctive characteristics of AI systems. Unlike conventional software, AI often produces probabilistic, changing, and difficult-to-explain outputs. Meske et al. (2022) therefore emphasize explainability as an important element of AI acceptance. Employees may consider an AI system useful and easy to operate but still hesitate to rely on it when its decisions cannot be understood. This distinction separates basic acceptance from the deeper integration of AI into everyday professional practice.

Cognitive load theory also helps explain employee adaptation to AI. Workers must continue performing their usual duties while learning how to interpret, verify, and apply AI-generated information. When these additional demands exceed employees' cognitive capacity, they may experience overload, avoid AI tools, or use them only superficially. Tarafdar et al. (2007) describe this problem through the concept of technostress, showing that technological complexity can increase role stress and reduce productivity. Similarly, the meta-analysis by Nastjuk et al. (2023) confirms that technology-related stress is generally associated with lower employee well-being and reduced use of information systems. These findings highlight the need to consider cognitive demands and technostress when designing AI implementation strategies.

2.2. PSYCHOLOGICAL AND ORGANIZATIONAL DIMENSIONS

Organizational change literature provides an additional perspective on employees' adaptation to AI. Change-management models, including Lewin's (1947) force-field analysis and Kotter's (1996) eight-step framework, identify readiness for change as an important condition for successful transformation. In the context of AI, psychological readiness refers to employees' cognitive and emotional preparedness to work with intelligent systems. Individuals who are open to learning, receptive to new experiences, and less resistant to change are generally better positioned to adapt (Brougham & Haar, 2017).

Perceived job insecurity is a major obstacle to this process. Brougham and Haar (2017) found that employees who view Smart Technology, AI, Robotics, and Algorithms as threats to their occupational roles report greater anxiety and weaker organizational commitment. These concerns may be particularly strong among older employees and workers performing routine tasks. Similarly, Yam et al. (2023) show that awareness of workplace automation can increase insecurity and encourage maladaptive behavior even when no actual job losses occur. This suggests that perceived threat, rather than realized displacement, is often the central psychological mechanism.

Job insecurity can also be measured reliably through validated instruments, such as the scale developed by Vander Elst et al. (2014). It may therefore be incorporated into conceptual and empirical models of AI adaptation as a measurable predictor or moderator. In particular, strong perceptions of employment threat may weaken the positive effects of training, organizational support, and other adaptation initiatives.

At the organizational level, successful digital transformation depends not only on technological infrastructure but also on culture, leadership, and talent management (Ha, 2026). Kane et al. (2019) argue that organizations achieve stronger employee engagement when AI is presented as a means of supporting and empowering workers rather than replacing them. Such framing can reduce insecurity, increase perceived usefulness, and strengthen employees' identification with the organization.

2.3. TRUST IN AI SYSTEMS

Trust is a central factor in AI adoption and has received growing scholarly attention. Glikson and Woolley (2020) distinguish three related dimensions of trust in AI: cognitive trust, based on assessments of system accuracy and reliability; affective trust, reflecting emotional confidence and comfort; and behavioral trust, demonstrated through willingness to rely on AI-generated recommendations. Although interconnected, these forms of trust may develop at different speeds and respond to different workplace conditions.

Research also highlights the importance of employees' first experiences with AI. Early errors, unclear outputs, or perceived unfairness can create lasting skepticism that later positive experiences may not easily overcome. By contrast, carefully managed implementation, supported by clear explanations, training, and opportunities for feedback, can establish trust and encourage long-term adaptation. Organizations should therefore place particular emphasis on employee support during the initial stages of AI deployment.

2.4. HUMAN-AI COLLABORATION AND IDENTITY

Recent research increasingly examines how AI affects professional identity and human-AI collaboration. Bankins et al. (2024) note that the psychological and relational effects of AI on employees remain less developed than research on its technical and economic consequences. This gap is especially relevant in IT organizations, where employees must continuously redefine their roles in relation to increasingly capable systems.

Jarrahi (2018) describes effective AI use as a form of human-AI symbiosis based on complementary strengths. AI is particularly effective at processing large datasets, detecting patterns, and producing predictions, whereas humans contribute contextual judgment, ethical reasoning, creativity, and social intelligence. From this perspective, successful adaptation does not require replacing human judgment but redirecting it toward more complex and higher-value tasks.

However, Raisch and Krakowski (2021) identify an automation–augmentation paradox. Although AI can improve efficiency and support decision-making, it may also reduce autonomy, weaken skills, and increase dependence on algorithmic outputs. Employees must therefore balance the benefits of AI assistance against the possible erosion of expertise and professional identity. Kellogg et al. (2020) similarly show that algorithmic management can reshape organizational power and workplace control, creating additional psychological pressure.

These effects are closely connected to employee motivation. Gagné et al. (2022) argue that algorithmic management influences motivation through employees' perceptions of autonomy, competence, and relatedness. Parent-Rocheleau and Parker (2022) further describe algorithms as active work designers that reshape task variety, feedback, and decision authority. In addition, Langer and Landers (2021) emphasize that fairness and transparency strongly influence whether employees accept automated decisions.

Dwivedi et al. (2021) conclude that successful AI integration requires alignment between technological design, organizational policies, and employee psychology. Psychological adaptation should therefore be treated as a central element of AI implementation rather than as a secondary consequence of technological change.

2.5. INDIVIDUAL DIFFERENCES AND DEMOGRAPHIC MODERATORS

In addition to organizational factors, individual differences can significantly shape employees' psychological adaptation to AI. Age is frequently identified as an important influence, as older workers may show lower initial acceptance, stronger concerns about job security, and slower adaptation. However, these effects can be reduced through appropriate training and organizational support (Brougham & Haar, 2017). Educational background and previous experience with technological change also matter, because employees who have successfully adapted to earlier innovations may be better prepared to respond to AI.

Gender differences appear less evident in IT environments, where technical competence and self-efficacy are often more evenly distributed. Personality traits may be more influential. Employees who are open to experience and comfortable with ambiguity tend to explore AI systems, seek additional information, and develop more accurate expectations about their capabilities. By contrast, individuals with higher neuroticism or lower tolerance for uncertainty may perceive AI as more threatening and require greater support.

These findings indicate that employee adaptation does not follow a single pattern. Organizations should therefore provide flexible and differentiated forms of training and support that reflect variations in age, experience, personality, and psychological readiness.

3. RESEARCH METHODOLOGY

3.1. REVIEW APPROACH: AN INTEGRATIVE, NARRATIVE CONCEPTUAL REVIEW

This study adopts an integrative narrative review rather than a PRISMA 2020 systematic review. It does not use a registered protocol, exhaustive reproducible searches, dual-reviewer screening, formal quality assessment, or quantitative evidence aggregation, and therefore does not claim the evidentiary strength of a systematic review.

Instead, the study aims to interpret and integrate a fragmented body of theoretical and empirical research into a coherent conceptual model. Narrative and integrative reviews are particularly appropriate when a field lacks a unified framework and includes diverse concepts, methods, and forms of evidence (Snyder, 2019; Torraco, 2005). As Snyder (2019) explains, such reviews may not follow a fully systematic search process and rely mainly on qualitative synthesis. This approach is suitable because research on employees' psychological adaptation to AI in IT workplaces remains dispersed and insufficiently consolidated.

3.2. LITERATURE IDENTIFICATION AND SELECTION

The literature was identified through a purposive rather than exhaustive search of Scopus, Web of Science, PsycINFO and Google Scholar. The search used combinations of terms related to psychological adaptation to AI, technology acceptance, trust in AI, job insecurity, technostress, and human-AI collaboration. It focused mainly on English-language publications from 2015 to 2026, while also including selected foundational studies, such as Davis (1989) and Lewin (1947). Sources were included when they addressed psychological, behavioral, or organizational aspects of AI adoption in professional settings. Purely technical, consumer-oriented, and non-citable materials were excluded. Additional studies were identified through backward citation tracking, which is common in narrative reviews. Because the study was not designed as a systematic review, no protocol was registered, no complete search log or screening count was maintained, and inclusion decisions were not independently verified by a second reviewer. No formal quality-assessment tool was applied. These methodological limitations are explicitly acknowledged and discussed further in Section 2.5.

3.3. ANALYTICAL STRATEGY

The analytical strategy involved three stages: identifying and grouping theoretical frameworks by disciplinary origin (information systems, organizational psychology, cognitive science, management science); organizing empirical and conceptual sources descriptively by predictor addressed, population studied (noting explicitly where a study was or was not IT-specific), evidence type, and main finding, summarized in Table 1; and synthesizing these sources qualitatively into an integrative conceptual framework proposing primary predictors, their plausible interrelationships, and their organizational implications. This coding was carried out narratively by the authors rather than through independent dual coding with reliability statistics, and should be read as an interpretive organization of the literature rather than a quantitatively validated classification.

3.4. SECONDARY STATISTICAL DATA

Contextual statistics on AI adoption rates, reskilling patterns, and employee risk perceptions were drawn from a commercial secondary aggregator (AIPRM, 2026) and a McKinsey & Company (2025) global survey, used only to illustrate the practical scale of adaptation challenges, not as primary empirical evidence for the proposed model. The original survey samples, exact denominators, question wording, and year-on-year comparability underlying the AIPRM-aggregated figures are not fully disclosed by the aggregator and were not independently re-verified against primary survey documentation; readers seeking precise methodological detail should consult the original McKinsey State of AI materials directly. The figures in Section 3.1 should accordingly be read as indicative of general workplace patterns rather than precise, independently verified parameters.

3.5. LIMITATIONS OF THE METHODOLOGICAL APPROACH

This review has four main limitations. First, it is an integrative narrative review rather than a PRISMA-based systematic review and should not be interpreted as offering the same level of evidentiary rigor. Second, it cannot establish causal relationships. Connections among the proposed predictors are therefore presented as interpretations derived from the literature rather than as findings demonstrated by this study. Statements that individual studies demonstrate particular effects refer only to the results reported in those studies.

Third, much of the reviewed evidence is based on general employee or knowledge-worker populations rather than IT professionals specifically. Its application to IT organizations should therefore be regarded as an interpretive extension. Fourth, the contextual statistics are subject to the sourcing limitations discussed in Section 2.4.

The proposed model should consequently be understood as a theoretically grounded set of testable propositions, not as a confirmed causal framework. Future research should examine it through longitudinal studies, experiments, mixed-methods case studies, and IT-specific samples. A protocol-driven PRISMA 2020 systematic review would also provide a valuable complementary contribution once the empirical literature becomes more developed.

3.6. OVERVIEW OF KEY LITERATURE INFORMING THE CONCEPTUAL MODEL

Table 1 summarizes the sources that most directly informed the predictors and propositions in Section 3.2, indicating evidence type, context, predictor/theme, and contribution to the synthesis. It is offered as a transparency aid consistent with the narrative review approach; it is illustrative of the core literature underlying the model, not an exhaustive or systematically screened evidence base, and does not constitute a PRISMA-style included-studies table.

Table 1. Overview of Key Literature Informing the Conceptual Model

Source	Context / Evidence Type	Predictor / Theme	Contribution to This Review
Davis (1989); Venkatesh et al. (2003)	Instrument development; theoretical integration (TAM/UTAUT)	Perceived usefulness	Foundational acceptance constructs extended to AI-specific use
Meske et al. (2022)	Conceptual review	Explainability	Positions explainability as an AI-specific extension of TAM
Tarafdar et al. (2007); Nastjuk et al. (2023)	Survey (223 orgs); meta-analysis	Technostress	Empirical and aggregate evidence linking ICT stress to productivity loss
Brougham & Haar (2017); Vander Elst et al. (2014); Yam et al. (2023)	Survey; psychometric validation; multimethod	Job insecurity	Establishes job insecurity as a measurable, threat-driven moderator
Glikson & Woolley (2020)	Narrative review of trust research	Trust in AI	Cognitive/affective/behavioral trust dimensions underlying the model
Kane et al. (2019); Edmondson (1999)	Practitioner synthesis; field study (51 teams)	Organizational support	Links organizational framing and psychological safety to adaptation
Jarrahi (2018); Raisch & Krakowski (2021)	Conceptual articles	Human-AI collaboration	Symbiosis and automation-augmentation paradox framing adaptation strain
Kellogg et al. (2020); Gagné et al. (2022)	Literature review; theoretical review (SDT)	Algorithmic management	Documents control shifts and motivational mechanisms behind strain
Dwivedi et al. (2021); Bankins et al. (2024)	Multidisciplinary/ multilevel reviews	Cross-cutting	Broad socio-technical framing; identifies the gap this review addresses
Noy & Zhang (2023)	Preregistered experiment (453 professionals)	Perceived usefulness	Experimental evidence of GenAI productivity and mixed affective response

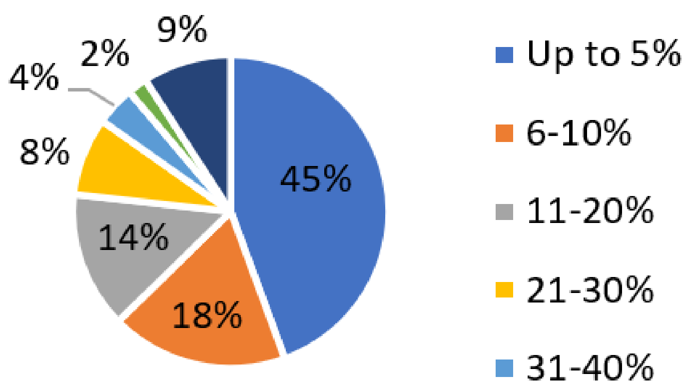
Source: Compiled by the authors based on the literature reviewed in this study

4. ANALYSIS AND RESULTS

4.1. CURRENT STATISTICAL CONTEXT OF AI ADOPTION IN THE WORKPLACE

Recent statistical evidence indicates that although corporate interest in artificial intelligence is high, the depth of workforce-level integration remains uneven and, in many organizations, still relatively limited. Data summarized by AIPRM from McKinsey's global survey (AIPRM, 2026) show that between July 2023 and July 2024, 44% of AI-using companies reskilled only up to 5% of their workforce due to AI use, while just 18% reskilled 6-10%. At the same time, 55% of organizations reskilled at least 6% of employees, suggesting that meaningful workforce transformation is taking place, albeit unevenly distributed across the corporate landscape.

Figure 1. Number of AI-using companies reskilling employees in AI, by workforce share



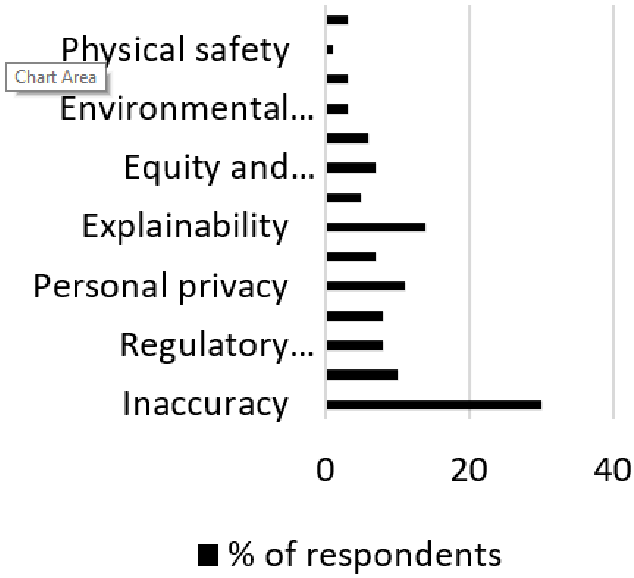
Source: https://www.aiprm.com/ai-adoption-statistics/ accessed on 01/05/2026

The IT sector is among the most intensive users of AI, with applications spanning software development, data analytics, cybersecurity, and IT operations. Consequently, IT professionals face multiple adaptation challenges, as AI functions not only as a work tool but also as a system that supports decision-making, monitors performance, and, in some cases, automates tasks previously performed by employees.

The success of AI adoption depends not only on the extent of implementation but also on employees' experiences with these systems. According to McKinsey & Company (2025), 51% of organizations using AI reported experiencing at least one negative consequence of AI adoption, with AI inaccuracy identified as one of the most common issues. Such experiences may undermine employees' initial trust and slow psychological adaptation.

Employee concerns extend beyond technical performance. McKinsey & Company (2025) reports that AI inaccuracy (30%) and limited explainability (14%) are the most frequently cited concerns, followed by personal privacy (11%), cybersecurity (10%), regulatory compliance (8%), intellectual property (8%), workforce displacement (6%), organizational reputation (5%), and equity and fairness (7%). Less frequently reported concerns include national security (3%), environmental impact (3%), political stability (3%), and physical safety (1%). Together, concerns about AI inaccuracy and explainability account for 44% of reported employee concerns, highlighting the critical role of trust, transparency, and reliable system performance in successful workplace adaptation.

Figure 2. Distribution of employee-reported concerns about AI use, by concern category



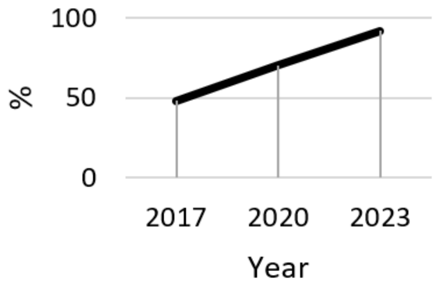
Source: https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai accessed on 01/05/2026

These findings show that employees experience AI not only as a productivity tool but also as a socio-technical system marked by uncertainty and limited trust. Effective use therefore requires psychological adaptation, including the ability to assess AI outputs critically, recognize when human judgment should prevail, and preserve professional autonomy when working with opaque or inconsistent systems.

Despite these challenges, the economic rationale for AI adoption remains strong. AIPRM (2026) reports that the proportion of firms achieving tangible benefits from AI increased from 48.4% in 2017 to 92.1% in 2023. Experimental evidence supports this trend. Noy and Zhang (2023) found that access to generative AI improved productivity and job satisfaction, although it also temporarily increased concerns about automation.

The workplace impact of AI is therefore defined by a dual reality. AI can generate substantial organizational and individual benefits, but its effective integration depends on addressing employee uncertainty, mistrust, and perceived risks. Psychological adaptation is consequently a central condition for translating technological capability into sustained workplace value.

Figure 3. The percentage of firms that benefit from AI adoption by year



Source: https://www.aiprm.com/ai-adoption-statistics/ accessed on 01/05/2026

These implications matter for psychological adaptation as a strategic priority: organizations that focus exclusively on technical AI performance while neglecting the human dimensions of adoption frequently find business benefits undermined by disengagement, sub-optimal utilization, and unaddressed resistance, whereas those investing proportionally in both technical quality and psychological support are better positioned to realize AI's full potential. Human-centered AI implementation is thus not a social-responsibility supplement but a core component of an effective adoption strategy.

4.2. ANALYTICAL FRAMEWORK: PSYCHOLOGICAL ADAPTATION TO AI AS A DYNAMIC SYSTEM

Psychological adaptation to AI in IT organizations is a dynamic and non-linear process involving continuous interaction between cognitive evaluation, emotional response, and behavioral change. Unlike conventional technologies, AI systems often operate autonomously, generate probabilistic outputs, and lack full transparency. Employees must therefore develop new ways of understanding, evaluating, and working with these systems.

The proposed conceptual model is summarized in five propositions:

P_1: *Cognitive, affective, and behavioral trust in AI positively influences psychological adaptation and serves as a foundation for other adaptation factors.*

P_2: *Organizational support positively influences adaptation and strengthens the relationship between trust and adaptation.*

P_3: *Psychological readiness and perceived usefulness positively influence the cognitive and behavioral dimensions of adaptation.*

P_4: *Perceived job security moderates these relationships, with low job security weakening the positive effects of trust, support, readiness, and usefulness.*

P_5: *Adaptation outcomes, including AI use, resistance, well-being, and performance, influence subsequent levels of trust and readiness, creating a continuous feedback cycle.*

These propositions are derived from the narrative synthesis and remain to be tested empirically.

At the cognitive level, employees form mental models to understand what an AI system does, how reliable it is, and when it may fail. When AI is perceived as opaque, employees may repeatedly verify its outputs, restrict its use to low-risk tasks, or ignore its recommendations. Explainability and appropriate training are therefore necessary for developing calibrated trust.

The emotional dimension includes reactions ranging from curiosity and confidence to anxiety and concern about professional relevance. Positive responses are more likely when AI is perceived as supporting employee capabilities without reducing autonomy. By contrast, systems associated with surveillance, job replacement, or loss of control may generate persistent resistance.

Behavioral adaptation is reflected in the frequency, depth, and context of AI use. Employees may recognize the usefulness of AI while remaining reluctant to rely on it in important decisions. Cognitive acceptance may therefore develop before meaningful behavioral integration.

These dimensions are connected through feedback loops. Positive experiences, such as accurate outputs and time savings, can strengthen trust and readiness, while unexplained errors may restore skepticism. Adaptation should consequently be viewed as an ongoing process that may need to restart when AI systems, organizational structures, or employee roles change.

4.2.1. KEY PREDICTORS AND THEIR INTERACTIONS IN ORGANIZATIONAL CONTEXT

Psychological adaptation to AI is shaped by several interrelated individual and organizational predictors.

Trust in AI appears to be one of the most important factors because it connects employees' perceptions of a system with their willingness to rely on it. Trust depends not only on accuracy but also on transparency, consistency, fairness, and predictability (Glikson & Woolley, 2020). In IT organizations, technically skilled employees may be especially sensitive to differences between expected and actual system behavior. Even an accurate system may fail to gain meaningful trust when its outputs cannot be explained. Explainability is therefore a central condition for trust, particularly during the early stages of implementation.

Organizational support includes formal resources, such as training, documentation, and technical assistance, as well as informal factors, including leadership behavior, peer support, and psychological safety. Employees are more likely to experiment with AI when they can ask questions and make mistakes without fear of appearing incompetent (Edmondson, 1999). Strong support cultures are associated with greater AI use and lower resistance, but support must continue beyond initial training (Kane et al., 2019).

Psychological readiness reflects employees' openness to change, confidence in learning, tolerance of uncertainty, and previous experience with technological change. Employees with high readiness are more likely to approach AI with curiosity and engage in self-directed learning, whereas those with low readiness may interpret it as a threat and avoid its use. Readiness may therefore influence how AI exposure affects employee well-being and adaptation (Brougham & Haar, 2017).

Perceived usefulness remains a key factor from technology acceptance theory (Venkatesh et al., 2003). In AI settings, however, usefulness depends not only on performance improvement but also on compatibility with existing workflows, interpretability, and employees' ability to recognize the contribution of AI to positive outcomes. Clear and visible benefits generally encourage adoption, while unclear or indirect benefits weaken motivation.

Perceived job security is proposed as an important moderator. When employees believe AI threatens their employment or career prospects, they may resist adoption even while recognizing its organizational value. This response may represent rational self-protection rather than simple resistance to change. By contrast, employees are more likely to engage with AI when it is credibly presented as a tool for augmentation rather than replacement.

These predictors interact rather than operate independently. Strong organizational support may compensate for low readiness, while visible usefulness can strengthen trust. Conversely, job insecurity combined with poor communication may create a negative cycle of disengagement and resistance. Organizations may then incorrectly interpret low use as a technical problem and invest further in deployment without addressing the underlying psychological barriers.

4.2.2. STRATEGIC IMPLICATIONS FOR AI IMPLEMENTATION IN IT ORGANIZATIONS

This analysis generates five evidence-grounded strategic implications that position human factors as a primary design constraint in AI implementation, not merely a technical afterthought. First, organizations should treat explainability as a core system requirement, weighted equally with accuracy in procurement, via interfaces that communicate confidence levels and key decision factors. Second, a continuous, embedded learning approach, iterative training, peer communities, hands-on experimentation, is more durable than one-time training events, given that competence requirements evolve as AI systems are updated. Third, strategic communication should address job security, fairness, and role relevance directly rather than focusing only on AI capabilities; transparent communication that acknowledges limitations and clarifies how roles will evolve substantially reduces threat perceptions, and leaders who openly model their own learning provide particularly influential demonstrations of organizational culture. Fourth, roles should be redesigned to leverage human-AI complementarity rather than simply adding AI tools to existing job descriptions, emphasizing creative problem-solving, contextual judgment, and ethical oversight where AI cannot substitute. Fifth, organizations should implement systematic monitoring of psychological indicators, trust, anxiety, role clarity, alongside conventional performance metrics, since without such monitoring, adaptation barriers remain invisible until they surface as measurable performance deficits.

5. DISCUSSION

The proposed framework contributes to understanding psychological adaptation to AI in three main ways. First, it presents adaptation as a dynamic and multidimensional process rather than a simple transition from non-use to adoption. The feedback loops between cognitive, emotional, and behavioral dimensions in P_5 help explain why AI use may stabilize, decline, or regress after initial implementation.

Second, the framework extends TAM and UTAUT to the specific characteristics of AI. Explainability is positioned as a possible link between perceived usefulness and behavioral intention, while organizational support is treated as an ongoing process rather than a one-time facilitating condition. Third, perceived job security is proposed as a moderator in P_4. Where employees view AI as a credible threat to their employment, training, explainability, and technical support may have weaker effects unless organizations first address concerns about displacement through clear and credible communication.

Although these propositions are consistent with the reviewed literature, they require empirical testing. For example, early experiences with AI may have a lasting influence on trust, but this relationship has not yet been adequately examined through longitudinal research. Generalizability also remains uncertain because much of the evidence comes from North American and Western European contexts. Cultural factors, including power distance and uncertainty avoidance, may alter the importance of leadership support, individual readiness, and other predictors.

From a practical perspective, the framework provides HR and IT managers with a diagnostic basis for evaluating employee readiness before, during, and after AI implementation. It also highlights an ethical concern: adaptation should not require employees to accept opaque monitoring, unexplained decisions, or poorly communicated restructuring. Trust, transparency, and organizational support are therefore important not only for performance but also for the responsible governance of technological change.

6. CONCLUSION

Psychological adaptation to AI in IT organizations is a complex and dynamic process that extends beyond traditional models of technology adoption. This review suggests that adaptation is influenced by five interrelated predictors: trust in AI, organizational support, psychological readiness, perceived usefulness, and perceived job security. Rather than operating independently, these factors interact across individual and organizational levels, forming the basis of the proposed conceptual propositions (P_1-P_5), which remain to be validated through empirical research.

The study contributes theoretically by conceptualizing adaptation as a process involving continuous interaction between cognitive, emotional, and behavioral dimensions, while extending established technology acceptance frameworks to the specific characteristics of AI. From a practical perspective, the findings highlight that successful AI implementation depends not only on technological capability but also on trust, transparency, effective communication, and sustained organizational support. Although AI is delivering measurable benefits for many organizations, employee concerns regarding explainability, system accuracy, and job security continue to present significant barriers to successful adoption.

The proposed framework also emphasizes the role of leadership in facilitating adaptation. Managers must not only adopt AI themselves but also create an environment that encourages learning, trust, and open communication throughout the implementation process. Future research should test the proposed model using longitudinal and cross-cultural designs, investigate leadership as a driver of psychological adaptation, and compare adaptation processes across industries with different levels of AI adoption.

Acknowledgment

Note on use of artificial intelligence (AI): An AI language model was used in this paper for translating the original text from Ukrainian to English and for grammatical correction following translation.

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