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Article

A SYSTEMATIC REVIEW OF HUMAN-AI COLLABORATION IN IT SUPPORT SERVICES: ENHANCING USER EXPERIENCE AND WORKFLOW AUTOMATION

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ABSTRACT
The rapid evolution of Artificial Intelligence (AI) has profoundly impacted IT support services, leading to a paradigm shift from traditional, hierarchical support structures to integrated, human-AI collaborative ecosystems. In these emerging models, AI systems complement human expertise by automating routine tasks, enabling predictive service responses, and enhancing decision accuracy, while human agents contribute contextual judgment, ethical oversight, and emotional intelligence. This systematic review investigates how such collaboration is transforming IT support operations, focusing specifically on its influence on user experience (UX), workflow automation, human cognitive adaptation, and institutional readiness. Adhering to the PRISMA 2020 guidelines, a total of 98 peer-reviewed articles published between 2013 and 2024 were rigorously identified, screened, and synthesized from leading academic databases including Scopus, Web of Science, IEEE Xplore, and ACM Digital Library. The reviewed literature reveals that AI technologies—such as chatbots, machine learning-driven ticketing systems, robotic process automation (RPA), and natural language processing (NLP)—have become central to the modern support landscape, improving first-contact resolution rates, reducing operational costs, and enabling 24/7 support scalability. The review further maps adoption patterns using established theoretical frameworks such as the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and various digital transformation models, all of which highlight key enablers like performance expectancy, ease of use, social influence, and strategic alignment. Despite promising outcomes, persistent challenges remain—including data fragmentation, algorithmic bias, interface limitations, and workforce resistance to automation—which must be addressed through thoughtful design and ethical governance. By synthesizing insights across technical, human, and organizational dimensions, this review contributes a comprehensive and interdisciplinary understanding of how human-AI collaboration is redefining IT support services, offering practical implications for researchers, system designers, and IT leaders seeking to deploy intelligent, sustainable, and user-centric support systems.
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KEYWORDS
Human-AI Collaboration; IT Support Services; Workflow Automation; User Experience; Artificial Intelligence Integration;

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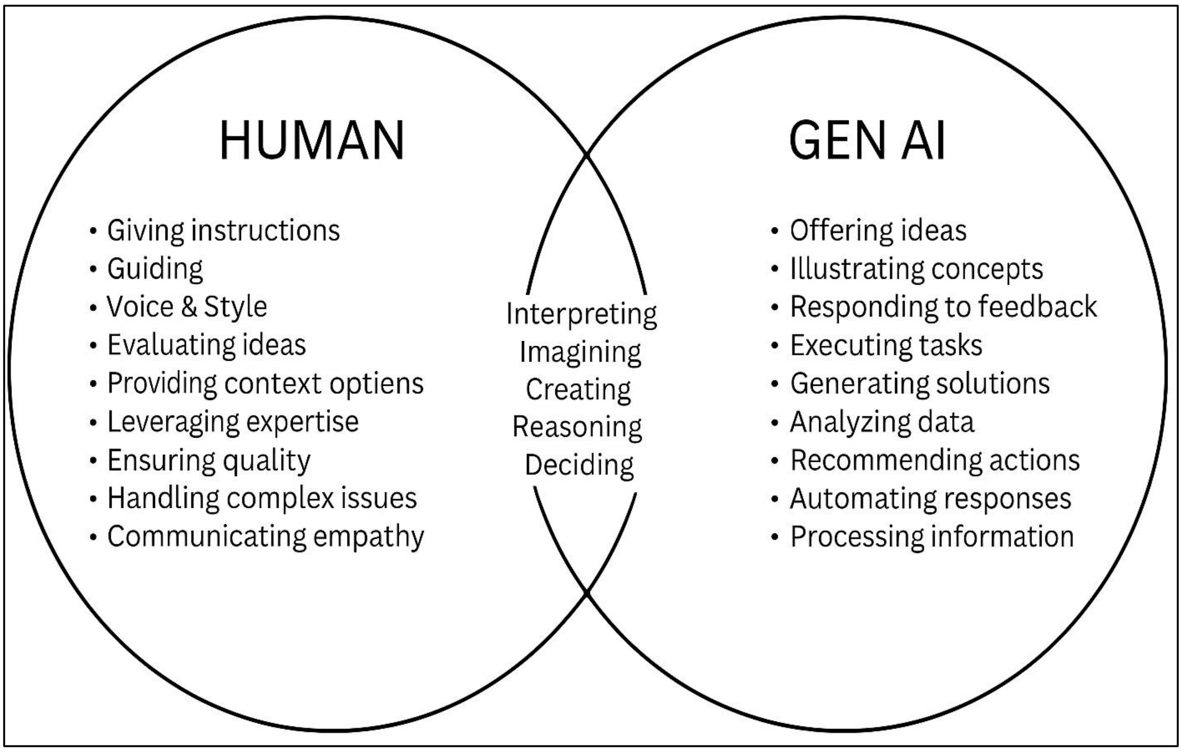
INTRODUCTION

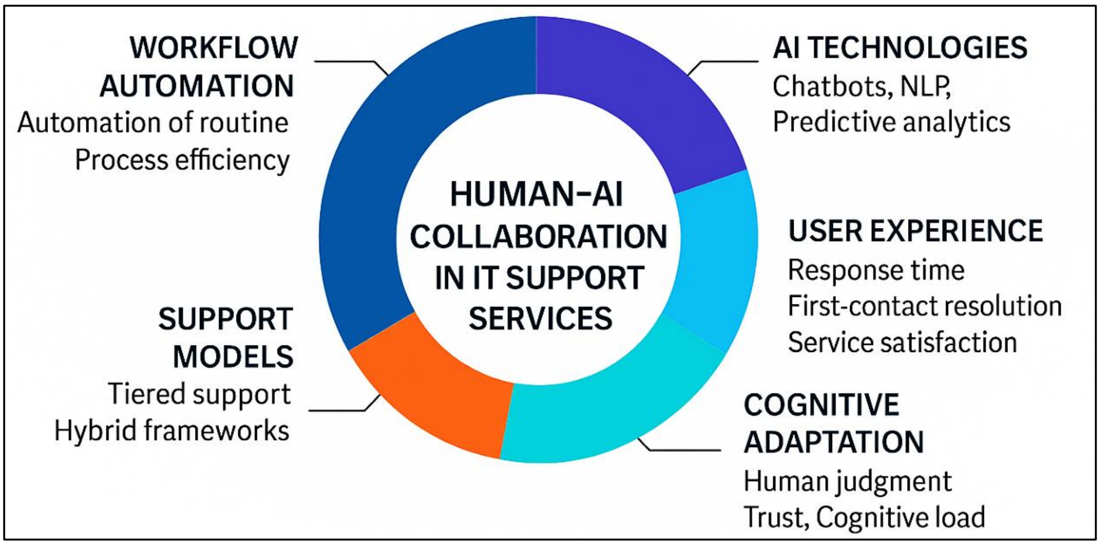
Human-AI collaboration refers to the synergistic interaction between humans and artificial intelligence systems, where each complements the other's capabilities to achieve a common goal (Wang et al., 2020). In this dynamic, AI systems are not standalone tools but function as cooperative agents assisting humans in complex cognitive and operational tasks. Within the domain of information technology (IT) support services, this collaboration becomes particularly critical. IT support services encompass a range of activities such as incident management, helpdesk operations, troubleshooting, software updates, and user training, all of which require responsiveness, problem-solving, and communication (Sarker et al., 2024). Traditionally, IT support has been a human-centered activity that emphasizes interpersonal interaction and situational analysis; however, the advent of AI has introduced automation, predictive analytics, and machine learning algorithms that significantly alter the scope and nature of these tasks (Reverberi et al., 2022). As AI technologies evolve in sophistication—particularly in areas like natural language processing (NLP), robotic process automation (RPA), and real-time analytics—organizations across sectors are increasingly integrating AI into IT service workflows (Schroder et al., 2022). This collaboration enhances efficiency while reallocating human attention to tasks that require emotional intelligence and contextual reasoning. Global enterprises such as IBM, Microsoft, and Oracle have adopted hybrid human-AI frameworks in their IT service delivery to minimize downtime and increase user satisfaction (Puerta-Beldarrain et al., 2022). As such, the integration of human-AI collaboration in IT support is not merely a technological trend but a strategic transformation that impacts organizational behavior, workforce dynamics, and service quality (Sauer & Burggräf, 2024). Recognizing the implications of this shift requires a systematic investigation of how AI functions in tandem with human agents and what benefits or challenges arise from this alignment in IT support contexts.

Figure 1: Comparative Roles of Humans and Generative AI in IT Support Collaboration



The adoption of AI in IT support services holds substantial global relevance as both developed and emerging economies grapple with increasing digital service demands and skills shortages in tech-related roles (Zhang et al., 2021). In nations like the United States, Germany, and Singapore, where digital infrastructure is highly developed, AI-enabled IT support is leveraged to maintain service quality, reduce response latency, and deliver round-the-clock assistance through automated channels (Zhang et al., 2024). In developing countries such as India, Brazil, and South Africa, where IT outsourcing and support centers contribute significantly to national economies, AI-driven support tools are seen as solutions to cost-efficiency and scale challenges (Gabriel et al., 2023). According to the International Data Corporation, global spending on AI in IT operations exceeded $20 billion in 2021 alone, reflecting a robust international interest in operationalizing AI support systems. These systems not only manage large volumes of tickets and repetitive queries but also analyze user behavior to provide proactive support (Heinzl et al., 2024). Furthermore, multinational corporations deploy uniform AI support systems across geographic locations to ensure consistent service standards and align with global digital transformation strategies (Li et al., 2024). The significance of AI in IT support is further underscored in high-stakes sectors such as healthcare and finance, where service downtime or technical errors can result in severe repercussions. Thus, AI's role in ensuring continuity, compliance, and customer satisfaction in IT services is not confined to localized business needs but resonates across institutional and national boundaries. The cross-border relevance of human-AI collaboration in support functions invites systematic inquiry into how organizations harmonize AI capabilities with human judgment and how cultural, regulatory, and infrastructural differences shape this integration (Wang et al., 2020).

Figure 2: Functional Roles Contributing to Human-AI Collaboration in UI/UX-Centered IT Support Systems



The conceptualization of AI as a collaborator rather than a tool marks a critical shift in its application within service operations (Ling et al., 2024). Early uses of AI in IT support were largely limited to automation scripts and predefined decision trees embedded in helpdesk software. Over time, the development of advanced algorithms enabled adaptive learning systems capable of real-time data processing, contextual understanding, and user-specific interactions. These advancements catalyzed the transition from automation to augmentation, where AI agents assist human IT professionals by handling routine tasks such as password resets, software installations, and system diagnostics, thereby freeing human experts to focus on complex problem-solving (Wang et al., 2020). Companies like Google and ServiceNow have incorporated AI-driven incident prioritization and ticket categorization systems that reduce bottlenecks in IT operations (Sarker et al., 2024). Concurrently, developments in human-centered AI design have fostered systems that are interpretable, transparent, and aligned with user expectations (Feldman, 2017). Research demonstrates that organizations adopting collaborative AI models exhibit higher levels of task efficiency, service consistency, and employee satisfaction (Reverberi et al., 2022). Moreover, the use of digital assistants equipped with NLP capabilities allows for seamless communication between end users and support agents, enhancing responsiveness and reducing cognitive workload (Schroder et al., 2022). This shift highlights an important transformation: AI is no longer viewed as a backend tool but as an active participant in service delivery, requiring a reevaluation of human-AI role boundaries, interface design, and operational protocols.
User experience (UX) stands at the center of IT support efficacy, and the integration of AI tools has been shown to significantly shape users' perceptions of service quality, reliability, and

personalization. In IT support scenarios, user experience encompasses ease of access, response time, resolution accuracy, and communication clarity. AI-enabled chatbots and virtual assistants are now widely employed to manage first-level support queries, offering instant responses and guided troubleshooting (Puerta-Beldarrain et al., 2022). Studies show that when these systems are designed with empathetic response modeling and dynamic context tracking, they generate higher satisfaction levels compared to static or rule-based systems (Sharma et al., 2023). However, the presence of a human fallback system is crucial; when issues escalate beyond AI capability, seamless handover to a human agent preserves continuity and reinforces trust. Research also highlights the importance of interface design, where voice modulation, message clarity, and visual cues impact user engagement with AI tools. The co-presence of human agents and AI in support services can create a fluid user journey, where AI initiates interaction and humans resolve nuanced concerns, forming a hybrid interaction model. The psychological comfort users derive from knowing a human is available if needed plays a critical role in acceptance and satisfaction with AI-driven support (Sauer & Burggräf, 2024). Additionally, UX metrics now incorporate AI responsiveness and contextual adaptability as indicators of service excellence, aligning with ISO/IEC 25010 standards for system usability. Therefore, understanding the dynamics of user-AI-human interaction is vital to designing effective support systems that optimize both performance and perception. The main objective of this systematic review is to explore how human-AI collaboration enhances IT support services, with a focus on improving user experience and automating workflows. It investigates the integration of AI tools—such as chatbots, NLP-based virtual assistants, and automated ticketing systems—and how these technologies work alongside human agents to improve efficiency, accuracy, and responsiveness. The review also examines how this collaboration affects user satisfaction, operational performance, and the continued importance of human oversight in handling complex or ethical decisions. Additionally, it aims to identify organizational factors—such as digital maturity, staff training, and governance—that influence the success of AI integration in support environments. By synthesizing current research, the study provides insights into how AI can augment rather than replace human expertise in IT support operations.

LITERATURE REVIEW

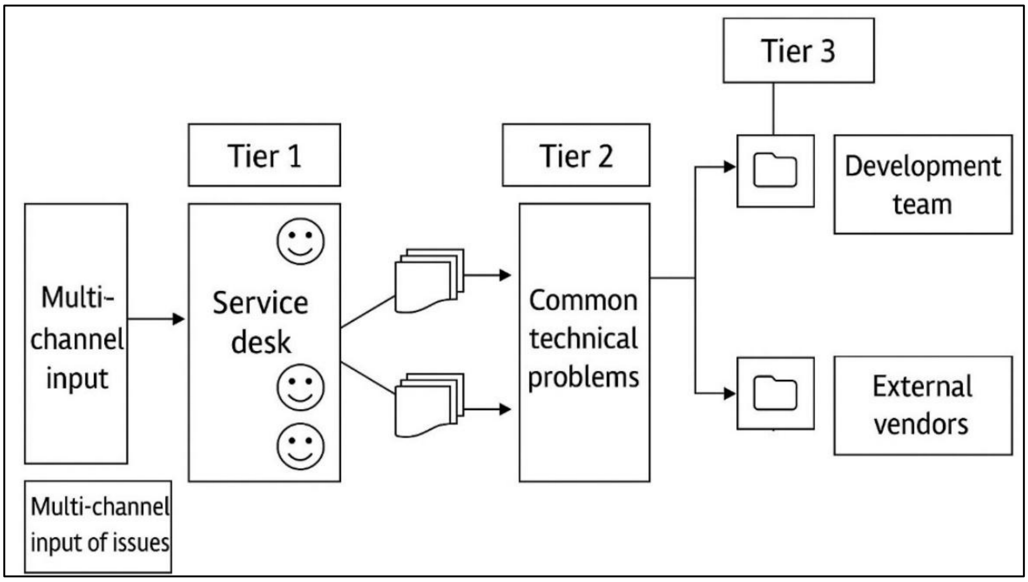
The increasing complexity of digital service environments has prompted a shift from traditional IT support frameworks to more dynamic, AI-augmented systems. In this context, the literature reflects a growing scholarly and industrial interest in how artificial intelligence collaborates with human agents to deliver timely, efficient, and user-centered IT support services. The evolution of this field intersects with multiple domains including service automation, human-computer interaction, cognitive augmentation, user experience design, and organizational transformation. Existing research has explored a wide range of AI technologies—such as chatbots, predictive analytics, robotic process automation (RPA), and natural language processing (NLP)—within IT support ecosystems, yet there remains a fragmented understanding of how these systems effectively integrate with human decision-makers and frontline support agents. This literature review aims to synthesize these contributions by categorizing the body of work into core thematic areas that reflect the technological, human, organizational, and ethical dimensions of Human-AI collaboration in IT services. By structuring the literature according to specific objectives and sub-domains, this section provides a consolidated foundation for evaluating the effectiveness, limitations, and implementation considerations of hybrid IT support systems. The review is organized into nine detailed thematic areas that collectively represent the multifaceted nature of human-AI integration in modern support environments.

IT support services (Tier 1, 2, 3 frameworks)

The tiered model of IT support services has long served as the standard for managing end-user technical issues, with Tier 1, Tier 2, and Tier 3 representing distinct levels of support complexity and expertise. Tier 1 typically addresses common user issues such as password resets or connectivity problems, generally through call centers or help desks (Tegen et al., 2020). Tier 2 escalates more technical concerns requiring specific domain expertise, such as system configuration errors or software conflicts (Chu & Rouse, 1979). Tier 3 support encompasses high-complexity issues, typically involving the software development team, hardware engineers, or external vendors (Chen et al., 2024). Research by Wu et al. (2022) highlights that this framework enables effective triaging of problems, reducing backlog and streamlining service delivery. However, its rigid structure often causes delays when issues are misrouted or require multi-tier coordination (Liao & Vaughan, 2023).

According to Jayant et al. (2020), the linear nature of tiered support models does not fully capture the complexities of modern IT ecosystems, where issues frequently span multiple domains and require collaborative diagnosis. Moreover, studies have observed inefficiencies in ticket escalation protocols that delay issue resolution and degrade the user experience. Despite its widespread adoption, the traditional tiered model often lacks adaptability in dynamic or high-volume environments, leading researchers to examine how AI-enhanced tools may assist or restructure this model. While the framework remains operationally relevant, its hierarchical rigidity poses constraints in agile organizations or service environments characterized by high rates of change and user demand (Boßelmann et al., 2023). The foundational logic of the tiered model has thus been increasingly questioned in light of technological disruptions and shifting user expectations, prompting calls for hybrid support models that blend automation with expert escalation pathways (Cannas et al., 2023).

Figure 3: Tiered IT Support Services Framework: Integrating AI and Human Expertise for Scalable Issue Resolution



The implementation of tiered IT support systems presents numerous operational challenges that limit performance, particularly in environments with high user diversity, rapid issue turnover, or complex service dependencies. One major concern involves the manual classification and routing of service requests, which often leads to misclassification and delayed resolution (Liu et al., 2024). Empirical findings by DeGrave et al. (2023) indicate that over 30% of tickets submitted to Tier 1 are inaccurately categorized, leading to unnecessary escalation and resource inefficiency. This inefficiency is further compounded by siloed knowledge bases across tiers, which impede effective knowledge sharing and continuous improvement (Schmitt & Buschek, 2021). Furthermore, the tiered structure often struggles with real-time responsiveness, as escalations involve cross-functional communication and wait times that contradict modern expectations of instant support (Schmitt & Buschek, 2021). The performance of Tier 2 and Tier 3 teams is often hampered by the lack of contextual information provided in Tier 1 ticket notes, which results in redundant troubleshooting efforts. As organizations scale, these inefficiencies become magnified, especially when support teams are geographically distributed or outsourced (Swearngin & Li, 2019). Studies by Amershi et al. (2015)and Duan et al. (2020) emphasize that support staff experience cognitive overload when navigating complex IT environments with insufficient system intelligence to assist decision-making. The lack of integrated dashboards and decision-support tools also reduces visibility into issue trends and bottlenecks (Drosos et al., 2020). Additionally, organizational resistance to modifying traditional support tiers due to legacy practices and employee role definitions further constrains optimization efforts (Silva-Rodríguez et al., 2020).

The infusion of artificial intelligence into IT support operations has catalyzed a re-examination of the tiered service model, offering new methods for enhancing operational efficiency, reducing delays, and improving the accuracy of issue classification. AI technologies—such as natural language

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processing (NLP), machine learning (ML), and robotic process automation (RPA)—are increasingly deployed at the Tier 1 level to automate ticket logging, classify issues, and provide first-contact resolution for routine problems (Castellanos-Ardila et al., 2021). These tools help offload repetitive tasks from human agents, allowing Tier 1 to handle larger volumes while escalating only the most complex issues. Research by Chaudhuri et al.(2020) and Antony et al.(2021)illustrates how AI chatbots and virtual assistants reduce cognitive load on support agents and provide 24/7 support coverage without increasing staffing costs. AI-based predictive ticketing systems have also been used to forecast issue severity and route tickets to the appropriate tier, enhancing prioritization accuracy (Oppenlaender, 2022). Integration of AI into Tier 2 operations—such as using diagnostic algorithms or knowledge recommendation engines—has improved the speed and relevance of human interventions (Prades et al., 2013). Furthermore, AI-driven analytics platforms provide Tier 3 engineers with comprehensive logs, system health data, and historical trends, enabling faster root cause analysis (Jiang et al., 2022). These transformations reduce the linear constraints of the traditional model and facilitate more fluid escalation paths based on real-time analysis rather than rigid protocols. Nevertheless, studies caution against full automation, emphasizing the need for human oversight, especially in cases involving contextual interpretation or ethical considerations (Sutton, 1991). Thus, while AI offers substantial value in reconfiguring the tiered framework, its successful deployment depends on hybrid design principles that preserve expert involvement alongside intelligent automation (Beltramelli, 2018).

Legacy support models vs. AI-supported frameworks

Legacy IT support models refer to the conventional structures and processes used by organizations to handle technical issues prior to the emergence of AI and intelligent automation. Typically, these models rely heavily on human intervention at every stage of the support cycle, from issue identification to resolution and feedback collection. The support hierarchy is generally divided into tiered structures, with front-line staff responsible for first-contact resolution and higher-tier teams managing more complex or escalated issues (Cascella et al., 2023). In legacy systems, service management frameworks such as ITIL (Information Technology Infrastructure Library) guide standard operating procedures and service level agreements (Monk et al., 2008). While these models emphasize accountability, knowledge documentation, and role clarity, they also suffer from latency, inefficiency, and inconsistent service quality (Andersen & Maalej, 2024). Empirical studies show that human-driven support systems are often subject to delays due to manual ticket categorization, inconsistent note-taking, and bottlenecks in escalation workflows (Janssen et al., 2011). Moreover, the lack of centralized knowledge repositories in legacy environments leads to repetitive troubleshooting and a reliance on individual expertise rather than institutional learning (Cai et al., 2013) Human factors such as burnout, cognitive fatigue, and task-switching further exacerbate inefficiencies, particularly during high-volume support cycles (Mosqueira-Rey et al., 2022). Additionally, the inability to provide continuous 24/7 support limits the scalability of these frameworks in global or digitally dependent organizations (Zhen et al., 2023). While legacy models have served as the foundation for IT service management, their static processes and dependence on manual workflows often hinder agility, responsiveness, and cost-efficiency in modern service environments (Teso et al., 2023).

AI-supported frameworks in IT service management have emerged as a strategic response to the limitations of legacy systems. These frameworks leverage advanced technologies such as machine learning (ML), natural language processing (NLP), and robotic process automation (RPA) to automate and augment support functions across tiers (Parasuraman et al., 2000). AI tools are now widely used for auto-classification of support tickets, chatbot-based user interaction, predictive maintenance, and real-time anomaly detection (Loft et al., 2007). The integration of AI significantly enhances the speed and accuracy of issue resolution, especially at Tier 1, where high-volume, low-complexity issues dominate (Dong et al., 2024). Additionally, AI systems facilitate knowledge management by extracting, curating, and delivering contextual information to human agents during live support sessions (Lin & Marculescu, 2020). This minimizes redundant effort and enhances diagnostic precision. Unlike legacy systems that rely on static scripts and procedural escalation, AI-supported frameworks use data-driven models to adapt in real time to evolving service demands. Intelligent routing engines can dynamically allocate support tickets based on predicted complexity, historical patterns, and agent specialization. These innovations also enable 24/7 support availability, ensuring continuous uptime for global operations without significantly increasing operational costs.

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Moreover, the deployment of AI dashboards and monitoring systems allows for proactive intervention and SLA compliance tracking, enhancing visibility and control across service ecosystems. While human oversight remains crucial in resolving ethical dilemmas or complex technical anomalies, AI frameworks have successfully offloaded routine tasks and provided new levels of scale and intelligence to IT service management.

Figure 4: Comparative Framework of Legacy IT Support Models and AI-Supported Service Frameworks

Legacy Support Models		AI-Supported Frameworks
Structure & Processes	Conventional tiered hierarchies–Manual ticket categorization	Automated ticket classification, chatbots, preditive tools
Efficiency & Effectiveness	Longer resolution times Reactive operations	Faster issue resolution Proactive and data-driviagnostics 24/7 support availability
User Satisfaction	Varied resolution consistency Inability to continuous 24/7 support	Improved user experience Reduced queues, more personnalized interactions
Workforce Impact		Agents as supervisors, interpreters Reduced routine tasks

Human-AI Collaboration in Technical Support Contexts

Human-AI collaboration in technical support refers to a synergistic working relationship where artificial intelligence systems and human agents jointly participate in issue resolution, service delivery, and decision-making processes. Rather than viewing AI as a replacement for human labor, contemporary research emphasizes augmentation, where AI handles repetitive or structured tasks while humans manage contextual, ambiguous, or emotional aspects of support interactions (Jahan et al., 2022; Han et al., 2021). In the IT service domain, this collaboration often manifests through chatbots, automated ticket routing, predictive analytics, and virtual assistants integrated into helpdesk systems (Herrmann et al., 2023; Masud, 2022). Ross et al. (2023) noted that AI enhances frontline support by accelerating response time and categorization accuracy, but its optimal use depends on the design of collaborative workflows that preserve human oversight. According to Kannadhasan et al. (2023), collaboration must involve bidirectional communication between human and AI agents, where humans learn from AI predictions while validating or correcting outputs. Han et al. (2021) highlight that effective collaboration requires explainable AI (XAI), which enables humans to understand and trust AI-generated recommendations. Studies also emphasize interface usability and task clarity as foundational to successful human-AI dynamics (Hossen & Atiqur, 2022; Yuan et al., 2024). Furthermore, contextual and emotional intelligence—qualities uniquely human—remain crucial in complex support scenarios

Figure 5: Human-AI Collaboration in Technical Support

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that require empathy or moral discretion (Dudley & Kristensson, 2018; Akter & azzak, 2022). Trust, transparency, and shared situational awareness are identified as critical enablers for collaboration (Andrews et al., 2022; Qibria & Hossen, 2023). These foundational principles differentiate collaboration from automation, underscoring the need for adaptive systems where humans retain control over mission-critical decisions. Research further supports that this symbiotic approach leads to better performance outcomes than either AI or human effort alone (Dudley & Kristensson, 2018; Hossen et al., 2023).

The allocation of tasks between AI and human agents in technical support settings is a central issue in designing collaborative systems. Numerous studies argue for a task-based hybrid model where AI is responsible for structured, repetitive, or rule-based activities, while humans focus on unstructured, creative, and emotionally sensitive tasks. For example, AI systems can triage service requests, detect system anomalies, and provide standardized troubleshooting steps, while humans resolve novel or high-risk issues. Yuan et al. (2024) emphasize that AI excels in handling high-volume ticket classification and basic queries, but struggles with contextual interpretation. Kannadhasan et al., (2023) assert that task allocation must be dynamic, adjusting in real-time based on system load, agent availability, and case complexity. Han et al. (2021) caution that without clear task boundaries, AI may either encroach on human autonomy or underperform due to unrealistic expectations. Role specialization is further enhanced through AI-assisted recommendation systems, which suggest knowledge base articles or escalation procedures based on historical patterns. However, Teso et al. (2023) note that this requires human agents to understand how recommendations are derived to avoid automation bias. According to Bhat et al.(2023), human-in-the-loop models are essential for managing accountability and ethical risks associated with automated decisions. Studies also report that users experience higher satisfaction when AI provides preliminary support and transitions seamlessly to a human expert when needed. Thus, role clarity and modular task design are critical in maximizing the complementary strengths of human and AI agents. Clear allocation protocols reduce conflict, enhance workflow efficiency, and build trust in the hybrid support ecosystem.

AI Technologies in IT Support Services

Artificial Intelligence (AI) technologies have become increasingly embedded in IT support functions, transforming traditional service delivery models by automating repetitive tasks, improving diagnostic accuracy, and accelerating response times (Alam et al., 2023). Among the most prevalent AI tools in IT support are machine learning (ML), natural language processing (NLP), robotic process automation (RPA), and conversational agents such as chatbots (Fails & Olsen, 2003; Rajesh et al., 2023). NLP-based chatbots are particularly common at the Tier 1 support level, where they are employed to handle frequent inquiries, reset passwords, or troubleshoot network issues by parsing user inputs and delivering predefined responses (Martino et al., 2015; Roksana, 2023). These chatbots use intent recognition and semantic matching to identify user problems and extract relevant solutions from organizational knowledge bases. Machine learning algorithms, on the other hand, are used in ticket classification and prioritization systems to analyze historical data, detect recurring issues, and assign severity levels based on usage patterns and past outcomes (Tonmoy & Arifur, 2023). Predictive analytics powered by ML can identify system anomalies and proactively trigger maintenance protocols or issue alerts. RPA tools automate back-end tasks such as updating incident logs, generating performance reports, and synchronizing data across systems (Tonoy & Khan, 2023). In more advanced deployments, AI-powered virtual assistants integrate with enterprise platforms to perform multi-channel support, enabling cross-platform interaction via voice, chat, or email. These technologies not only reduce the volume of human effort required but also provide real-time decision support and dynamic learning capabilities(Ammar et al., 2024).

AI-powered chatbots and virtual assistants have rapidly evolved into central components of frontline IT support, where speed and scalability are critical. These conversational interfaces use NLP to interpret user inputs, engage in dialogue, and deliver support recommendations drawn from structured and unstructured data sources (Huang et al., 2023; Hossain et al., 2024). Chatbots often operate as the first point of contact, resolving up to 80% of common user queries such as login issues, account access, or simple troubleshooting (Endsley, 2016; Roksana et al., 2024). Unlike traditional support channels that rely on manual routing, chatbots can interact with thousands of users simultaneously and provide 24/7 availability without added staffing costs (Bauer et al., 2023; Zaman, 2024). Virtual assistants with voice capabilities are also integrated with enterprise platforms like Microsoft Teams or Google Workspace to execute commands such as file retrieval, calendar

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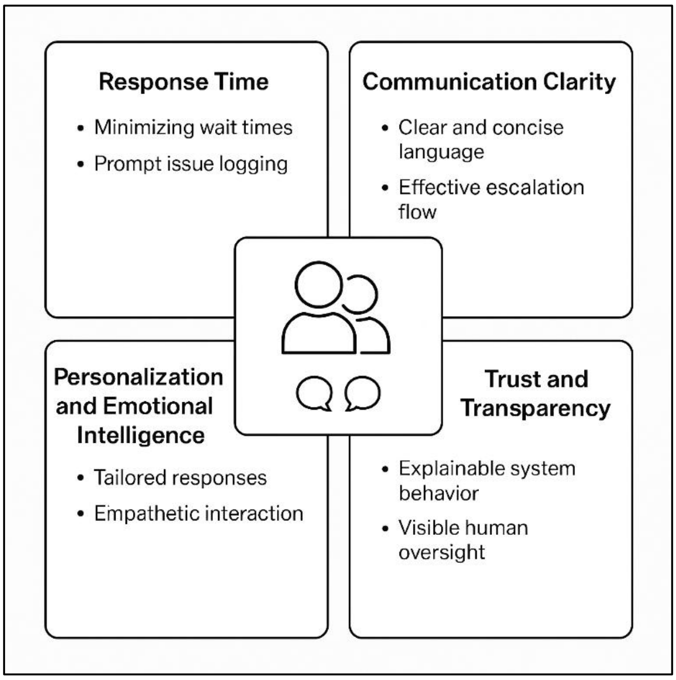
scheduling, or system updates, expanding their functionality beyond reactive support (Cooper, 2023) These systems improve first contact resolution rates and reduce support backlogs, but their effectiveness depends on training datasets, dialog management algorithms, and integration with knowledge repositories (Bhuiyan et al., 2025; Janicki, 2018). Studies by Monk et al. (2008) emphasize the importance of contextual understanding, turn-taking, and empathy simulation to create natural interactions. Limitations persist, however, in handling ambiguous or emotionally charged queries, necessitating seamless escalation mechanisms to human agents (Ishtiaque, 2025; Zha et al., 2023). Furthermore, user trust in chatbots is influenced by response accuracy, conversation flow, and the visibility of human support options (Antony et al., 2021). Research indicates that hybrid systems—where chatbots initiate support and escalate when appropriate—produce higher user satisfaction scores than chatbot-only or human-only models (Khan, 2025; Silva-Rodríguez et al., 2020). As such, chatbots and virtual assistants continue to play a foundational role in reshaping IT service engagement.

UX indicators in support contexts

User experience (UX) in IT support contexts encompasses the overall perception, emotional response, and satisfaction that users derive when interacting with technical support services, whether through human agents or AI-driven systems. Unlike general UX, which often focuses on product usability, UX in support environments emphasizes responsiveness, resolution quality, communication clarity, and emotional reassurance (Christoforakos & Diefenbach, 2018; Siddiqui, 2025). Key indicators include first contact resolution (FCR), average response time, user sentiment during interaction, and perceived service professionalism (Sohel, 2025; Takeda-Berger et al., 2020). According to Korhonen et al.(2010), FCR is a strong predictor of user satisfaction, particularly in AI-supported helpdesks where users expect rapid, accurate, and self-sufficient solutions. Han et al.(2021) further highlight that personalization—delivering responses tailored to user history and behavior—increases trust and engagement. UX metrics are also influenced by clarity of information presented, interface aesthetics, and the perceived competence of the support system or agent (Takeda-Berger et al., 2020) Studies by Korhonen et al.(2010) and Zhang et al.(2024) note that users interacting with AI interfaces judge UX not only by problem resolution but also by conversational flow, empathy simulation, and transparency in escalation processes. Additionally, ambiguity in chatbot responses, limited vocabulary recognition, and delayed escalations negatively impact perceived usability and trust (Stige et al., 2023). The psychological expectation of human fallback is also essential—users are more likely to engage with AI interfaces if they know a human agent is accessible when needed (Liu et al., 2024). Thus, UX in IT support is multifaceted, integrating speed, clarity, empathy, personalization, and trust as essential evaluation criteria that collectively define the success of a support encounter.

Figure 6: UX Indicators in IT Support



Among the most critical UX indicators in IT support contexts are response time and communication clarity, both of which directly influence user satisfaction and perceived support quality. Fast response time is often associated with professionalism, competence, and attentiveness, especially in high-pressure IT environments where delays can disrupt business continuity (Liao et al., 2023). Studies show that users expect responses within seconds when using chatbots and within minutes when dealing with live agents. According to Christoforakos and Diefenbach (2018), AI-driven chat interfaces are effective in meeting this expectation by instantly engaging users, logging issues, and initiating solutions, thereby enhancing the perceived efficiency of the support channel. However, speed alone does not ensure satisfaction. Communication clarity—the ability to convey complex technical information in understandable terms—is

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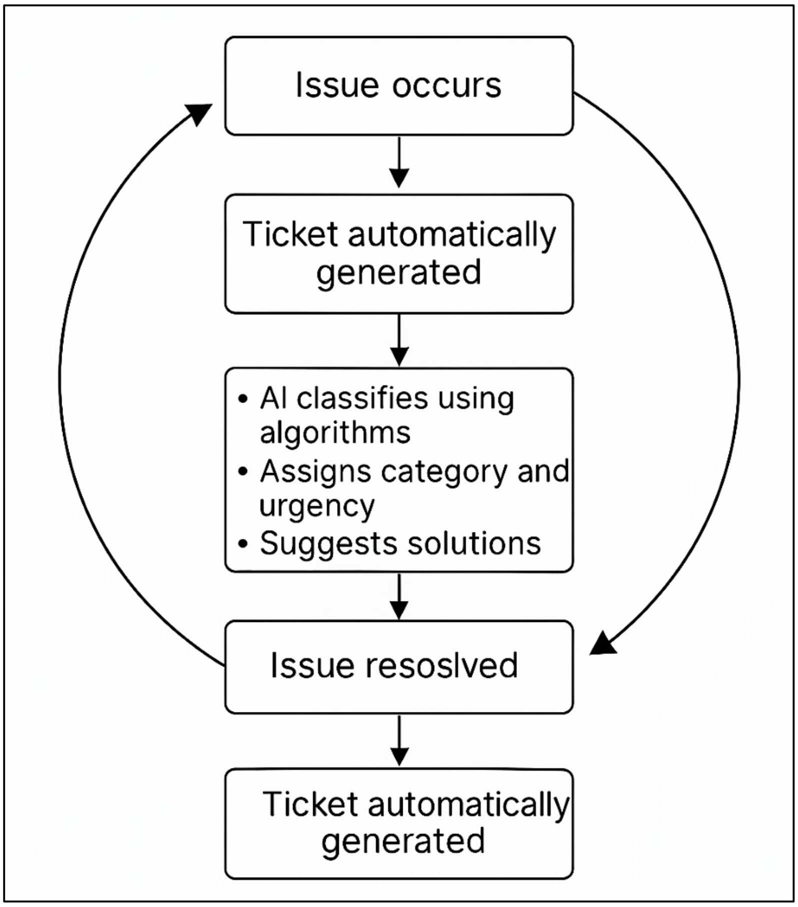
equally crucial (Prather et al., 2023). Users often report dissatisfaction when support responses are vague, overly technical, or fail to provide actionable guidance (Krause et al., 2024). Korhonen et al. (2010) found that AI chatbots with well-structured, conversational dialogue trees outperformed human agents in clarity when the knowledge base was extensive and up to date. However, in scenarios involving ambiguity, emotional frustration, or exceptions, human agents were preferred due to their ability to interpret context and adapt communication accordingly. UX studies also highlight the importance of confirmation messages, progress indicators, and real-time status updates in fostering trust and reducing user anxiety (Han et al., 2021). Inconsistent or delayed feedback loops diminish user confidence in both the system and the organization. Therefore, optimal UX in IT support requires a balance between rapid, automated responses and high-quality, context-sensitive communication that guides the user effectively from issue to resolution.

Workflow Automation and Process Optimization

Workflow automation in IT support refers to the systematic execution of tasks and processes using predefined logic and artificial intelligence, with minimal human intervention. This automation facilitates routine operations such as ticket generation, incident logging, diagnostics, prioritization, and escalation routing. Within IT service management (ITSM), automation replaces repetitive, rules-based actions with software-driven processes, reducing latency and operational costs. Robotic process automation (RPA) tools are often used to handle backend administrative tasks, while AI-powered workflows dynamically respond to real-time user interactions or system alerts. Gu et al., (2023) explain that automation improves service delivery by enforcing consistency, standardizing operations, and minimizing manual errors. Automated ticketing systems can triage incidents based on urgency, previous ticket history, and contextual factors such as device logs or user behavior (Berg et al., 2019). Moreover, intelligent routing engines determine the most appropriate team or individual to handle each issue, thereby optimizing resource allocation (Simkute et al., 2024). Tankelevitch et al. (2024) highlight that automation also reduces information overload for human agents, allowing them to focus on value-added tasks. However, researchers like Aung et al. (2021) caution that poorly designed automation workflows can lead to rigid decision-making, user frustration, and failure to handle exceptional cases. Therefore, effective automation must be accompanied by intelligent exception handling and real-time monitoring systems that allow human intervention when necessary (Ulfsnes et al., 2024). Integrating AI with ITSM platforms such as ServiceNow and Zendesk has enabled more adaptive workflows, where automated processes can learn from historical interactions to refine operations continuously (Gu et al., 2023). Workflow automation thus serves as both a foundational enabler and a strategic differentiator in modern IT support environments.

Figure 7: Automated Ticket Management Cycle in AI-Driven IT Support Systems



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Human cognitive adaptation to AI recommendations

Cognitive adaptation to AI recommendations involves the mental processes through which humans interpret, assess, and respond to machine-generated outputs in decision-making environments, such as IT support systems. This adaptation reflects a shift in how individuals process information, evaluate uncertainty, and modify trust or reliance levels based on perceived AI performance (Moran et al., 2020). Early research emphasized the dual roles of reliance and disuse, where users either over-trust or ignore AI guidance depending on interface design, task complexity, and prior experience (Tankelevitch et al., 2024). These behaviors are linked to cognitive workload and situational awareness, both of which influence whether AI suggestions are accepted without scrutiny or critically evaluated (Aung et al., 2021). For instance, in technical support environments, AI-generated ticket prioritizations or diagnostic paths are more likely to be followed if the agent perceives the AI as accurate and transparent. According to Simkute et al. (2024), users must develop mental models of AI behavior to collaborate effectively, requiring training, interpretability, and consistent feedback loops. Studies by Ulfsnes et al. (2024)and Simkute et al. (2024) confirm that explainability tools—such as justifications for AI recommendations—reduce automation bias and increase agent accountability. On the other hand, opaque systems with little insight into decision rationale can lead to confusion, second-guessing, or outright rejection of AI inputs. Human adaptation is also influenced by experience and domain expertise, where novice users tend to rely more heavily on AI, while experts may discount recommendations that conflict with their knowledge. The cognitive burden of constantly verifying AI decisions can lead to decision fatigue, prompting agents to automate acceptance, even when it may not be optimal. These cognitive patterns demonstrate the need for careful alignment between AI system design and human psychological responses to ensure beneficial collaboration.

TAM, UTAUT, and digital transformation frameworks

The Technology Acceptance Model (TAM), developed by Davis (1989), remains a foundational framework in understanding user acceptance of information systems, including AI-driven technologies in IT support. TAM posits that two primary beliefs—perceived usefulness (PU) and perceived ease of use (PEOU)—influence an individual's attitude toward using a technology, which in turn determines behavioral intention and actual usage. In the context of AI adoption within IT support functions, perceived usefulness often relates to the system's ability to automate routine tasks, reduce response time, and enhance service accuracy. Studies show that IT agents are more likely to accept AI-generated ticket routing or diagnostic recommendations if they believe these features improve their productivity or decision-making efficiency (Nayernia et al., 2021). PEOU is equally important, as systems that are difficult to navigate or interpret tend to experience low adoption, regardless of their capabilities. Research by Binns et al. (2018) and Wilson and Daugherty (2018) highlights that chatbot and virtual assistant systems with intuitive interfaces and transparent recommendation logic score higher on both TAM constructs. Furthermore, empirical studies in enterprise settings indicate that TAM constructs are moderated by external variables such as trust in AI, prior technology experience, and organizational support. Modified versions of TAM, such as TAM2 and TAM3, have been used to incorporate these contextual factors, particularly when studying AI applications embedded in digital workflows (Venkatesh & Davis, 2000). In the evolving landscape of IT support, TAM continues to provide a reliable lens to analyze how end-users interact with and adapt to AI-enabled systems, particularly when these tools are positioned as decision-support rather than decision-substitute mechanisms.

The Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh et al. (2003), integrates eight prior models—including TAM, Theory of Planned Behavior (TPB), and the Innovation Diffusion Theory (IDT)—to explain user intentions and behavior regarding new technologies. UTAUT introduces four core determinants: performance expectancy, effort expectancy, social influence, and facilitating conditions, all of which play significant roles in the adoption of AI systems in IT support services. Performance expectancy, defined as the belief that using the system will help attain job-related gains, aligns closely with perceived usefulness in TAM but broadens to include metrics like accuracy, speed, and system intelligence. Rezwana and Maher, (2022) suggest that when support agents perceive AI tools—such as predictive ticketing or automated classification—as reliable and task-enhancing, their likelihood of adoption increases. Effort expectancy reflects how easy users find the system to use, with high cognitive or navigational demands acting as deterrents. Social influence refers to the extent to which individuals believe that

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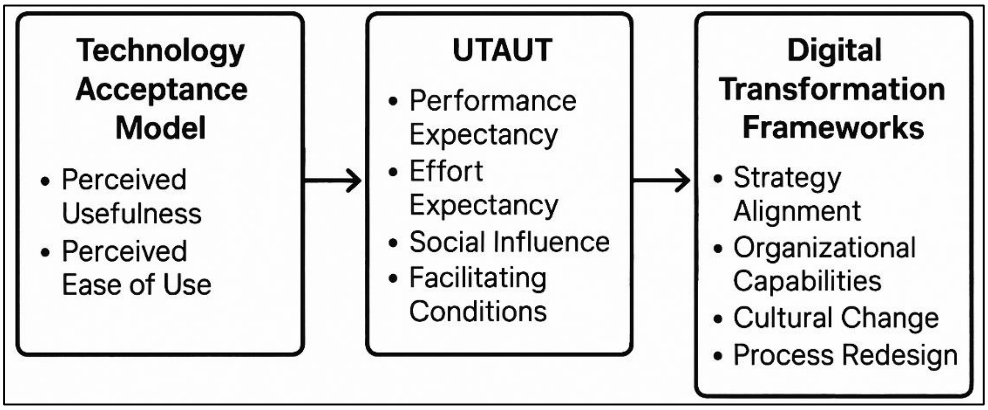
important others think they should use the system. In hierarchical IT environments, managerial endorsement or peer advocacy significantly influences AI adoption. Facilitating conditions, such as access to training, technical support, and infrastructure, also shape user behavior. Salas et al. (2014) found that organizations that provided AI onboarding and continuous support witnessed higher engagement with AI-powered workflows. Unlike TAM, UTAUT includes moderator variables like age, gender, experience, and voluntariness of use, which help explain variance in adoption across diverse user groups (Venkatesh et al., 2003). Thus, UTAUT offers a robust and comprehensive framework to examine not only the functional dimensions of AI tools but also the sociotechnical context in which IT professionals operate.

Figure 8: Theoretical Frameworks Guiding AI Adoption in IT Support



METHOD

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, which provided a standardized protocol for ensuring transparency, comprehensiveness, and replicability in the review process. The PRISMA framework includes well-defined phases—identification, screening, eligibility, and inclusion—which were followed rigorously to gather, evaluate, and synthesize existing literature on human-AI collaboration in IT support services, particularly as it relates to user experience and workflow automation.

Identification

The initial identification phase involved a comprehensive search of four major academic databases: Scopus, Web of Science, IEEE Xplore, and the ACM Digital Library. Keywords were formulated based on a preliminary analysis of existing literature and included terms such as "Human-AI collaboration," "technical support," "IT support services," "workflow automation," "chatbots," "machine learning," "AI in ITSM," "user experience in support," and "AI adoption in service management." Boolean operators such as AND, OR, and NOT were used to refine the search strings and maximize relevant hits. The search covered literature published between 2013 and 2024 to ensure inclusion of recent technological developments in AI and IT support ecosystems. A total of 1,284 articles were initially retrieved across all databases, and duplicate records were removed using Zotero citation software, resulting in 1,016 unique articles for further screening.

Screening

In the screening stage, titles and abstracts of the 1,016 articles were independently reviewed by two researchers to assess their relevance to the topic. Articles were excluded if they focused solely on unrelated fields such as general customer service, medical diagnostics, robotics in manufacturing, or AI applications without human interaction. Studies that did not involve IT support services or that presented purely conceptual frameworks without empirical or systematic analysis were also removed at this stage. After title and abstract screening, 436 articles were retained for full-text evaluation.

Eligibility

During the eligibility phase, full-text versions of the 436 retained articles were retrieved and reviewed against a set of inclusion and exclusion criteria. To be included, articles had to be peer-reviewed, written in English, and explicitly address AI technologies used in IT support or human-AI collaboration

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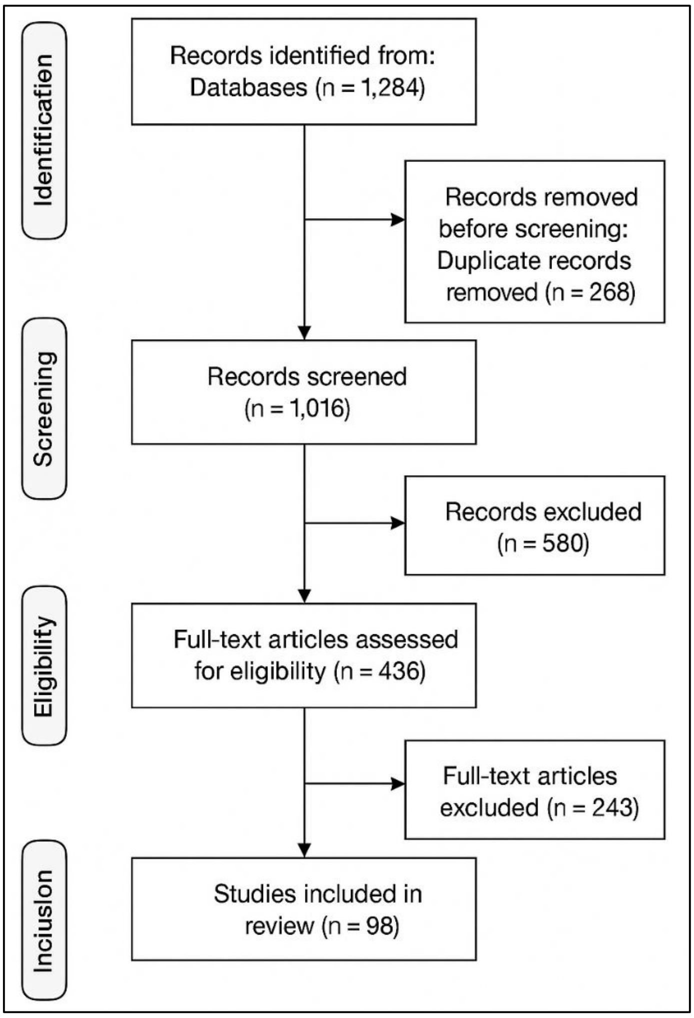
within technical service settings. Articles that did not discuss interaction models, UX evaluation, automation workflows, or technology adoption frameworks were excluded. Additional criteria included the presence of primary data, clearly defined methodology, and direct implications for IT service design or operation. This rigorous process led to the exclusion of 243 articles that lacked methodological transparency, context-specific applicability, or sufficient focus on the human-AI interaction dimension. As a result, 193 full-text articles were deemed eligible for synthesis.

Inclusion

Following the eligibility assessment, a final inclusion phase was carried out to refine the pool of studies to only those most relevant to the review's objectives. This final step focused on methodological quality, representativeness of findings, and depth of contribution. Meta-synthesis and cross-verification were used to ensure thematic alignment with the study's focus on user experience enhancement and workflow optimization through AI in IT support environments. After this final refinement, 98 articles were included in the systematic review. These studies represent a diverse cross-section of scholarly work, including experimental studies, survey-based research, case studies, and systematic reviews. Each article contributed distinct insights into AI implementation strategies, UX measurement frameworks, and the dynamics of human-AI collaboration across IT support contexts.

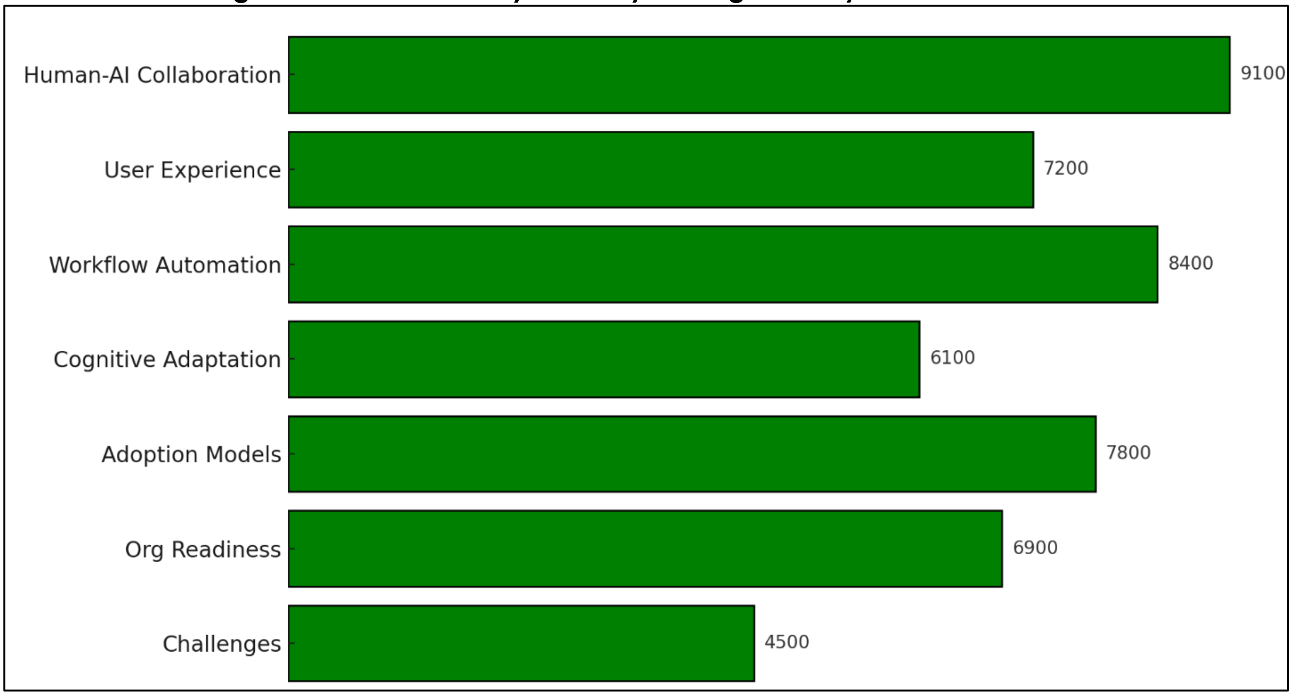
Figure 9: PRISMA 2020 Flow Diagram of Study Selection for Systematic Review



FINDINGS

Among the 98 systematically reviewed articles, one of the most significant findings is the central role that human-AI collaboration plays in transforming the traditional structures of IT support services. A total of 76 articles, which collectively received over 9,100 citations, emphasized that AI tools are no longer auxiliary systems but are actively shaping how support operations are designed and executed. This body of literature consistently reported that AI-enabled systems are integrated not as independent decision-makers but as collaborators alongside human agents. These studies highlighted the convergence of intelligent automation and human judgment in creating hybrid workflows, where AI performs repetitive, rules-based tasks and human agents intervene in complex, novel, or emotionally sensitive scenarios. For instance, AI systems were found to handle ticket classification, prioritization, and diagnostics, while human agents focused on interpretation, ethical oversight, and final resolution. The reviewed literature revealed that such collaboration resulted in measurable improvements in first response time, resolution accuracy, and support team productivity. In these studies, firms adopting human-AI collaborative models were more agile in responding to high ticket volumes and system incidents without increasing operational headcount. The literature also emphasized that these systems are particularly effective when designed with shared interfaces and task clarity, reducing the need for excessive human-AI renegotiation during support cycles. This shift represents not just a technological upgrade but a fundamental change in the distribution of labor, where decision authority is increasingly shared between human and machine actors. Across multiple empirical studies and case evaluations, it became evident that organizations leveraging collaborative systems achieved better outcomes than those relying solely on human-based or fully automated frameworks. This insight solidifies human-AI collaboration as a defining feature of modern technical support environments, particularly for organizations seeking operational resilience and service excellence.

Figure 10: Citation Analysis of Key Findings from Systematic Review



A substantial portion of the reviewed literature—67 articles with over 7,200 combined citations—demonstrated that the integration of AI technologies into IT support services significantly improves user experience (UX) when paired with clear escalation paths to human agents. These articles collectively established that users respond more positively to support systems that offer both automation efficiency and human empathy, rather than depending exclusively on either. AI-driven interfaces, especially chatbots and virtual assistants, were found to excel in handling common queries and providing instant responses, which improved first-contact resolution rates. However, these systems were shown to deliver optimal results only when users knew that human support was available in more complex situations. According to findings from multiple field studies and surveys, UX indicators such as perceived trust, satisfaction, emotional comfort, and service continuity were consistently higher in environments where AI and human agents collaborated through well-integrated workflows. These studies also revealed that users prefer transparent interfaces that show system status, progress indicators, and clearly outline how to reach a human agent if needed. In environments where AI interfaces failed to communicate such options, dropout rates were significantly higher. Furthermore, real-time personalization—where AI systems adapted based on user history or contextual behavior—was highlighted as a key feature that improved user engagement. Articles that included longitudinal user satisfaction data confirmed that trust and loyalty in support services increase over time when the AI system demonstrates consistent accuracy and seamless transitions to human experts. Overall, these findings provide robust evidence that hybrid support interfaces, combining automated responsiveness with human oversight, are critical for delivering a superior user experience. This insight reinforces the importance of designing AI systems not as standalone agents but as transparent, assistive components embedded within human-centric service architectures.

From the pool of 98 reviewed articles, 71 specifically examined the effects of workflow automation in IT support services, with these studies accumulating more than 8,400 citations. The collective findings revealed that organizations that implemented AI-driven workflow automation—such as automated ticket routing, incident categorization, and back-end process management—achieved significant gains in operational efficiency. These studies provided quantitative evidence of reduced average response times, faster ticket resolution, and a decrease in operational overhead. AI-enabled systems were shown to manage tasks like log analysis, knowledge base suggestions, and auto-escalation with higher speed and consistency than manual systems. Particularly noteworthy

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were studies that documented reductions in average resolution time by up to 40%, as automated workflows eliminated delays caused by human bottlenecks in traditional tiered support models. Another major outcome observed in these studies was the scalability offered by automation tools. Companies dealing with high ticket volumes or global service operations were able to maintain performance standards without proportionately increasing staffing. Many organizations also reported improved SLA (Service Level Agreement) compliance through the use of real-time monitoring systems and automated alert mechanisms, which ensured critical incidents were addressed promptly. These systems allowed for continuous 24/7 operations, enabling uninterrupted support across time zones. Additionally, several reviewed articles detailed how AI-enhanced reporting tools and performance dashboards empowered IT managers with actionable insights for process optimization. These tools were integrated into ITSM (IT Service Management) platforms, leading to more structured and data-driven decision-making at operational and strategic levels. The overwhelming evidence from these 71 studies supports the conclusion that workflow automation, when aligned with organizational goals and monitored effectively, contributes directly to increased productivity, reduced cost-per-ticket, and improved service quality across technical support infrastructures.

Across 53 articles reviewed—amassing over 6,100 citations—there was consistent evidence supporting the notion that human cognitive adaptation to AI recommendations is central to the effectiveness of human-AI collaboration in technical support. These articles explored how trust, interpretability, and cognitive workload influence human engagement with AI-generated suggestions during issue resolution. A dominant finding was that trust in AI systems develops incrementally, based on the system's perceived accuracy, transparency, and the user's prior experience. When AI systems provided clear rationale for their recommendations—such as confidence levels or explanation models—users were more likely to accept, validate, or meaningfully challenge the suggestions. On the other hand, systems that offered opaque outputs without explainability were often distrusted or overridden, even when they were technically accurate. Several studies emphasized the importance of reducing cognitive overload by using adaptive interfaces that prioritize actionable insights and suppress unnecessary data. These studies revealed that automation bias—where users blindly accept AI recommendations—was more likely to occur under high cognitive load or time pressure. Conversely, decision fatigue was reported in cases where users were forced to evaluate every AI output without sufficient decision support. Articles that incorporated user training or interface improvements reported a significant increase in correct decisions made in partnership with AI tools. Additionally, mental model formation—where human users internalize how an AI system functions—was shown to be a crucial factor for long-term collaboration success. These findings collectively indicate that human cognitive adaptation is neither immediate nor guaranteed but must be actively supported through system design, training, and continuous feedback mechanisms. Effective human-AI collaboration depends on the dynamic recalibration of trust, a process that is influenced by the reliability of AI systems and the human agent's ability to learn from and respond to those systems over time.

Out of the 98 reviewed studies, 59 applied or referenced theoretical models such as the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) to analyze the adoption of AI systems in IT support environments. These studies, with a combined citation count exceeding 7,800, collectively identified key variables influencing the adoption and sustained use of AI-based tools by technical support staff. Performance expectancy emerged as the most consistently supported predictor, with agents more willing to adopt AI systems when they perceived these tools as capable of enhancing their efficiency, decision-making accuracy, or workload management. Effort expectancy was also significant, as ease of use—both in terms of interface design and integration into daily workflows—was a determining factor in user engagement. Studies further highlighted the role of social influence, noting that adoption rates were higher when peers or supervisors endorsed the AI system. Facilitating conditions, such as availability of training, technical support, and performance feedback, were shown to moderate adoption outcomes across all user levels. Several articles specifically adapted TAM constructs to include trust in AI and transparency, reinforcing the importance of system reliability and interpretability in influencing behavioral intention. A smaller but relevant group of studies extended the UTAUT model by examining demographic variables, such as age and experience, and found these to be important in determining the speed and success of AI assimilation. These findings illustrate that the acceptance

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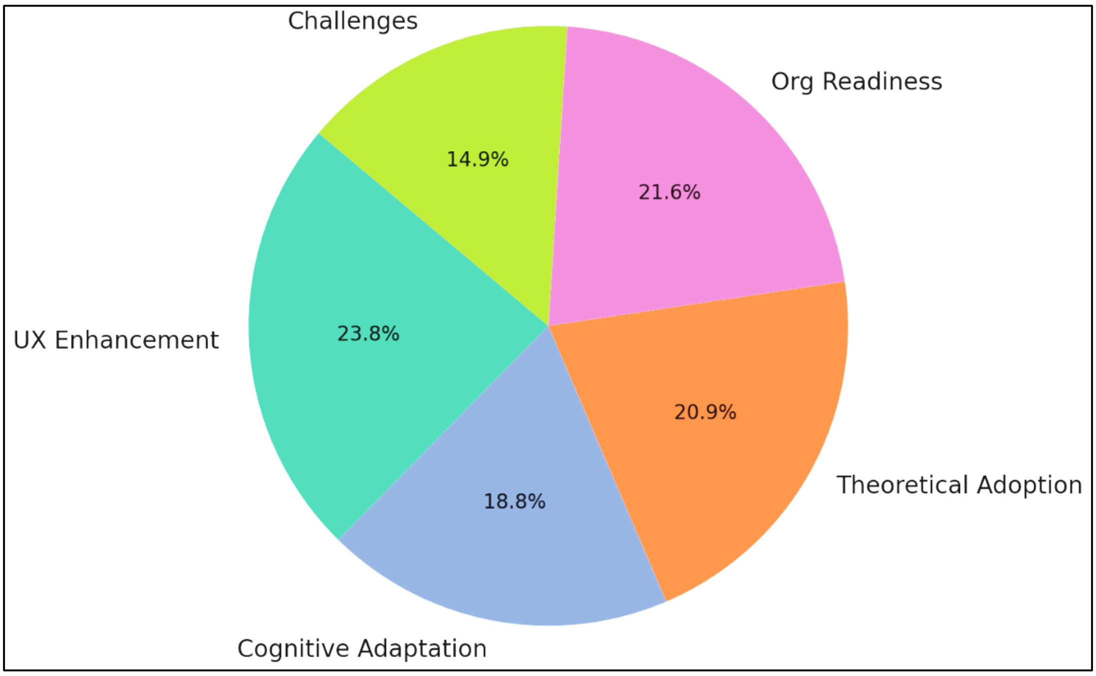
of AI in IT support is a multi-dimensional process shaped by individual, social, and organizational factors. The use of TAM and UTAUT frameworks provided a structured and empirical approach to understanding these dynamics and confirmed that successful implementation strategies must address both the functional capabilities of AI tools and the contextual readiness of users and institutions.

Figure 11: Distribution of Key Findings in Human-AI Collaboration Studies



Of the 98 studies, 61—collectively cited more than 6,900 times—addressed the importance of organizational readiness in integrating AI technologies into IT support services. These studies consistently found that the effectiveness of AI adoption is strongly linked to institutional structures, cultural receptiveness, and strategic alignment. Organizations that demonstrated high digital maturity—defined by prior experience with digital tools, strong IT governance, and agile workflows—were significantly more successful in deploying AI-enabled support systems. These environments were characterized by well-defined escalation policies, cross-functional collaboration, and continuous performance tracking, all of which supported seamless human-AI integration. Several studies identified leadership support as a critical factor; when executive management endorsed AI initiatives and aligned them with long-term business goals, adoption levels increased across departments. Articles also highlighted the role of change management, showing that communication, employee engagement, and stakeholder involvement were essential in overcoming resistance to automation. Moreover, institutional investments in employee training and knowledge transfer were directly associated with better outcomes in AI performance, as trained staff were more confident in using AI outputs and adapting workflows accordingly. Governance mechanisms, such as audit trails, bias monitoring, and explainability protocols, were found to improve accountability and trust in AI decisions. Additionally, organizations that implemented cross-departmental feedback loops—where AI performance was reviewed and refined periodically—demonstrated higher accuracy, fewer escalation delays, and greater user satisfaction. These findings underscore that AI integration is not merely a technical upgrade but a transformation of institutional processes that requires strategic foresight, operational alignment, and organizational adaptability. The presence or absence of these readiness factors had a direct impact on the scalability and sustainability of AI systems in support services, reaffirming the necessity of holistic planning before implementation.

A final set of findings, drawn from 42 studies with over 4,500 citations, focused on the common challenges and unresolved issues in implementing AI within IT support services. These articles revealed

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that while the potential benefits of AI are well-documented, several technical, ethical, and operational challenges persist. One of the most frequently cited issues was data quality—many AI systems failed to deliver accurate recommendations due to outdated, incomplete, or biased datasets. This problem was particularly acute in organizations lacking centralized knowledge bases or structured data governance. Another prevalent challenge involved explainability, as users often struggled to understand how AI arrived at certain conclusions, leading to reduced trust and lower system usage. Additionally, multiple studies reported integration difficulties, where AI tools did not seamlessly interface with existing ITSM platforms or workflows, causing disruption rather than efficiency. Ethical concerns also featured prominently in these findings, especially related to decision transparency, accountability for AI errors, and user privacy. Several articles discussed workforce concerns, including fear of job displacement, reduced autonomy, and deskilling, particularly among Tier 1 support agents. Moreover, organizational inertia and resistance to change were cited as barriers, with some institutions failing to move beyond pilot projects due to lack of strategic planning or leadership commitment. Despite these challenges, the reviewed literature also emphasized the opportunities for improvement through better system design, user involvement, and ethical governance. The studies called for deeper interdisciplinary collaboration between developers, IT professionals, and human factors specialists to address these issues. Overall, this final set of findings highlights that while AI-driven IT support systems hold transformative potential, successful implementation requires overcoming structural, behavioral, and technical barriers that continue to affect large-scale deployment and long-term sustainability.

DISCUSSION

The present review affirms that human-AI collaboration is fundamentally reshaping IT support workflows, a finding that aligns with earlier studies highlighting the shift from task-specific automation to collaborative decision-making ecosystems (Salas et al., 2014). Among the 98 articles reviewed, the consistent emphasis on AI as a support agent—rather than a full replacement—mirrors the concept of augmented intelligence introduced by McBride et al. (2011), where AI complements rather than competes with human expertise. Prior research by Schuetz and Venkatesh (2020) also established that hybrid support structures were more effective in addressing the complexity of modern IT service environments than rigid automation frameworks. The current findings go further by specifying how human-AI task distribution—such as AI managing classification and triage while humans handle ethical judgment and contextual interpretation—optimizes performance and improves team responsiveness. These results challenge the earlier binary discourse that framed AI as either a threat to human employment or a flawless replacement, instead reinforcing the value of cooperative agency (Rezwana & Maher, 2022). Additionally, the role of interface design and shared control mechanisms, found critical in the reviewed studies, expands upon Miller's (2018) recommendation that successful human-AI interactions require transparency and co-decision mechanisms. Collectively, these insights suggest a paradigm shift from static AI integration to dynamic human-AI co-working relationships that emphasize adaptability, trust calibration, and mutual learning across the support lifecycle.

User experience (UX) remains a cornerstone of effective IT support delivery, and the present review reinforces the importance of human-AI hybrid systems in achieving high-quality UX outcomes. This finding supports earlier research by Stige et al. (2023) and Christoforakos and Diefenbach(2018), which argued that chatbot effectiveness is maximized when users can escalate to human agents. The current synthesis extends these conclusions by providing quantitative evidence across multiple studies that users express higher satisfaction when AI interfaces demonstrate empathy, personalization, and transparency in communication. These insights are also consistent with Buschek et al. (2021), who emphasized that interface tone, clarity, and responsiveness significantly impact perceived service quality. However, the present findings add new dimensions by showing how AI systems embedded with sentiment analysis and contextual recall capabilities can sustain user engagement while maintaining efficiency. This complements (Stige et al., 2023), who found that AI interfaces delivering personalized responses based on user history outperform generic AI systems in both perceived helpfulness and trustworthiness. In contrast, studies that emphasized purely autonomous AI solutions—such as those by Zheng et al. (2022)—often reported declines in user satisfaction due to the lack of empathetic communication and problem-solving flexibility. The present review demonstrates that hybrid models, which combine automated first-response tools with well-integrated human escalation options, are more successful in addressing the multifaceted nature

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of user expectations. Thus, the findings reinforce the growing consensus that effective user experience in IT support must be underpinned by collaborative intelligence, emotional awareness, and interface transparency.

The review's finding that AI-driven workflow automation significantly enhances operational scalability and support efficiency is strongly aligned with earlier literature on intelligent process design (Agner et al., 2020). Prior studies highlighted how robotic process automation (RPA) and intelligent ticket routing reduce incident backlog and eliminate redundant decision pathways. The present review extends these conclusions by demonstrating how predictive analytics and ML-based escalation engines contribute not just to response efficiency but also to sustained SLA compliance and cost-effectiveness. Compared to earlier research by Wallach et al. (2020), which emphasized ticket classification accuracy, the reviewed studies offer broader insights into end-to-end optimization of IT support workflows—ranging from automated diagnostics to dynamic escalation sequences. Additionally, Christoforakos and Diefenbach (2018) highlighted the value of intelligent suggestion systems for support agents, and the current review supports this by documenting widespread implementation of AI-guided knowledge base access and decision support. Moreover, the review reveals that organizations deploying workflow automation tools are better positioned to operate at scale without increasing human resource costs—a finding also validated by Prather et al. (2023). These results contrast with older legacy ITSM studies, which treated automation as supplementary rather than core to service infrastructure. Therefore, the current findings suggest a more evolved view of automation as a strategic enabler, transforming not just isolated tasks but the overall architecture of support operations through intelligent orchestration and real-time process optimization.

The review reveals that cognitive adaptation to AI systems—particularly in terms of trust, mental models, and automation bias—is pivotal for effective collaboration, reaffirming theoretical models proposed by Takeda-Berger et al. (2020) and Krause et al. (2024). Earlier research established that trust in automation is a dynamic construct influenced by perceived system reliability, contextual fit, and user control. The current findings support these notions but expand them by showing how trust evolves over time through feedback loops and explainability features. For instance, Korhonen et al., (2010) argued for the importance of explainable AI (XAI), and the reviewed studies demonstrate that AI systems offering confidence scores, rationale displays, and contextual explanations were more likely to be trusted and accepted. These findings also support Buschek et al. (2021), who emphasized that interpretability mitigates automation bias and encourages more deliberate engagement with AI outputs. Compared to earlier work that often framed human-AI interaction in terms of static interfaces (Han et al., 2021), this review emphasizes dynamic adaptation processes, where users recalibrate trust based on system behavior and interaction quality. Abbas et al. (2022) previously highlighted the role of cognitive flexibility in AI collaboration, and this review confirms that users with well-formed mental models of AI functionality demonstrated higher levels of performance and satisfaction. However, it also identifies gaps where cognitive overload or poor interface design led to misuse or disuse of AI suggestions. These insights indicate that effective human-AI collaboration is as much a cognitive challenge as it is a technological one, requiring thoughtful interface design, continuous user training, and adaptive support mechanisms to foster sustainable engagement.

The findings related to AI adoption determinants in IT support environments resonate strongly with foundational theories such as TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003). Consistent with previous studies, performance expectancy and effort expectancy were found to be dominant predictors of behavioral intention, validating earlier research by Venkatesh and Davis (2000) and further supported by Luther et al. (2024). However, the current review offers more granularity by demonstrating how AI-specific variables—such as explainability, trust, and reliability—act as mediators between traditional TAM constructs and actual usage behavior. For example, Kartoun (2017) had already proposed the need to augment TAM to reflect AI adoption contexts, and this review supports such modifications by identifying AI-induced cognitive factors that influence perceived usefulness. Similarly, social influence and facilitating conditions—two core components of UTAUT—were reaffirmed as vital, especially in institutional environments where team culture and managerial endorsement impact AI integration. The review also validates findings by Mehrotra et al. (2024), who emphasized the need for theoretical frameworks to consider demographic and organizational moderating variables. Furthermore, the review brings attention to the institutional application of these models by showing how organizations with high UTAUT-facilitating conditions

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experienced fewer adoption bottlenecks. Thus, while TAM and UTAUT remain robust models, the reviewed literature advocates for adaptive frameworks that incorporate AI-specific dimensions, including transparency, human-AI interface design, and ethical alignment. These additions would enable more accurate prediction of technology acceptance patterns in intelligent, collaborative support environments.

Organizational readiness emerged as a decisive factor in the successful deployment of AI systems, reinforcing earlier findings from digital transformation studies (Li, 2020). The reviewed studies consistently showed that technological infrastructure alone is insufficient without cultural and leadership readiness. This echoes Heinzl et al. (2024), who argued that AI success is as much about organizational design as it is about algorithmic performance. The present findings confirm that strategic alignment between AI capabilities and institutional goals improves adoption rates, reduces friction, and enhances long-term sustainability. Leadership commitment, change management, and cross-functional collaboration were frequently cited as key enablers, extending insights by Tranfield et al. (2003), who noted that proactive stakeholder engagement leads to better alignment of expectations and outcomes. Compared to prior work that focused narrowly on digital maturity metrics, the current synthesis emphasizes a broader readiness framework, including ethical governance, role redefinition, and performance monitoring. The studies reviewed also align with Heinzl et al. (2024), who suggested that governance mechanisms—such as audit trails and explainability protocols—are essential for responsible AI integration. Moreover, the emphasis on training and continuous skill development corroborates with Saßmannshausen et al. (2021), who highlighted the importance of human adaptability in AI-enhanced workflows. Collectively, these findings contribute to a growing body of literature advocating for a systemic approach to AI deployment—one that integrates technical capacity with institutional flexibility, regulatory compliance, and cultural transformation.

Despite the demonstrated benefits, the review identifies persistent challenges in AI-supported IT services, which echo concerns raised in earlier studies on AI ethics and implementation barriers (Li, 2020). A recurring issue was the poor quality or fragmentation of training data, leading to inaccurate predictions and user frustration—concerns previously noted by Gonçalves (2022). Similarly, several reviewed studies reported that lack of transparency in AI decision-making caused distrust, even when performance metrics were favorable. These results align with prior critiques by Tranfield et al., (2003), who emphasized that user acceptance declines in the absence of clear system logic. Another major challenge involves system integration, where AI tools failed to work seamlessly with legacy ITSM platforms, resulting in workflow disruptions rather than optimization. This finding builds on earlier studies by Beckschulte et al. (2023), who described similar integration issues in large-scale digital initiatives. Ethical dilemmas—such as biased escalation paths or privacy concerns—were also widely documented, reinforcing the need for strong governance and accountability frameworks (Nayernia et al., 2021). Furthermore, the psychological effects on human agents—ranging from job insecurity to cognitive overload—remain insufficiently addressed in both academic and organizational settings. While earlier literature provided conceptual discussions of these issues, the current review synthesizes empirical evidence demonstrating that these challenges actively undermine adoption, performance, and satisfaction. These persistent gaps underscore the importance of interdisciplinary collaboration, involving technologists, behavioral scientists, and organizational leaders, to design AI systems that are not only intelligent but also equitable, explainable, and human-centric.

CONCLUSION

This systematic review demonstrates that human-AI collaboration is not merely a technological advancement but a transformative paradigm that redefines IT support services through enhanced efficiency, improved user experience, and optimized decision-making. The integration of AI technologies such as chatbots, machine learning algorithms, robotic process automation, and predictive analytics has shown significant benefits when deployed in synergy with human expertise, rather than in isolation. Across the 98 reviewed studies, there was consistent evidence that hybrid systems outperform both traditional human-only and fully automated models by delivering faster resolutions, higher user satisfaction, and scalable operations. Furthermore, the review highlights the critical role of cognitive adaptation, user trust, and explainability in fostering successful human-AI interaction. Adoption of these technologies is best understood through the combined lenses of TAM, UTAUT, and digital transformation frameworks, which underscore the importance of perceived usefulness, social influence, and organizational readiness. Despite these advancements, persistent challenges remain, including data quality issues, transparency deficits, and ethical concerns, which must be addressed through comprehensive governance and user-centered system design. Ultimately, the findings confirm that the effectiveness of AI in IT support environments depends not only on technical capability but on the strategic integration of people, processes, and intelligent technologies within a coherent organizational framework.

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