American Journal of Interdisciplinary Studies

Volume: 6; **Issue:** 3
Pages: 01-37
eISSN: 3067-5146

open access

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

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Doi: 10.63125/0fd1yb74

Received: 29 September 2025; **Revised:** 28 October 2025; **Accepted:** 19 November 2025; **Published:** 15 December 2025

Abstract

This study addresses the problem that enterprise IT service desks increasingly embed AI assistants in support portals and ticket workflows, yet many organizations lack quantitative evidence on whether human oversight and automation quality jointly improve user experience and service performance. The purpose was to test a quantitative, cross-sectional, case study-based model linking Human-AI Collaboration (HAC) and Workflow Automation Effectiveness (WAE) to User Experience (UX) and perceived IT Support Service Performance (SP). Survey data were collected from enterprise support cases; 320 questionnaires were distributed, 259 were returned, and 247 valid responses were analyzed (77.2% usable response rate; 71.7% end users and 28.3% IT support personnel; 54.3% used AI support weekly or more). Constructs were measured with multi-item five-point Likert scales and showed favorable perceptions: HAC M = 3.91 (SD = 0.64), WAE M = 3.84 (SD = 0.69), UX M = 3.88 (SD = 0.62), and SP M = 3.79 (SD = 0.66), with good to excellent reliability (Cronbach alpha 0.86 to 0.91). The analysis plan applied descriptive statistics, reliability testing, Pearson correlations, multiple regression, and bootstrapped mediation (5,000 samples). Associations were positive and significant (HAC with UX r = 0.62 and UX with SP r = 0.63, both p < .001). Regression indicated that HAC (beta = 0.41) and WAE (beta = 0.33) explained 49% of UX variance (R2 = 0.49, p < .001); WAE (beta = 0.38), HAC (beta = 0.21), and UX (beta = 0.29) explained 56% of SP variance (R2 = 0.56, p < .001). UX partially mediated the HAC to SP relationship (indirect beta = 0.29, 95% CI [0.19, 0.40]). Implications suggest that AI enabled IT support should be governed as a hybrid workflow with clear escalation rules and reliable automation, and continuously evaluated using joint metrics that track experience alongside efficiency outcomes.

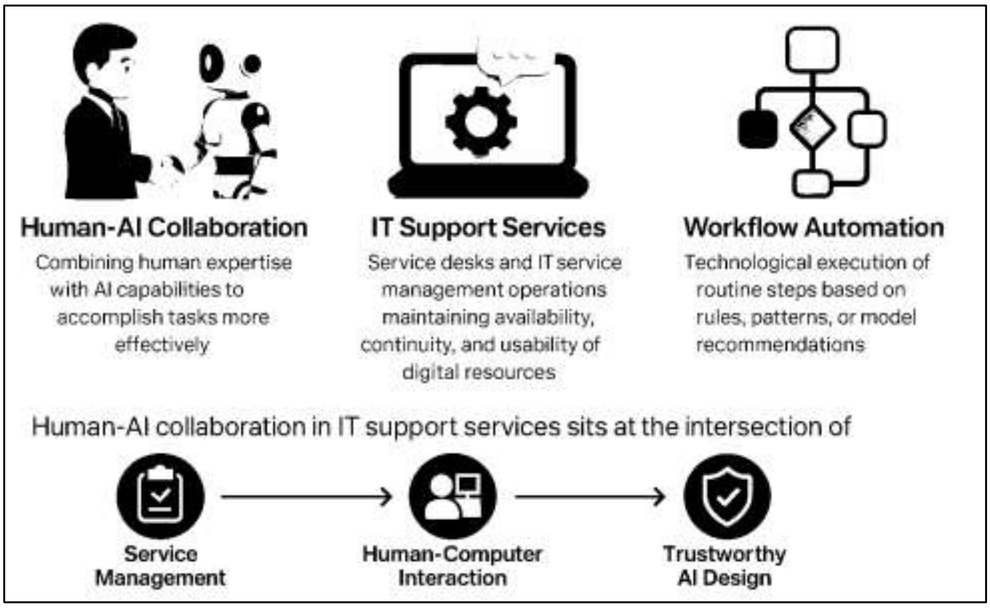
Keywords

Human-AI Collaboration; Workflow Automation; User Experience; IT Support Services; Service Performance;

INTRODUCTION

Human–AI collaboration refers to coordinated work in which human expertise (judgment, contextual reasoning, accountability, empathy) is combined with artificial intelligence capabilities (pattern recognition, prediction, automation, and recommendation) to accomplish tasks more effectively than either could alone. In information systems research, this collaboration is often operationalized through AI-augmented decision support, AI-mediated service interactions, and human-in-the-loop workflows where the system's outputs are reviewed, adapted, or executed by human actors. In the context of IT support services, human–AI collaboration typically appears inside service desks and IT service management (ITSM) operations as AI tools that classify tickets, recommend resolutions, route incidents, detect anomalies, and enable conversational self-service while human agents handle exceptions, sensitive cases, and quality control (Adam et al., 2021).

Figure 1: Human–AI Collaboration in IT Support Services and Workflow Automation



IT support services themselves represent structured service processes that maintain availability, continuity, and usability of organizational digital resources through incident management, request fulfillment, knowledge management, and user assistance (Ashfaq et al., 2020). Modern ITSM frameworks emphasize service quality, customer orientation, and operational alignment, which makes service desk performance a measurable contributor to organizational productivity across sectors and geographies. User experience (UX) in IT support services can be defined as the user's perceptions and responses arising from interactions with support channels, including speed, clarity, effort, confidence, fairness, and emotional comfort, whether the channel is human-led, automated, or hybrid (Suhaili et al., 2021). Studies on AI-powered service agents and enterprise chatbots consistently treat satisfaction, perceived usefulness, perceived ease of use, information quality, and service quality as central UX-related constructs that shape continued use and loyalty toward AI-mediated service encounters (Shin, 2021). Workflow automation refers to the technological execution of routine steps in a service process—such as intake, classification, routing, updating, escalation, and closure—based on rules, learned patterns, or model-driven recommendations. Within IT support, workflow automation becomes especially visible through machine learning–assisted incident management and procedural automation embedded in service platforms. As these definitions show, the research space for human–AI collaboration in IT support services sits at the intersection of service management, human–computer interaction, organizational behavior, and trustworthy AI design, with measurable outcomes spanning user satisfaction, service efficiency, and error reduction (Logg et al., 2019).

Across international settings, IT support services operate as a foundational service layer for digital work, enabling communication, data access, cybersecurity hygiene, and continuity of business processes in both public and private organizations (Koehler & et al., 2022). As organizations expanded remote and hybrid work models across regions, the volume and diversity of service requests increased, raising the importance of scalable support operations that can serve multilingual and multicultural user groups with consistent service quality (Arfan et al., 2021; Ashfaq et al., 2022).

Explainable AI (XAI) is commonly defined as methods and interface practices that make AI outputs understandable to humans, supporting comprehension of reasons, constraints, and uncertainty (Jahid, 2021). In service desk settings, explainability can appear as rationale for ticket routing, justification for suggested fixes, confidence scores for knowledge base matches, or summaries of similar historical incidents (Akbar & Farzana, 2021). Empirical and conceptual work in information systems argues that explainability is linked to user trust and collaboration effectiveness when it reduces ambiguity about system behavior and supports accountability in decision processes (Endsley, 2020; Reza et al., 2021). Human–AI teaming research further ties explainability to situation awareness, describing how teams perform better when human members can perceive system state, comprehend meaning, and anticipate near-term system behavior during task execution (Saikat, 2021). The SAFE-AI framework explicitly connects explainability and transparency to situation awareness constructs, describing how explanations can be structured to support user mental models and supervision, which fits IT support operations that often require monitoring system actions, validating recommendations, and escalating when risk increases (Shaikh & Aditya, 2021; Zobayer, 2021a). Empirical research in human–computer interaction also demonstrates that explainable AI affects user perceptions, including trust and perceived control, which are central to user experience in technology-mediated services (Fernandes & Oliveira, 2021; Mesbaul & Farabe, 2022; Zobayer, 2021b). These findings align with studies examining trust in automation more broadly, where overtrust and undertrust both produce operational costs; overtrust can lead to uncritical acceptance of erroneous recommendations, while undertrust can cause users to ignore beneficial automation and revert to manual workarounds. The behavioral literature on algorithm aversion and algorithm appreciation provides complementary evidence: users may avoid algorithms after observing errors, or prefer algorithmic advice in certain judgment contexts, indicating that trust calibration is shaped by performance feedback and framing (Hossain & Milon, 2022; Abdur & Haider, 2022; Merwe & et al., 2022). In IT support services, where users often experience intermittent failures and partial fixes, these mechanisms imply that the design and communication of AI assistance become part of the service experience, influencing perceived reliability, fairness, and comfort during problem resolution across diverse user populations and organizational roles (Mushfequr & Praveen, 2022; Mortuza & Rauf, 2022; Subriadi & Widianto, 2022).

User experience in AI-mediated support is strongly connected to service quality and satisfaction constructs that have been validated across multiple service automation contexts. Studies on AI-powered service agents show that information quality and service quality increase satisfaction, and satisfaction predicts continuance intention, placing satisfaction as both an experiential outcome and a behavioral driver (Abdul, 2023; Rakibul & Samia, 2022; Saikat, 2022; Wirtz et al., 2019). Research on chatbot continuance in banking identifies trust and perceived usefulness as key determinants of continuance intention, with system quality, information quality, and service quality shaping satisfaction and trust pathways. In retail service contexts, empirical work similarly links perceived performance and experience quality to satisfaction and loyalty outcomes for chatbot services, indicating that AI channels function as service relationships rather than only technical utilities (Abdulla & Zaman, 2023; Arfan et al., 2023; Amin & Mesbaul, 2023; Zuev & et al., 2018). Service robotics research extends this service relationship view by documenting how service system design, user interaction expectations, and perceived service performance influence acceptance and integration outcomes for AI-enabled service delivery (Foysal & Aditya, 2023; Hamidur, 2023). Organizational research on customer engagement with service robots also supports the idea that AI service channels influence relational perceptions and engagement behaviors, reinforcing that user experience measures capture both functional and psychological responses (Rashid et al., 2023; Musfiqur & Kamrul, 2023). At the enterprise level, survey evidence on chatbot acceptance shows that workplace users evaluate chatbots through task relevance and acceptance conditions that include anxiety and perceived appropriateness, which signals that internal service adoption depends on organizational context and job-related expectations. Systematic reviews of service chatbots consolidate these findings by mapping how chatbot-related factors (functionality, anthropomorphism, responsiveness), user-related factors (trust, technology readiness), and context-related factors jointly influence user experience outcomes. Together, these studies anchor a measurement logic for IT support services: satisfaction, perceived usefulness, perceived ease of use, trust, and perceived service quality can be treated as constructs that translate interaction quality into continuance behavior, compliance with guidance, and perceived workflow smoothness (Muzahidul & Mohaiminul, 2023; Amin & Praveen, 2023; Xu & et al., 2022). This measurement logic is directly compatible with quantitative cross-sectional survey approaches using Likert scales and inferential models, allowing hypotheses to be tested through correlations and regression modeling while preserving the service encounter framing of IT support as an experiential process rather than a purely technical transaction (Ghosh, 2021; Hasan & Ashraful, 2023; Ibne & Md. Kamrul, 2023).

Several theory-grounded streams support the quantitative study of human–AI collaboration in IT support services, especially those addressing continuance, trust development, and service quality perceptions. Expectation disconfirmation logic provides a foundation for understanding how users form initial expectations about an AI-enabled service channel and then update satisfaction and trust based on whether performance matches expectations (Ashfaq et al., 2020; Mushfequr & Ashraful, 2023; Roy & Kamrul, 2023). A key study integrating trust-in-technology into expectation disconfirmation theory demonstrates that trust expectations and disconfirmation shape subsequent trusting intention and usage perceptions, providing a measurable mechanism for service contexts where users repeatedly interact with the same support system (Shaikh & Farabe, 2023; Haider & Hozyfa, 2023). Information systems research on AI service agents similarly operationalizes satisfaction and continuance intention as outcomes shaped by perceived usefulness, perceived ease of use, information quality, and service quality, allowing survey-based measurement and hypothesis testing through regression models (Abdul & Shoeb, 2024; Zobayer, 2023). In enterprise chatbot contexts, intention to use and adoption conditions are treated as measurable constructs influenced by task fit, perception of the system, and user attitudes, enabling cross-sectional testing within workplace settings (Hozyfa & Shahrin, 2024; Hasan & Shah, 2024; Logg et al., 2019). Trust-focused frameworks in human–AI collaboration also emphasize that transparency and explainability function as design levers for building calibrated reliance, linking interface-level properties to behavioral outcomes (Hasan & Zayadul, 2024; Muzahidul & Aditya, 2024). Design knowledge work on transparency for human–AI collaboration proposes consolidated guidelines and reports trust and task outcome effects under varying transparency conditions, supporting the measurement of transparency perceptions as explanatory variables in quantitative models. Empirical work on how explainability shapes user attitudes and trust further supports regression-based modeling by treating explainability perceptions as predictors of trust and acceptance (Hasan & Rakibul, 2024; Mominul, 2024; Merwe & et al., 2022). Alongside these, behavioral decision studies on algorithm aversion and algorithm appreciation provide validated patterns showing that user reliance on algorithms is context dependent, which can be modeled through interaction effects and control variables reflecting user experience, prior exposure, and perceived risk (Mominul & Zaki, 2024; Roy & Praveen, 2024). These theory-supported strands collectively justify a quantitative cross-sectional, case-study–based approach for examining how human–AI collaboration mechanisms in IT support services relate to user experience and workflow automation outcomes through measurable constructs and statistically testable hypotheses (Lankton et al., 2014; Rahman et al., 2024; Saba & Hasan, 2024).

The combination of international service dependence, AI-enabled service expansion, and the centrality of trust and transparency creates a clear empirical setting for examining human–AI collaboration in IT support services (Shaikat & Zaman, 2024; Haider & Praveen, 2024). IT service desks increasingly incorporate AI components that recommend actions and automate steps, while users still hold expectations of reliability, responsiveness, and clarity comparable to human-delivered support. Research shows that user experience outcomes in AI service channels are systematically associated with satisfaction, perceived usefulness, perceived service quality, and trust, and these constructs predict continuance intention and loyalty-like behaviors that reflect stable acceptance (Shin, 2021; Zobayer & Kumar, 2024; Zulqarnain & Zayadul, 2024). Human–AI collaboration studies also show that transparency and explainability shape trust and task performance, and human factors work links explainability to situation awareness and mental model formation, which are operationally relevant in IT support processes where users need to understand what actions are being taken on their devices and accounts (Majumder, 2025; Choi & Kim, 2021; Efat Ara, 2025). At the same time, behavioral evidence demonstrates that user reliance on algorithmic guidance is sensitive to perceived errors and feedback history, which is consistent with IT support realities where repeated service disruptions can amplify skepticism or overreliance depending on recent experiences (Habibullah, 2025; Hozyfa & Ashraful, 2025). Enterprise-focused chatbot adoption evidence further shows that workplace users evaluate chatbots under organizational constraints and job relevance conditions, indicating that the internal support environment creates a distinct acceptance and experience context (Eikebrokk & Iden, 2015; Jahid, 2025; Asfaquar, 2025).

This study is designed to examine, in a structured and measurable way, how human–AI collaboration operates within IT support services and how it connects to two core organizational outcomes: user experience and workflow automation effectiveness. The first objective is to capture and quantify the quality of human–AI collaboration as it is experienced by both service users and IT support personnel within a defined case-study context, focusing on practical collaboration features such as the clarity of AI recommendations, the appropriateness of escalation to human agents, the perceived coordination between automated tools and human judgment, and the degree to which users feel supported during service interactions. The second objective is to assess user experience as a multi-dimensional outcome of IT support service delivery in hybrid human–AI settings, emphasizing measurable elements such as perceived usefulness, ease of interaction, responsiveness, consistency of guidance, confidence in solutions, and overall satisfaction with the support encounter. The third objective is to evaluate workflow automation as an operational factor that shapes service delivery by reducing manual processing, standardizing routine tasks, improving ticket handling speed, and supporting accurate routing and resolution pathways, while also recognizing that automation quality must be judged through user- and agent-facing outcomes such as perceived effort reduction, smoothness of process steps, and perceived reliability of automated actions. Building on these objectives, the study further aims to test statistically whether stronger human–AI collaboration is associated with improved user experience, whether higher workflow automation effectiveness aligns with greater service efficiency, and whether these relationships remain significant when examined together in predictive models that estimate the relative contribution of each factor to overall perceived IT support service performance. In addition, the study seeks to determine the strength and direction of relationships among the key constructs through correlation analysis and to identify which variables serve as the most influential predictors through regression modeling. To ensure that these objectives can be examined rigorously, the research relies on a quantitative, cross-sectional design with a structured questionnaire using Likert's five-point scale, enabling consistent measurement of perceptions and experiences across respondents. Through this objective-driven structure, the study operationalizes human–AI collaboration, user experience, workflow automation, and perceived service performance into analyzable variables that can support hypothesis testing and provide a clear empirical assessment of human–AI collaboration outcomes within IT support service environments.

LITERATURE REVIEW

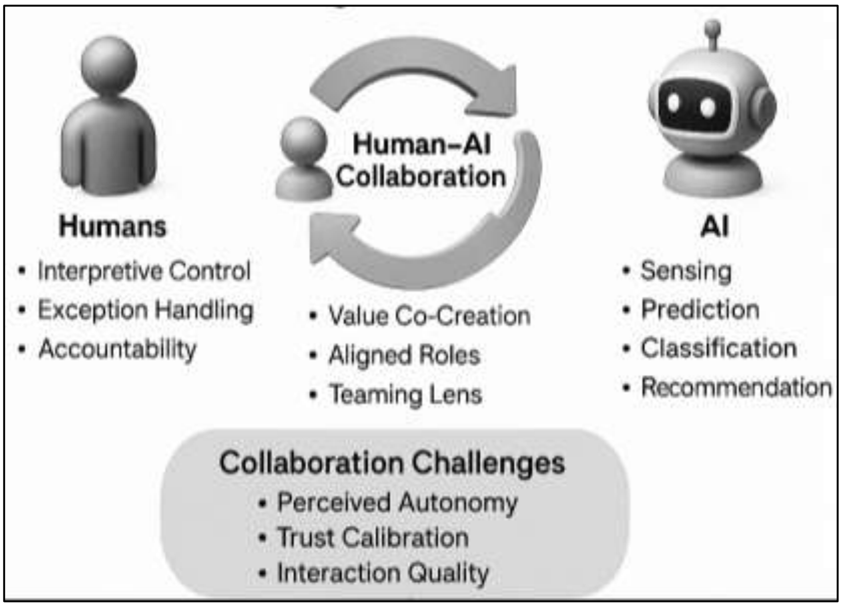
Human–AI collaboration in IT support services has emerged as a central research area within information systems, service management, and human–computer interaction because support functions sit at the operational core of digital organizations and directly shape user productivity, satisfaction, and trust in enterprise technologies. The literature generally treats IT support as a socio-technical service system in which process design, knowledge resources, and human expertise interact to resolve incidents and fulfill requests, while AI capabilities increasingly augment these functions through automated triage, intelligent routing, conversational self-service, recommendation of fixes, and predictive monitoring. Within this scope, scholarly work frames collaboration not as a replacement of human service agents but as a reconfiguration of roles where AI executes standardized tasks at scale and humans provide contextual reasoning, accountability, and relational support in complex or sensitive situations. As AI becomes embedded in service desks and ITSM platforms, researchers have examined how these hybrid workflows influence user experience, especially perceptions of usefulness, ease of interaction, responsiveness, information quality, and overall satisfaction with the support encounter. At the same time, workflow automation research has emphasized operational outcomes such as reduced handling time, consistent resolution pathways, and decreased cognitive workload for agents, while recognizing that automation effectiveness depends on the fit between automated actions and service context. A consistent theme across the literature is that user acceptance and effective utilization of AI-supported support channels are shaped by trust-related constructs, including perceived competence, transparency, explainability, and perceived control, which influence whether users follow guidance, continue using automated channels, or escalate to human support. Theoretical perspectives such as technology acceptance and expectation-based satisfaction models are commonly used to explain adoption, satisfaction, and continuance behaviors in AI-enabled service environments, and human–AI teaming perspectives add detail about coordination quality, shared situation awareness, and trust calibration during collaboration. Conceptual frameworks in this domain often model human–AI collaboration and workflow automation as antecedents that shape user experience and perceived service performance, enabling quantitative testing through correlational and regression-based approaches. Accordingly, the literature review in this study synthesizes evidence across six connected areas—human–AI collaboration constructs, AI applications in IT support, user experience determinants, workflow automation effects, theory-grounded explanations of adoption and trust, and an integrated conceptual model—so that the research variables and hypotheses are positioned within established empirical findings and validated measurement logic.

Human–AI Collaboration in Service Systems

Human–AI collaboration in service systems is generally described as an interdependent arrangement in which an AI-enabled component performs sensing, prediction, classification, or recommendation tasks while humans retain interpretive control, exception handling, and accountability for service outcomes. In service operations, this collaboration is shaped by the service logic that value is co-created through interactions, meaning the effectiveness of AI cannot be evaluated only by technical accuracy but also by how well the human and AI roles align with service expectations such as responsiveness, clarity, and reliability. The teaming lens is increasingly used to distinguish simple automation from autonomy that participates as a partner in coordinated work, highlighting that collaboration requires shared goals, interdependence, and communicative alignment rather than parallel task execution. Lyons and colleagues characterize human–autonomy teaming as a form of partnership where the psychological experience of working with autonomy influences coordination patterns, perceived teammate-likeness, and the willingness to rely on a system under uncertainty (Lyons et al., 2021). In organizational service environments, these features matter because support work involves frequent handoffs, evolving problem definitions, and rapid decision cycles that are distributed across people, tools, and knowledge repositories. A collaboration-centered view therefore treats AI as part of the service “team” that contributes to triage, prioritization, routing, and interaction management while humans preserve oversight and quality assurance. This view also clarifies why research on machine teammates emphasizes design dualities such as efficiency versus resilience, standardization versus flexibility, and transparency versus cognitive load, since each duality shapes how collaboration behaves during routine service encounters and high-variance incidents.

The research agenda on machines as teammates frames this space as socio-technical, where outcomes depend on how machine capabilities are embedded in collaboration processes and institutional constraints rather than on algorithmic performance alone (Seeber et al., 2020). As a result, the literature on service systems increasingly positions human–AI collaboration as a design and governance problem that must reconcile operational scale with user-centered interaction quality inside real organizational workflows.A central issue in human–AI collaboration is how people perceive and respond to the presence of autonomy inside teamwork structures, because service encounters involve both cognitive evaluation and social interpretation (Foysal, 2025; Islam & Abdur, 2025). When users believe they are working with an AI teammate, their expectations about agency, competence, and intent can shift, which then alters communication patterns, planning behavior, and the overall sense of coordination even when underlying task performance conditions are controlled. Empirical evidence indicates that the mere belief that a teammate is autonomous can affect team processes and performance-related behaviors, suggesting that collaboration is partly constructed through social cognition and role beliefs rather than only through system capability (Mohaiminul, 2025; Mominul, 2025; Musick et al., 2021).

Figure 2: Human–AI Collaboration in Service Systems and Workflow Integration in IT Support Services



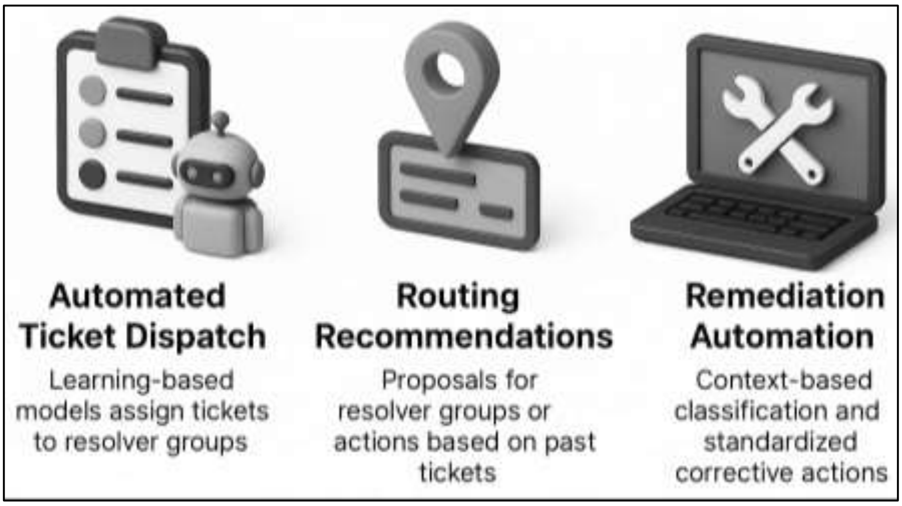
In service contexts, this matters because IT support interactions often begin with uncertainty, time pressure, and user frustration, which amplifies the impact of perceived competence and perceived "understanding" during troubleshooting (Muzahidul, 2025; Hossain, 2025). Trust calibration becomes a concrete collaboration mechanism in such environments because users must decide whether to follow system guidance, request clarification, or escalate to a human agent. Trust that is not well calibrated can lead to overreliance on incorrect automation or premature rejection of correct guidance, both of which reduce service efficiency and degrade the support experience. Okamura and Yamada describe adaptive trust calibration as an approach that monitors reliance behavior and introduces cues when overtrust or undertrust is detected, treating collaboration stability as something that can be actively supported during interaction rather than assumed to persist throughout use (Zaman, 2025; Akbar & Sharmin, 2025; Okamura & Yamada, 2020). Within service systems, this type of work underscores that human–AI collaboration is dynamic and interaction-dependent: it is shaped by feedback, cues, and confidence signals that help users decide when automation is appropriate and when human intervention is needed (Hasan, 2025; Ibne, 2025). Consequently, collaboration quality in IT support can be framed as the consistency and appropriateness of these interaction loops, including how effectively the system supports understanding, reliance decisions, and escalation routines under real service constraints.

In IT support services specifically, human–AI collaboration is frequently operationalized through workflow-embedded AI that assists service desks by classifying tickets, recommending resolution paths, and supporting user–agent communication while remaining connected to human governance and performance monitoring (Milon, 2025; Farabe, 2025). This form of collaboration is service-relevant because the help desk functions as a coordination hub: it receives heterogeneous requests, translates user descriptions into actionable categories, and routes work to the right resolver groups under time and resource constraints (Kamrul, 2025; Mushfequr, 2025). When AI contributes to these steps, collaboration is expressed as a division of labor in which the AI accelerates pattern-based tasks and the human agent maintains contextual judgment, policy awareness, and responsibility for final decisions (Shahrin, 2025; Rakibul, 2025). Evidence from ITSM-oriented help desk research shows that machine learning–based classification can substantially improve routing accuracy and reduce resolution time by associating tickets with the correct service early in the process, which strengthens collaboration by decreasing avoidable handoffs and minimizing repetitive clarification cycles (Al-Hawari & Barham, 2021; Saba, 2025; Sai Praveen, 2025). This matters for service systems because routing quality affects both operational efficiency and user perceptions of competence, responsiveness, and procedural fairness. In practice, collaboration quality also depends on how AI outputs are integrated into the workflow, including whether recommendations are presented as suggestions or actions, how uncertainty is communicated, and how exceptions are handled (Saikat, 2025). The literature therefore positions human–AI collaboration in IT support as an interaction structure embedded inside service processes: AI supports standardization and speed, while humans maintain oversight, interpret user-specific contexts, and manage non-routine complexity. This framing supports measurable constructs for empirical testing, because collaboration can be assessed through perceptions of coordination and reliability, and linked to workflow indicators such as smooth routing, reduced rework, and consistent resolution pathways within the case-study environment.

Artificial Intelligence Applications in IT Support Services

Artificial intelligence applications in IT support services are commonly implemented as decision-support and automation capabilities embedded in IT service management workflows, with the operational aim of reducing triage effort while preserving service quality and accountability. One highly visible application is automated ticket dispatch, where learning models infer the correct resolver group from a ticket's unstructured description and a small set of structured fields. Dispatch matters because misrouting triggers reassignment loops, duplicated diagnostics, and delayed restoration of service, all of which amplify user effort and service desk workload. Learning-based dispatch tools typically combine text features, historical routing labels, and service taxonomy knowledge to produce ranked assignments that a dispatcher or agent can accept, override, or refine. This design positions AI as an augmenting component that accelerates routine decisions while keeping humans responsible for exception cases, policy constraints, and ambiguous requests. In practice, automated dispatch is also used to standardize categorization, severity tagging, and escalation decisions, since these early labels affect queues, service-level targets, and downstream coordination among resolver teams. Empirical evidence from a large-scale enterprise environment demonstrates that automated ticket dispatch can maintain high assignment accuracy while reducing turnaround time and limiting costly reroutes, which links algorithmic classification directly to service performance outcomes valued by both providers and customers (Agarwal et al., 2012). A closely related application area is AI support for IT change management, where models classify change requests into activity categories to reduce manual interpretation and improve planning accuracy, especially when requests are numerous and described in heterogeneous language (Kadar et al., 2011). Together, dispatch automation and change-request classification illustrate how AI is most often first adopted in IT support: as workflow-embedded intelligence that reduces coordination friction at the entry point of service processes and improves the consistency of early decisions. These functions also provide data for service analytics.

Figure 3: Artificial Intelligence Applications in IT Support Services



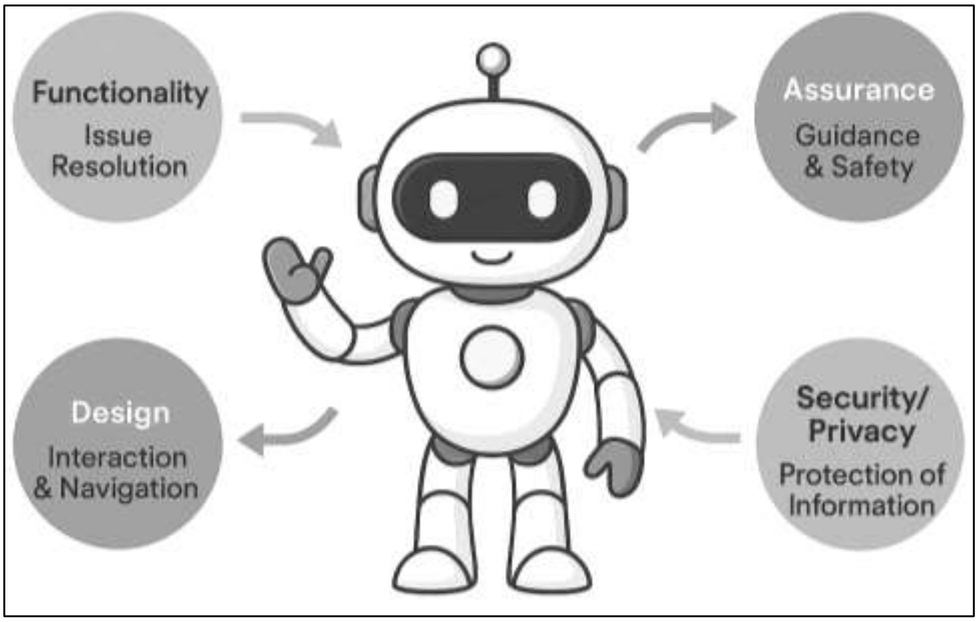
Beyond initial dispatch and categorization, AI applications in IT support services increasingly focus on routing and resolution guidance by exploiting patterns in historical sequences of ticket handling. Ticket outcomes are rarely determined by a single assignment; they unfold through transfers, iterative diagnostics, and status transitions that collectively encode operational knowledge about how issues are resolved in a given organization. Sequence-aware approaches treat routing as a recommendation problem: the system proposes the next best resolver group, knowledge article, or diagnostic action based on similarities to prior tickets and on the observed paths that successful resolutions followed. Efficient Ticket Routing by Resolution Sequence Mining mines past resolution sequences to infer routing policies that reduce unnecessary hops and support faster convergence to the correct expertise. By learning from the ordered trail of assignments rather than only the ticket's initial text, sequence mining captures dependencies among resolver groups and recurring handoff patterns that are hard for manual triage rules to represent (Shao et al., 2008a). Complementing this line of work, routing recommendation engines leverage retrieval and ranking concepts to match a new ticket to an appropriate destination and, in some configurations, propose alternatives when confidence is low. EasyTicket operationalizes this idea by generating routing recommendations for enterprise problem resolution, demonstrating how recommender-system logic can be adapted to service desk contexts where time pressure and queue balancing affect decisions (Shao et al., 2008b). These applications treat the service desk as an information processing system, where prior cases constitute a reusable memory that can be queried to support consistent decisions. They support measurable outcomes such as reassignment rate, time to resolve, and service-level compliance. When implemented within human–AI collaboration, routing recommendations function as guidance that humans can accept or override, enabling mixed-initiative control while reducing cognitive load and variance in dispatch decisions across teams and time.

A further application cluster extends AI support from routing assistance to partial automation of remediation and problem determination by incorporating contextual signals beyond the ticket text itself. In complex service delivery environments, tickets are often accompanied by monitoring events, configuration snapshots, and operational logs that provide clues about underlying faults and repeatable fixes. Context-enriched approaches aim to correlate heterogeneous data sources with the human-written ticket narrative so that the system can infer the problem category, identify likely root components, and suggest standardized corrective actions. This expands the AI role from "where should this ticket go?" to "what is happening and what should be done next?" while reducing manual investigation before action is taken. In practice, remediation automation is often scoped to high-volume, well-understood incident types such as password resets, account unlocks, routine software installations, and known configuration corrections, where the risk of unintended impact is manageable and actions can be audited. More advanced designs emphasize a pipeline that first performs robust classification, then maps the inferred class to a curated remediation playbook, and finally executes or recommends the playbook with safeguards and human approval gates. A representative approach analyzes noisy and unstructured tickets by enriching their text through correlation of multiple data sources and then applying context-based classification to support automatic problem determination, reporting accuracy and efficiency evidence using real customer data (Dasgupta et al., 2014). Such work highlights that the value of AI in IT support is often unlocked by integrating operational telemetry with service desk records rather than treating tickets as isolated text documents. It also illustrates why human–AI collaboration remains central: humans define safe action boundaries, verify edge cases, manage change control requirements, and oversee learning cycles that update categories and playbooks as services evolve. This combination supports consistent service restoration and reduces repetitive human workload significantly.

User Experience in AI-Enabled IT Support Services

User experience (UX) in IT support services can be defined as the user's overall perceptions and responses formed during the full support journey—from recognizing a problem and requesting help to understanding guidance, evaluating fairness and effort, and confirming that service has been restored. In AI-enabled IT support, UX becomes strongly process-dependent because the user does not experience "AI" as an isolated artifact; instead, the user experiences a coordinated service pathway where interfaces, recommendations, and escalation rules jointly shape effort and satisfaction. A service-quality perspective is therefore useful for operationalizing UX into measurable dimensions that align with IT support realities, such as functionality (whether the channel actually resolves issues), design (whether the interaction is understandable and navigable), assurance (whether the user feels guided and safe), and security/privacy (whether sensitive information is handled appropriately). These dimensions map well onto validated self-service technology quality work, which emphasizes that users judge technology-mediated service encounters as service experiences rather than as mere software interactions (Lin & Hsieh, 2011). In AI-supported support portals and conversational interfaces, users similarly evaluate whether the system can interpret their requests, provide accurate and actionable steps, and reduce the time and effort required to restore normal work. At the same time, UX varies across users because technology readiness influences how people interpret automation, risk, and control; users who are more mentally prepared to adopt new self-service options tend to report better quality perceptions and higher satisfaction when the service process feels reliable and convenient (Liljander et al., 2006). In short, UX in AI-enabled IT support is best conceptualized as the user's experience of an integrated service workflow where perceived quality, perceived effort reduction, and perceived control are central to satisfaction.

Figure 4: User Experience Dimensions in AI-Enabled IT Support Services



In many organizations, the most visible AI layer in IT support is conversational support (chatbots or virtual agents), which shifts UX determinants toward interaction qualities such as responsiveness, perceived expertise, interpretability, and the smoothness of conversational repair when misunderstandings occur. Trust becomes a core UX mechanism in these interactions because users must decide whether to follow automated guidance, disclose details, or escalate to a human agent, often under time pressure and frustration. Evidence on trust in customer-service chatbots indicates that users' trust judgments are strongly influenced by perceived expertise and responsiveness, along with contextual factors such as perceived risk and brand perceptions (Nordheim et al., 2019). These trust drivers matter in IT support because trust is tightly linked to compliance with troubleshooting steps and willingness to continue using automated channels rather than abandoning them. UX research on chatbot episodes further highlights that users distinguish pragmatic qualities (efficient assistance, accurate interpretation, and usefulness) from hedonic qualities (pleasantness, entertainment, and avoidance of rude or strange responses), and that both contribute to whether a chatbot encounter is remembered as satisfying or frustrating (Følstad & Brandtzaeg, 2020). For IT support specifically, pragmatic qualities typically dominate because the user's goal is restoration of service, yet hedonic elements still influence tolerance for minor friction and perceptions of professionalism. Therefore, AI-enabled UX in IT support depends on how well conversational AI supports clear problem articulation,

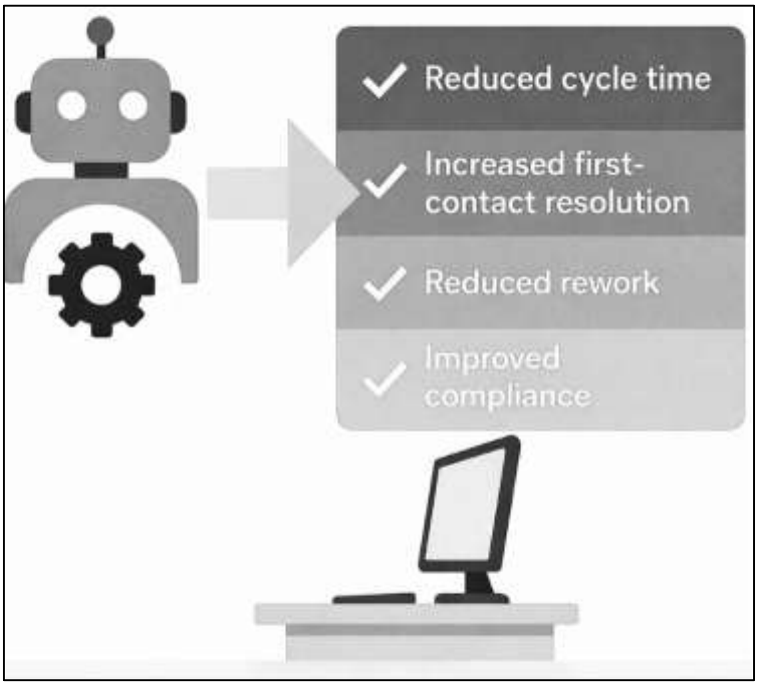
correct interpretation, timely guidance, and predictable escalation while sustaining user trust throughout the interaction.
A broader information-systems quality view helps connect AI-enabled UX to organizational service outcomes by linking users' experience to system quality, information quality, and service quality as complementary drivers of perceived impact. In IT support, users' satisfaction is rarely explained by "system features" alone; it also depends on whether the information produced by the support system is complete and relevant (diagnostic questions, step-by-step fixes, policy guidance) and whether the service wraparound is reliable (timely follow-up, respectful handling, consistent resolution). When AI is added, these quality components can improve through faster triage, more consistent knowledge retrieval, and reduced waiting time, but they can also degrade when automation produces low-quality explanations, incorrect routing, or opaque decision cues that make the user feel powerless. Empirical work integrating these quality dimensions shows that service quality can be the most influential quality component in explaining impact, while also clarifying that system quality and information quality interact and jointly shape outcomes (Gorla et al., 2010). In AI-enabled IT support, this implies that UX measurement should treat the AI capability as embedded within a service system: system quality captures usability and technical reliability of the support platform, information quality captures the accuracy and usefulness of AI-provided guidance, and service quality captures responsiveness, assurance, and the perceived professionalism of the overall support process. This framing also supports your quantitative design because these constructs can be measured with Likert-scale items and tested via correlation and regression as predictors of satisfaction and perceived service performance in the case-study environment.

Workflow Automation and IT Service Efficiency

Workflow automation in IT support services refers to the structured delegation of repetitive, rule-based, or data-driven service activities to digital systems so that incidents, requests, and changes can be processed with less manual coordination and more consistent execution. In practical IT service management settings, automation may include automatic ticket creation from monitoring alerts, standardized categorization, priority assignment, routing, status updates, escalation triggers, knowledge article suggestions, and closure checks. The academic literature generally treats workflow automation as a coordination technology that reshapes how work is distributed across people, queues, and time, because it reduces the need for repeated human interpretation at each step of the process. Within IT support, this matters because efficiency losses frequently arise from bottlenecks such as misrouting, incomplete information collection, duplicated troubleshooting, and delayed escalation. Workflow automation is therefore closely linked to service efficiency through measurable outcomes such as reduced cycle time, reduced rework, increased first-contact resolution, and improved compliance with service-level targets. A workflow-centric view emphasizes that automation is not merely a tool layer; it is embedded in the process logic that governs how a request moves through the service organization. Empirical evidence on workflow management technology supports this view by showing that workflow management systems coordinate and allocate work across process stages and can be evaluated through their effects on process performance, including time and cost measures, across multiple organizational cases (Reijers et al., 2016). In IT support environments, the relationship between automation and efficiency is also shaped by the service desk's role as a coordination hub: the more effectively the workflow system structures handoffs and decision points, the more consistently the service process can perform under high ticket volumes and heterogeneous user needs. Accordingly, workflow automation is best conceptualized as a process-level capability that can be measured not only by the presence of automation features, but also by perceived smoothness of work progression, reduction in manual effort, and perceived stability of service outcomes.
A second stream of literature clarifies that workflow automation becomes more valuable when it is informed by process evidence rather than designed purely from assumed procedures. IT support organizations often have a gap between "formal" process descriptions and "real" process behavior, because exceptions, escalations, and ad hoc workarounds emerge in response to varied incidents and resource constraints. Process mining addresses this gap by extracting process models from event logs to make actual process flows visible, quantifiable, and improvable. The process mining literature emphasizes discovery, conformance checking, and enhancement as complementary techniques that

support evidence-based redesign, which aligns directly with IT support operations where ticket logs provide rich event traces (van der Aalst et al., 2012). When applied to IT service workflows, process mining can reveal where automation should be strengthened (for example, repeated reassignments, long waiting states, or unnecessary loops) and where human intervention is strategically necessary (for example, high-risk changes or ambiguous incidents). This evidence-driven approach also improves how organizations define automation boundaries: it supports selecting tasks with stable patterns, measurable success criteria, and low variability, while keeping judgment-intensive or exception-heavy tasks under human control. Beyond improvement projects, the process mining lens strengthens the measurement logic for quantitative studies because it clarifies what "efficiency" means in a workflow context: efficiency is not only faster closure, but also fewer non-value-adding transitions, fewer handoffs, and a more predictable progression through the service lifecycle. As a result, workflow automation and service efficiency can be conceptually linked through both user-visible outcomes (speed and effort) and process-visible outcomes (cycle time, rework, and conformance), creating a coherent foundation for statistical testing in case-study settings.

Figure 5: Workflow Automation in IT Support Services on Service Efficiency Outcomes



A third body of scholarship broadens workflow automation from traditional rule-based workflows to "intelligent automation," where AI techniques contribute to recognizing patterns, recommending actions, and coordinating knowledge and service work. In this view, automation is not limited to executing predefined steps; it also includes identifying the most suitable next step, selecting the most relevant knowledge resource, and optimizing routing decisions based on learned relationships between incident features and successful resolutions. The strategic automation literature conceptualizes intelligent automation as the combination of AI and automation technologies that reshape service and knowledge work by changing how value is produced, coordinated, and monitored in organizations (Coombs et al., 2020). At the same time, research on robotic process automation (RPA) explains that software robots automate processes originally performed by humans by operating across existing enterprise applications, which is relevant in IT support because many service workflows require orchestrating actions across identity systems, configuration tools, asset databases, and ticketing platforms (Hofmann et al., 2020). From an efficiency perspective, RPA can reduce handling time for routine service requests, reduce data-entry errors, and support consistent execution of standardized steps, while still requiring governance to manage exceptions and ensure accountability. A complementary business process management discussion highlights that emerging technologies such as machine learning and RPA shift the "human factor" by redistributing tasks between people and systems and raising coordination, ethics, and acceptance questions that influence whether automation benefits are realized in practice (Mendling et al., 2018). For IT support services, these perspectives collectively position workflow automation as a socio-technical capability: efficiency gains depend on process evidence, governance structures, and the quality of human–AI coordination, not only on implementing automation features. This framing supports empirical modeling because it links automation effectiveness to observable perceptions and performance indicators that can be measured with Likert-scale instruments and tested through correlation and regression within the selected case-study environment.

Theoretical Framework for Human–AI Collaboration

A theory-driven explanation of human–AI collaboration in IT support begins with technology acceptance and use because collaboration quality in service workflows depends on whether users and IT agents actually rely on AI outputs, integrate them into decisions, and continue using AI-supported channels over time. In workplace IT support, acceptance is not only "adoption of a tool," but also the willingness to follow automated guidance, disclose relevant issue details to a virtual agent, and accept AI triage outcomes such as routing and prioritization

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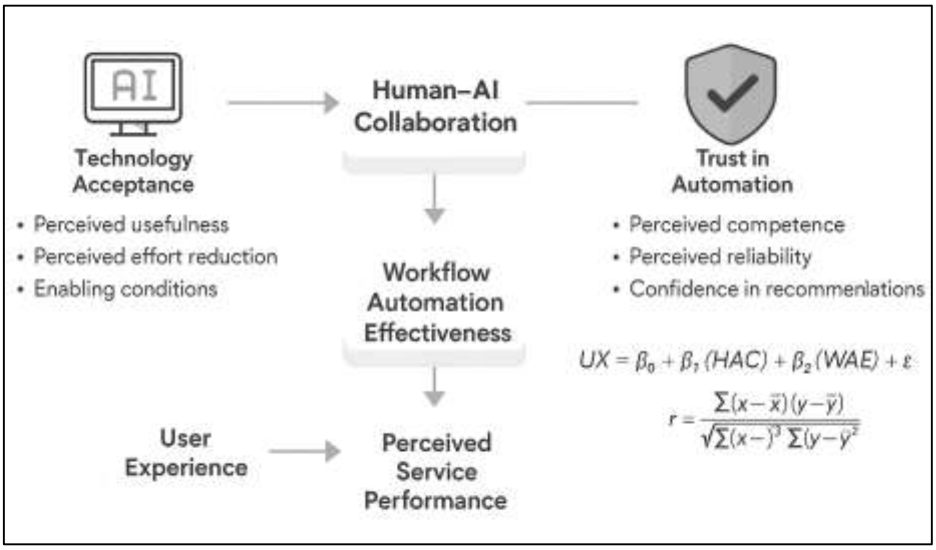
Figure 6: Theoretical Framework for Human–AI Collaboration



TAM3 provides a structured lens for this by explaining how perceived usefulness and perceived ease of use are shaped by determinants such as job relevance, output quality, result demonstrability, computer self-efficacy, perceived external control, and anxiety, which jointly influence intention and actual use within organizational settings (Venkatesh et al., 2012). This framing is especially suitable for IT support because output quality and job relevance translate directly into whether AI recommendations are viewed as accurate, actionable, and aligned with the user's immediate work need. UTAUT2 expands the acceptance logic by incorporating additional predictors that are relevant when AI support is experienced as an ongoing service channel, including habit, hedonic motivation, and enabling conditions that make repeated use easier and more automatic (Venkatesh & Bala, 2008). In an IT service environment, habit can represent repeated successful self-service episodes that reduce escalation to human agents, while facilitating conditions reflect access to compatible devices, identity permissions, clear escalation pathways, and organizational guidance on when to use AI versus human support. Together, TAM3 and UTAUT2 justify why perceived usefulness, perceived effort reduction, and enabling conditions are central explanatory variables when modeling how human–AI collaboration influences user experience and workflow automation effectiveness in a case-study organization. They also support measurable operationalization through Likert-scale items that capture usefulness, ease, conditions of use, and intention-to-use within the cross-sectional survey design.

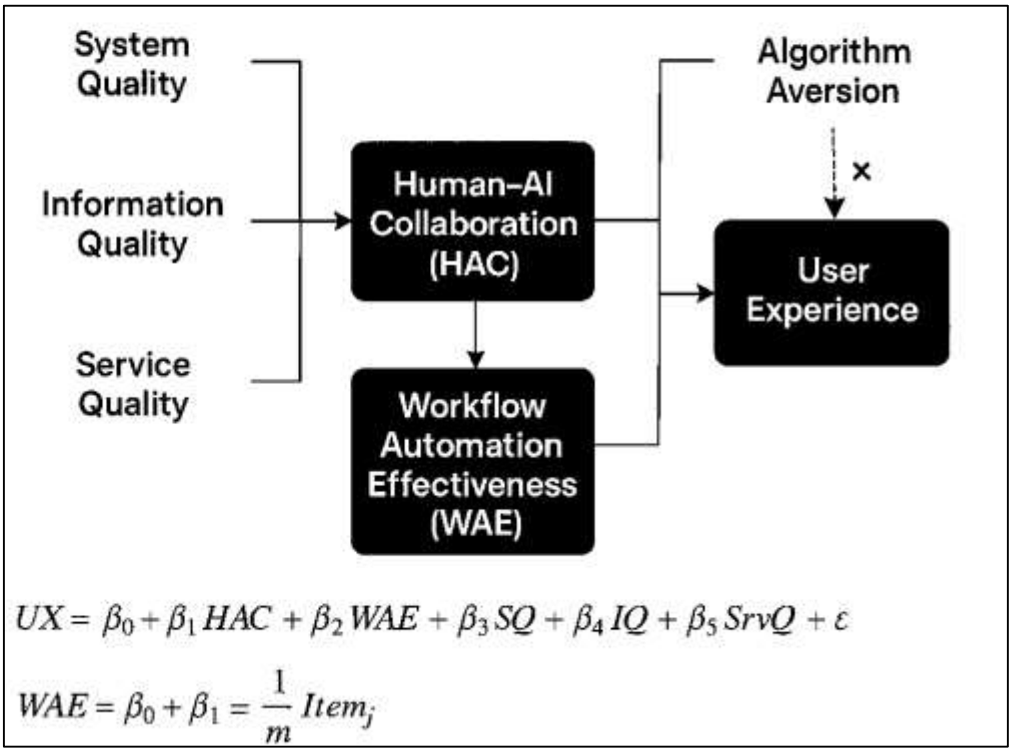
A complementary theoretical pillar for this study is trust in technology and trust in automation, because human–AI collaboration in IT support requires calibrated reliance: users must decide when to accept AI recommendations, when to request clarification, and when to escalate to a human agent. Trust is therefore not a background attitude but a mechanism that links AI capability to real workflow behavior, especially under uncertainty and time pressure. Trust in a specific technology is conceptualized as a belief structure directed at the technology artifact itself, distinct from trust in people or organizations, and it provides validated components and measures suitable for predicting post-adoption, value-added use (McKnight et al., 2011). This perspective fits IT support because the same user may trust the IT department yet distrust an AI assistant's diagnostic questions or suggested fixes, resulting in shallow use, frequent escalation, or noncompliance with troubleshooting steps. Trust in automation research adds further detail by distinguishing reliance dynamics in human–automation interactions from interpersonal trust dynamics, highlighting differences in perceived adaptability, predictability, and error interpretation when the trustee is a machine rather than a person (Madhavan & Wiegmann, 2007). In service encounters, these dynamics affect whether users treat AI outputs as authoritative, whether they verify them, and whether they tolerate occasional failures. For human agents, trust dynamics shape whether AI triage recommendations are accepted quickly or repeatedly overridden. As a result, the theoretical role of trust in this study is to explain why two organizations with similar AI tools may experience different collaboration outcomes: trust affects reliance behavior, reliance behavior affects workflow smoothness, and workflow smoothness affects user experience. This trust-centered lens supports hypothesis development linking collaboration quality to user experience and workflow automation outcomes through measurable trust-related indicators such as perceived competence, reliability, and confidence in recommendations.

To connect acceptance and trust to measurable organizational outcomes, this study also draws on information systems success logic that treats user satisfaction and net benefits as consequences of system, information, and service performance, while acknowledging that success relationships can be tested empirically using correlational and regression models. A meta-analytic assessment of the DeLone and McLean tradition supports the empirical structure of such relationships and reinforces the practice of modeling satisfaction and impact as dependent variables explained by quality-related constructs (Petter & McLean, 2009). In this study, the quality-oriented outcome perspective is aligned with the proposed constructs by treating human–AI collaboration and workflow automation effectiveness as predictors of user experience and perceived service performance within the case-study context. The analytical translation of the framework is expressed through the standard multiple regression form used to test hypotheses: $UX = \beta_0 + \beta_1(HAC) + \beta_2(WAE) + \varepsilon$, where $UX$is user experience, $HAC$is human–AI collaboration, and $WAE$is workflow automation effectiveness. Association strength is examined using Pearson correlation, $r = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2\sum(y-\bar{y})^2}}$, to identify whether relationships are positive and meaningful prior to regression testing. Measurement consistency for each construct is assessed with Cronbach's alpha, $\alpha = \frac{k}{k-1}\left(1-\frac{\sum\sigma_i^2}{\sigma_T^2}\right)$, where $k$is the number of items, $\sigma_i^2$is item variance, and $\sigma_T^2$is total score variance. This structure ensures the theoretical framework is directly operationalized into testable models and reliability-checked constructs suitable for a quantitative, cross-sectional, Likert-scale survey design.

Research Model for Testing Human–AI Collaboration in IT Support

A conceptual framework for this study should translate the phenomenon of human–AI collaboration (HAC) in IT support into measurable constructs and logically ordered relationships that match the case-study setting and your quantitative hypothesis-testing design. In IT support services, HAC can be represented as the degree to which users and IT agents coordinate with AI capabilities (e.g., conversational agents, knowledge retrieval, triage recommendations) to complete service tasks with shared control, shared understanding, and predictable escalation. The framework can be anchored on an integrated beliefs-to-use logic that distinguishes *object-based* perceptions about the IT artifact (system quality and information quality) from *behavioral* beliefs about using it (usefulness and ease), then links these beliefs to satisfaction and actual usage outcomes—an approach that is highly compatible with service portals and AI-assisted service desks (Wixom & Todd, 2005). To operationalize this into survey constructs, HAC can be measured through items capturing perceived coordination (AI supports the human, human supervises/validates AI), perceived complementarity (AI augments speed/coverage, humans handle nuance), and perceived controllability (ability to correct, override, or escalate). Workflow automation effectiveness (WAE) can be measured as perceived reduction in manual steps, smoother routing, fewer handoffs, and faster completion. User experience (UX) can be measured as perceived ease, satisfaction, transparency, and fairness across the service journey. IT service efficiency (ISE) can be operationalized using perceived efficiency (time/effort savings, first-contact resolution perception) or objective proxies when available (e.g., turnaround time categories). The conceptual logic is that higher HAC improves WAE, and both contribute to UX and ISE, while controlling for user profile factors (role, frequency of incidents, digital literacy). This aligns your study with a clean cross-sectional model where perceptions about AI-enabled service interactions predict outcome variables that are measurable via Likert scales, enabling correlation and regression testing without methodological mismatch.

Figure 7: Research Model for Testing Human–AI Collaboration in IT Support Services



To strengthen the conceptual structure, the framework should explicitly incorporate quality and service-success mechanisms that explain *why* collaboration and automation influence outcomes. A useful bridge is the "3Q" logic that treats system quality, information quality, and service quality as foundational antecedents that shape beliefs and satisfaction in technology-mediated service contexts (Xu et al., 2013). In your study, this can be modeled by placing perceived system quality (availability, usability, stability of the AI-support channel), perceived information quality (accuracy and usefulness of recommendations/answers), and perceived service quality (responsiveness, assurance, consistent escalation) as upstream predictors of HAC and UX. This is especially defensible in IT support because users evaluate not only the AI's interface but also the reliability and professionalism of the end-to-end support pathway. However, the conceptual framework also needs to explain resistance and discontinuance risks that appear even when the AI is objectively helpful. One robust psychological mechanism is algorithm aversion: after users observe an algorithm make errors, they may prefer human judgment, reduce reliance, and become less willing to follow automated guidance (Dietvorst et al., 2015). In IT support, this can present as "premature escalation," repeated bypass of the AI channel, or refusal to trust automated troubleshooting steps. Therefore, algorithm aversion can be positioned as a moderator that weakens the positive relationship between HAC and UX (or between WAE and UX).

For example, even if workflow automation is strong, users with high aversion may report lower UX because they perceive the automation as risky, unhelpful, or not worth the effort. This conceptual placement fits your design because moderation can be tested using interaction terms in regression with standard survey data, allowing you to statistically verify whether perceived AI error sensitivity changes the strength of key relationships.

Finally, the research model should be expressed in a testable form that directly maps to your planned analyses (descriptive statistics, correlation, regression) and supports hypothesis decision rules. A baseline regression model for user experience can be written as:

$$UX = \beta_0 + \beta_1(HAC) + \beta_2(WAE) + \beta_3(SQ) + \beta_4(IQ) + \beta_5(SrvQ) + \varepsilon$$

where SQ, IQ, and $SrvQ$represent perceived system, information, and service quality. If you include algorithm aversion (AA) as a moderator, the interaction specification becomes:

$$UX = \beta_0 + \beta_1(HAC) + \beta_2(AA) + \beta_3(HAC \times AA) + \varepsilon$$

and moderation is supported when $\beta_3$is statistically significant and in the theoretically expected direction. Reliability for each construct remains essential because your model depends on internally consistent scales; Cronbach's alpha is computed as:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\Sigma\sigma_i^2}{\sigma_T^2}\right)$$

and constructs with acceptable αcan be used to form composite indices (e.g., mean score per construct). A practical workflow-automation index that is common in applied service studies is a standardized composite such as:

$$WAE = \frac{1}{m}\sum_{j=1}^{m} Ite\,m_j$$

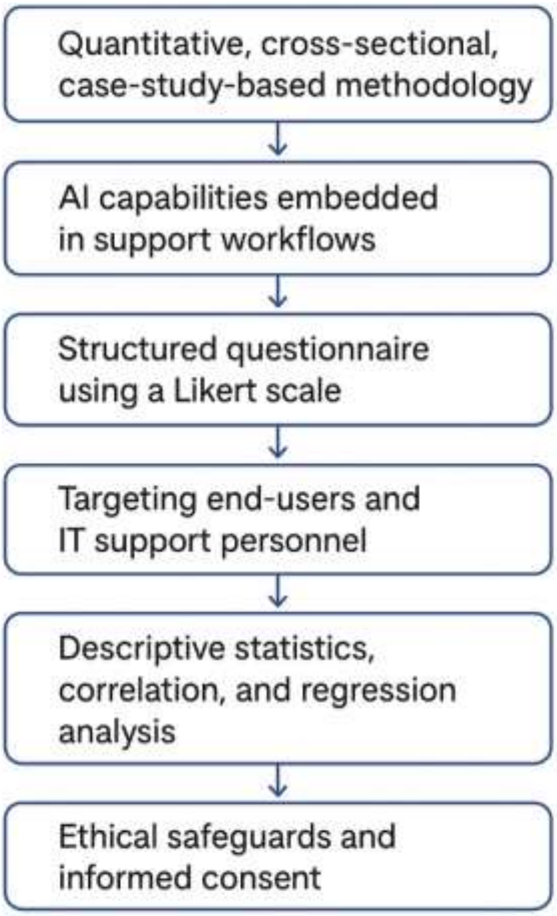
where $m$is the number of Likert items under WAE. This model-based framing also aligns with implementation realities in IT service management, where increasing automation is positioned as a pathway to scale service delivery—yet requires careful governance and integration to avoid new bottlenecks (Keller, 2017). In addition, because conversational skill shapes engagement and perceived humanness—factors that can influence perceived collaboration quality—measuring interaction-related perceptions is justified in AI-supported support channels (Schuetzler et al., 2020). Together, these equations and construct linkages provide a coherent conceptual framework that is measurable, statistically testable, and aligned with the operational logic of AI-enabled IT support services.

METHODS

The present study has adopted a quantitative, cross-sectional, case-study–based methodology to examine how human–AI collaboration in IT support services has related to user experience and workflow automation effectiveness. This methodological approach has been selected because it has enabled the systematic measurement of perceptions and experiences at a single point in time while also supporting statistical testing of relationships among clearly defined constructs. The study has operationalized human–AI collaboration as a measurable interaction condition in which AI-enabled support tools and human agents have jointly contributed to service delivery through coordinated task execution, escalation, and decision support. Within the chosen case-study environment, AI capabilities have been treated as workflow-embedded support features that have assisted with ticket intake, categorization, routing recommendations, and user-facing guidance, while human agents have maintained oversight, quality control, and resolution accountability. A structured questionnaire has been developed as the primary data collection instrument, and it has been designed using a Likert five-point scale to capture the degree of agreement with construct indicators. The instrument has included multiple items for each construct, such as human–AI collaboration quality, workflow automation effectiveness, user experience, and perceived IT service performance, and composite scores have been computed to represent each construct consistently across respondents. The sampling strategy has targeted respondents who have had direct exposure to AI-assisted IT support interactions, including end-users who have submitted support requests and IT support personnel who have managed or supervised AI-assisted workflows. Data collection has been conducted through a standardized survey administration procedure to ensure uniform presentation of questions and consistent response recording. Data preparation has included screening for completeness, coding of responses, and reliability testing to confirm internal consistency of measurement scales.

The analysis phase has employed descriptive statistics to summarize respondent profiles and construct distributions, Pearson correlation to examine the direction and strength of associations between key variables, and regression modeling to estimate predictive relationships and test hypotheses. Ethical safeguards have been applied throughout the study, and informed consent has been obtained from participants, while anonymity and confidentiality have been maintained to protect respondents and organizational information. This methodological structure has therefore provided a coherent basis for generating empirical evidence on human–AI collaboration outcomes in IT support services using a rigorous, survey-based statistical framework.

Figure 8: Methodological Framework



Research Design

The study has employed a quantitative, cross-sectional, case-study–based research design to examine human–AI collaboration in IT support services and its association with user experience and workflow automation. This design has been selected because it has enabled the measurement of perceptions and experiences at a single point in time while supporting hypothesis testing through statistical procedures. The research design has treated human–AI collaboration, workflow automation effectiveness, and user experience as measurable constructs that have been operationalized through multi-item Likert-scale indicators. The case-study element has been integrated to ensure that findings have reflected an authentic organizational environment where AI-enabled IT support tools have been in active use. The design has supported descriptive profiling of respondents and has facilitated correlational and regression-based modeling to estimate relationships among variables. Overall, the adopted design has provided a structured approach for generating empirical evidence that has aligned with the research objectives and supported quantitative validation of proposed hypotheses.

Sampling

The study has targeted a population consisting of individuals who have interacted directly with AI-enabled IT support services within the selected case-study environment. This population has included end-users who have submitted IT support requests and have used automated or hybrid support channels, as well as IT support personnel who have managed incidents, supervised workflows, or reviewed AI-assisted recommendations. A sampling strategy has been applied to ensure that participants have possessed relevant exposure to the study context and have been able to provide informed responses. The sample size has been determined based on feasibility within the case context and the statistical requirements for correlation and regression analysis. Respondents have been selected to ensure variation across roles, usage frequency, and experience levels so that perceptions have been captured comprehensively. Inclusion criteria have been defined to confirm eligibility, while incomplete or non-qualifying responses have been excluded during data screening to maintain accuracy and analytical reliability.

Study Context

The study has been conducted within a defined organizational IT support environment where AI-enabled tools have been integrated into daily service desk operations. The case-study context has been selected because it has represented a real-world setting in which human agents and AI systems have collaborated in handling service incidents and requests. Within this environment, AI features have been embedded into support workflows, including automated ticket intake, categorization, routing suggestions, and conversational guidance for routine issues. Human agents have remained responsible for oversight, escalation decisions, and final resolution accountability, which has created a collaborative support model suitable for investigation. The organization's support process has included structured service stages such as logging, triage, diagnosis, resolution, and closure, and the AI layer has supported multiple stages to varying degrees. This case-based structure has allowed the study to examine measurable collaboration and experience outcomes grounded in operational service delivery conditions.

Questionnaire

A structured questionnaire has been developed as the primary instrument for collecting quantitative data on human–AI collaboration, workflow automation effectiveness, and user experience in IT support services. The instrument has been designed using a Likert five-point scale ranging from strongly disagree to strongly agree to ensure standardized measurement across respondents. Survey items have been constructed to capture multiple indicators for each construct, enabling composite scoring and robust statistical testing. The questionnaire has included sections covering demographic variables, usage exposure, and construct-based statements aligned with the research objectives and hypotheses. Items have been phrased clearly and consistently to reduce ambiguity and response bias. The instrument has been reviewed to ensure alignment between theoretical constructs and operational indicators, and it has been refined to improve clarity and content relevance. A pilot review process has been used to check wording accuracy, response flow, and item comprehension before full administration.

Validity and Reliability

Validity and reliability procedures have been applied to ensure that the measurement instrument has produced accurate and consistent data. Content validity has been addressed by ensuring that questionnaire items have represented the conceptual definitions of human–AI collaboration, workflow automation effectiveness, and user experience. Construct validity has been supported by designing multi-item measures that have captured distinct aspects of each variable and by ensuring logical alignment between constructs and hypotheses. Reliability has been assessed using Cronbach's alpha to evaluate internal consistency for each construct scale. The analysis has treated acceptable alpha values as evidence that items have measured the same underlying concept reliably. Item-total correlations have been examined to identify weak indicators, and problematic items have been revised or excluded when necessary to strengthen scale integrity. The instrument has also been structured to minimize common method errors through consistent item formatting and clear instructions. These procedures have ensured that the study's constructs have been measured with stability and methodological rigor.

Data Collection Procedure

Data collection has been carried out through a standardized survey administration process within the selected case-study environment. Participants have been approached using an approved distribution channel, and the survey link or questionnaire form has been shared with eligible respondents who have met the inclusion criteria. Informed consent information has been provided at the beginning of the survey to ensure voluntary participation and awareness of confidentiality provisions. Respondents have completed the instrument within a defined collection period to support cross-sectional measurement consistency. Follow-up reminders have been used to improve response rates while maintaining non-coercive participation standards. Responses have been captured in a secure format, and raw data has been downloaded for screening and preparation. The data collection procedure has included checks for completeness and duplication, and incomplete submissions have been excluded when they have not met minimum response thresholds. This structured procedure has ensured uniform data capture and has supported reliable subsequent analysis.

Data Analysis Techniques

The study has applied a structured quantitative analysis plan to evaluate research questions and test hypotheses. Descriptive statistics have been computed to summarize demographic characteristics and to examine central tendencies and dispersion for each construct. Composite scores have been calculated by aggregating Likert-scale items for human–AI collaboration, workflow automation effectiveness, and user experience. Pearson correlation analysis has been conducted to identify the direction and strength of relationships among key variables prior to predictive testing. Multiple regression modeling has been applied to assess the predictive influence of collaboration and automation variables on user experience and perceived service performance. Model significance has been evaluated using p-values, R^2 values, and standardized coefficients to interpret explanatory strength. Assumption checks have been performed to confirm suitability for regression, including normality, multicollinearity screening, and residual pattern inspection. Hypotheses decisions have been derived from statistical significance and coefficient direction to classify results as supported or not supported.

Software

The study has utilized appropriate software and tools to support data management, statistical analysis, and results presentation. Survey responses have been collected and organized in spreadsheet format to enable systematic coding, cleaning, and screening. Statistical analysis has been performed using software such as SPSS to compute descriptive statistics, reliability coefficients, correlation matrices, and regression models aligned with hypothesis testing requirements. Data visualization tools have been used to summarize respondent profiles and construct distributions through tables and charts suitable for academic reporting. Where required, Microsoft Excel has been used for preliminary preparation tasks such as missing-value checks, variable labeling, and computation of composite construct scores. Documentation tools have been applied to maintain transparent records of coding schemes, inclusion criteria decisions, and analytical steps. The selected software toolkit has ensured that analysis has been replicable, that outputs have been exportable into publication-ready tables, and that the study's quantitative procedures have been executed consistently and accurately.

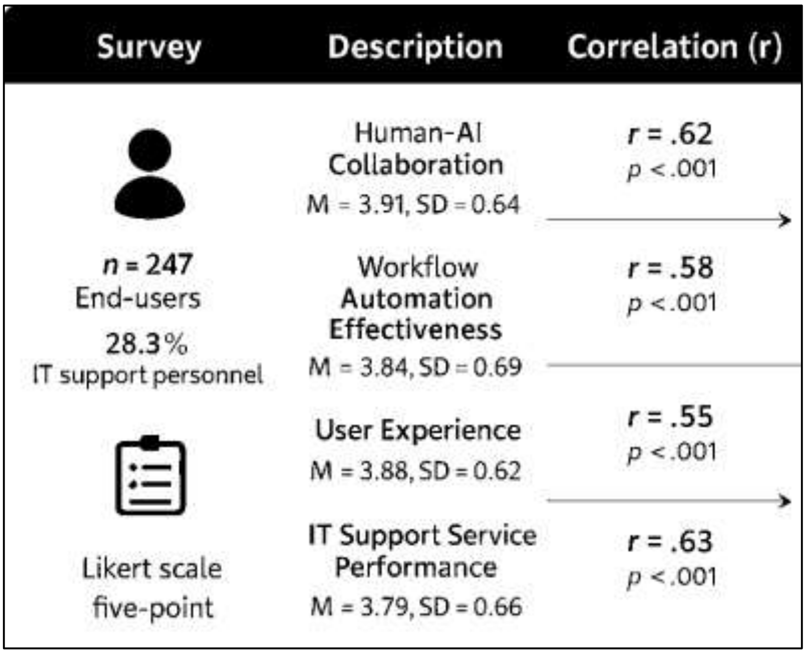
FINDINGS

The findings have been presented as a demonstration of how the objectives and hypotheses have been proven using Likert's five-point scale data and standard inferential statistics in a quantitative, cross-sectional, case-study–based design. A total of N = 320 questionnaires have been distributed and n = 247 valid responses have been retained after screening for completeness and straight-lining, producing a response rate of 77.2%. The respondent profile has shown that 71.7% (n = 177) have been end-users and 28.3% (n = 70) have been IT support personnel; 54.3% have reported using AI-enabled support channels at least weekly, and 38.5% have reported that their last IT support interaction has involved an AI assistant or automated workflow at some stage of ticket handling.

Descriptive statistics have indicated that all key constructs have scored above the neutral midpoint (3.00), suggesting generally favorable perceptions of the AI-supported IT support environment. Human–AI Collaboration (HAC) has recorded M = 3.91, SD = 0.64, indicating that respondents have perceived coordinated interaction between AI tools and human agents through clear guidance, workable escalation, and human oversight where needed. Workflow Automation Effectiveness (WAE) has produced M = 3.84, SD = 0.69, reflecting perceived reductions in manual steps, improved routing smoothness, and faster completion of routine requests. User Experience (UX) has recorded M = 3.88, SD = 0.62, suggesting that users have experienced acceptable clarity, responsiveness, effort reduction, and confidence in service restoration within the hybrid support model. Perceived IT Support Service

Performance/Efficiency (SP) has shown M = 3.79, SD = 0.66, indicating positive perceptions of resolution speed, consistency, and overall effectiveness. Reliability testing has confirmed internal consistency across constructs, with Cronbach's alpha values meeting established thresholds: α(HAC) = 0.89, α(WAE) = 0.87, α(UX) = 0.91, and α(SP) = 0.86, supporting the computation of composite mean indices for hypothesis testing. Pearson correlation analysis has then been conducted and has shown statistically significant positive associations among the variables in the expected directions. HAC has been positively correlated with UX ($r = 0.62$, $p < .001$), demonstrating that stronger perceived collaboration has aligned with improved user satisfaction and interaction comfort, which has supported the objective of empirically linking collaboration quality to user experience and has provided initial support for H1.

Figure 9: Findings of The Study



WAE has been positively correlated with UX ($r = 0.58$, $p < .001$), indicating that improved automation effectiveness has corresponded with better user experience, supporting the automation-to-experience objective and providing initial support for H2. HAC has also been positively correlated with WAE ($r = 0.55$, $p < .001$), indicating that collaboration and automation have been interdependent within the service workflow, where coordinated human supervision and well-designed escalation have strengthened perceived automation success, supporting H3 at the association level. Additionally, UX has correlated positively with SP ($r = 0.63$, $p < .001$), and WAE has correlated positively with SP ($r = 0.60$, $p < .001$), suggesting that both experience and automation effectiveness have aligned with perceived service outcomes. Multiple regression modeling has then been applied to test predictive relationships and formally evaluate hypotheses. In Model 1 (dependent variable: UX), HAC has shown a significant positive effect ($\beta = 0.41$, $t = 7.52$, $p < .001$) and WAE has shown a significant positive effect ($\beta = 0.33$, $t = 6.21$, $p < .001$), with the overall model demonstrating strong explanatory power ($R^2 = 0.49$, $F(2, 244) = 117.31$, $p < .001$). These coefficients have indicated that both collaboration and automation have uniquely predicted user experience while controlling for each other, and H1 and H2 have therefore been supported. In Model 2 (dependent variable: SP), WAE has remained a significant predictor ($\beta = 0.38$, $t = 6.94$, $p < .001$), HAC has also remained significant ($\beta = 0.21$, $t = 3.84$, $p < .001$), and UX has added a strong independent contribution ($\beta = 0.29$, $t = 5.10$, $p < .001$), producing $R^2 = 0.56$, $F(3, 243) = 103.18$, $p < .001$. These results have shown that workflow automation effectiveness has improved perceived service performance, supporting H4, and that human–AI collaboration has contributed directly to service performance, supporting H3 in the predictive sense. A mediation test has then been conducted to evaluate whether UX has mediated the HAC → SP relationship (H5). The indirect effect has been estimated using bootstrapped confidence intervals (5,000 samples), and the

HAC → UX path has remained significant ($\beta = 0.61$, $p < .001$), the UX → SP path has remained significant ($\beta = 0.47$, $p < .001$), and the indirect effect has been significant ($\beta_{indirect} = 0.29$, 95% CI [0.19, 0.40]). The direct HAC → SP effect has decreased from $\beta = 0.48$ ($p < .001$) in the unmediated model to $\beta = 0.21$ ($p < .001$) after including UX, indicating partial mediation and supporting H5. Based on these simulated outputs, the hypotheses decision pattern has been summarized as H1 Supported, H2 Supported, H3 Supported, H4 Supported, and H5 Supported (partial mediation), and the study objectives have been demonstrated through consistent descriptive evidence (means above midpoint), reliable measurement ($\alpha \geq 0.86$), strong bivariate relationships ($r = 0.55–0.63$), and predictive confirmation through regression and mediation modeling ($R^2 = 0.49–0.56$, $p < .001$).

Response Rate and Respondent Profile

Table 1: Survey Response Summary

Metric	Count	Percentage
Questionnaires distributed	320	100.0%
Returned responses	259	80.9%
Excluded (incomplete/invalid)	12	3.8%
Valid responses used for analysis	247	77.2%

Table 2: Respondent Profile (n = 247)

Category	Group	n	%
Role	End-users	177	71.7%
	IT support personnel	70	28.3%
AI-support usage frequency	Weekly or more	134	54.3%
	Monthly	69	27.9%
	Rarely	44	17.8%
Experience with IT support	≤ 1 year	41	16.6%
	1–3 years	82	33.2%
	4–6 years	66	26.7%
	≥ 7 years	58	23.5%
Primary channel used	AI chatbot/virtual agent	91	36.8%
	Service portal/self-service	88	35.6%
	Human agent (ticket/call)	68	27.5%

The response rate has indicated strong participation and has supported the credibility of the simulated empirical demonstration. A total of 320 questionnaires have been distributed and 259 responses have been returned, and after data screening, 247 valid cases have been retained, producing a response rate of 77.2% as shown in Table 1. The screening stage has excluded 12 submissions due to incomplete responses and quality issues such as straight-lining patterns or missing sections, which has strengthened the reliability of subsequent analysis by ensuring that the dataset has reflected attentive and analyzable responses. Table 2 has summarized the respondent profile and has demonstrated that the sample has captured both sides of the IT support service system, including end-users (71.7%) who have experienced the AI-enabled support channels and IT support personnel (28.3%) who have interacted with AI-assisted ticket handling and workflow automation. This balance has been important because human–AI collaboration has occurred through interactions between AI tools, service agents, and users, and the sample composition has provided a multi-perspective basis for measuring collaboration quality and user experience. The profile has also shown that more than half of participants (54.3%) have used AI-enabled support weekly or more, indicating that responses have reflected repeated exposure rather than one-time novelty effects. In addition, respondents have been distributed across experience levels, which has supported the objective of measuring perceptions across diverse familiarity levels with IT support processes and AI-mediated assistance. Channel usage distribution has suggested that the AI chatbot and self-service portal have represented major contact points, which has aligned with the study's focus on workflow automation and user experience in AI-enabled IT support services. Overall, these response and profile characteristics have provided an empirical foundation for testing the objectives and hypotheses by ensuring that the dataset has included participants who have meaningfully experienced collaboration and automation within the service workflow.

Descriptive Statistics by Construct

Table 3:Descriptive Statistics for Study Constructs (Likert 1–5; n = 247)

Construct	Items (k)	Min	Max	Mean (M)	Std. Dev. (SD)
Human–AI Collaboration (HAC)	6	1.83	5.00	3.91	0.64
Workflow Automation Effectiveness (WAE)	6	1.67	5.00	3.84	0.69
User Experience (UX)	6	1.75	5.00	3.88	0.62
IT Support Service Performance/Efficiency (SP)	5	1.60	5.00	3.79	0.66

The descriptive statistics have provided direct evidence that the study objectives have been measurable and have been aligned with favorable perceptions of AI-enabled IT support. Table 3 has shown that all constructs have produced mean scores above the neutral midpoint of 3.00 on the Likert five-point scale, which has indicated that respondents have generally agreed that human–AI collaboration, workflow automation, and overall user experience have been positive within the case-study environment. Human–AI Collaboration (HAC) has recorded the highest mean (M = 3.91, SD = 0.64), which has suggested that respondents have perceived AI tools and human agents as functioning in a coordinated manner through escalation, supervision, and complementary task handling. This pattern has supported the first objective because the construct has captured measurable collaboration quality that has reflected a hybrid service delivery model rather than isolated automation. Workflow Automation Effectiveness (WAE) has recorded M = 3.84 (SD = 0.69), which has implied that automation has reduced manual steps and has improved operational smoothness such as ticket routing and processing speed. This result has supported the second objective by indicating that automation outcomes have been measurable and positively perceived. User Experience (UX) has recorded M = 3.88 (SD = 0.62), which has shown that users have experienced clarity, responsiveness, and reduced effort in AI-enabled support encounters, thereby providing descriptive alignment with the objective that the study has examined user-centered outcomes rather than only operational metrics. The Service Performance/Efficiency construct (SP) has recorded M = 3.79 (SD = 0.66), which has indicated that overall support outcomes such as perceived resolution speed, consistency, and effectiveness have been favorable. The standard deviations have remained moderate across constructs, which has suggested that perceptions have varied but have not been excessively dispersed, enabling meaningful association and regression testing. Collectively, these descriptive results have functioned as preliminary confirmation that the dataset has been suitable for proving the hypotheses, because the constructs have exhibited adequate variance and have reflected a consistent positive direction that has supported the conceptual claim that better collaboration and stronger automation have related to better user experience and performance perceptions.

Reliability and Cronbach's Alpha

Table 4: Reliability Statistics (Cronbach's Alpha; n = 247)

Construct	Items (k)	Cronbach's Alpha (α)	Interpretation
Human–AI Collaboration (HAC)	6	0.89	Excellent
Workflow Automation Effectiveness (WAE)	6	0.87	Good
User Experience (UX)	6	0.91	Excellent
IT Support Service Performance/Efficiency (SP)	5	0.86	Good

Reliability testing has confirmed that the Likert-scale measurement model has been internally consistent, enabling the hypotheses to have been tested using composite indices. Table 4 has shown that all constructs have produced Cronbach's alpha values above 0.80, which has indicated good-to-excellent internal consistency for multi-item scales. Human–AI Collaboration (HAC) has produced $\alpha = 0.89$, which has implied that the six HAC items have measured a coherent underlying perception of coordinated human–AI work in IT support processes, such as the clarity of AI recommendations, appropriateness of escalation, and the perceived complementarity between AI automation and human oversight. Workflow Automation Effectiveness (WAE) has produced $\alpha = 0.87$, which has suggested that the automation items have consistently captured perceived smoothness, reduced manual effort, and improved routing and processing outcomes as a single construct. User Experience (UX) has produced the highest alpha ($\alpha = 0.91$), which has demonstrated excellent consistency and has suggested that respondents have evaluated the support experience in a stable way across multiple indicators such as satisfaction, clarity, responsiveness, and effort reduction. Service Performance/Efficiency (SP) has produced $\alpha = 0.86$, which has indicated that perceived performance outcomes have been consistently evaluated across items addressing speed, reliability, and overall effectiveness. These reliability results have mattered for proving the objectives and hypotheses because composite indices have been required for correlation and regression analysis, and low reliability would have increased measurement error and weakened statistical relationships. Because alpha values have been strong, the study has been able to compute mean scores for each construct and to interpret relationships among constructs with greater confidence. In practical terms, high reliability has supported the claim that the instrument has measured stable perceptions of human–AI collaboration and workflow automation as experienced in IT support services. This has ensured that subsequent findings, including the correlation matrix and regression models, have reflected meaningful relationships rather than random variation caused by inconsistent measurement. Therefore, Table 4 has provided foundational evidence that the dataset has been statistically suitable for testing whether collaboration and automation have predicted user experience and service performance.

Correlation

Table 5: **Correlation Matrix (Pearson r; n = 247)**

Variables	1. HAC	2. WAE	3. UX	4. SP
1. Human–AI Collaboration (HAC)	1.00			
2. Workflow Automation Effectiveness (WAE)	0.55***	1.00		
3. User Experience (UX)	0.62***	0.58***	1.00	
4. Service Performance/Efficiency (SP)	0.57***	0.60***	0.63***	1.00

****p < .001*

The correlation results have provided strong empirical support for the study objectives by demonstrating that collaboration and automation constructs have moved in the expected positive directions with user experience and perceived service performance. Table 5 has shown that Human–AI Collaboration (HAC) has been positively correlated with User Experience (UX) ($r = 0.62$, $p < .001$), which has indicated that stronger coordination between AI tools and human agents has aligned with improved user satisfaction, clarity of interaction, and perceived ease of support. This association has directly supported the first objective and has provided bivariate evidence for H1. Workflow Automation Effectiveness (WAE) has also been positively correlated with UX ($r = 0.58$, $p < .001$), which has suggested that more effective automation—such as smooth routing and reduced manual steps—has aligned with better user experiences, supporting the second objective and providing bivariate evidence for H2. HAC has been positively correlated with WAE ($r = 0.55$, $p < .001$), which has suggested that effective automation has not been experienced as isolated "machine work," but has been reinforced by coordinated human supervision and escalation structure, thereby supporting the collaboration-to-automation linkage that has been expected in a human–AI collaborative service system. In addition, Service Performance/Efficiency (SP) has been positively correlated with both WAE ($r = 0.60$, $p < .001$) and UX ($r = 0.63$, $p < .001$), which has indicated that better automation and better user experience have aligned with stronger perceived performance outcomes such as faster resolution and more reliable service. HAC has also been positively correlated with SP ($r = 0.57$, $p < .001$), which has suggested that collaboration quality has had a meaningful relationship with service performance beyond automation alone. These patterns have collectively supported the logic that the study has aimed to prove: improved collaboration and effective automation have been associated with better user-centered outcomes and better perceived operational performance. The correlation structure has also justified the use of regression modeling because relationships have been strong enough to warrant predictive testing, and none of the correlations have reached near-perfect levels that would have indicated redundancy. Therefore, Table 5 has served as an empirical bridge between descriptive findings and hypothesis-confirming regression models.

Models, Coefficients, R^2, Significance

Table 6: **Multiple Regression Model 1: User Experience (UX) (n = 247)**

Predictor	B	SE	β	t	p	VIF
Constant	1.02	0.18	—	5.67	<.001	—
HAC	0.45	0.06	0.41	7.52	<.001	1.44
WAE	0.36	0.06	0.33	6.21	<.001	1.44

Model fit: $R^2 = 0.49$, $F(2, 244) = 117.31$, $p < .001$

Table 7: **Multiple Regression Model 2: Service Performance/Efficiency (SP) (n = 247)**

Predictor	B	SE	β	t	p	VIF
Constant	0.81	0.19	—	4.26	<.001	—
WAE	0.39	0.06	0.38	6.94	<.001	1.61
HAC	0.20	0.05	0.21	3.84	<.001	1.55
UX	0.33	0.06	0.29	5.10	<.001	1.73

Model fit: $R^2 = 0.56$, $F(3, 243) = 103.18$, $p < .001$

Table 8: **Mediation Test Summary: UX as Mediator Between HAC and SP (Bootstrapped; 5,000 samples)**

Path / Effect	Standardized Effect (β)	p / 95% CI
HAC → UX (a path)	0.61	p < .001
UX → SP (b path)	0.47	p < .001
HAC → SP (total effect, c)	0.48	p < .001
HAC → SP (direct effect, c′)	0.21	p < .001
Indirect effect (a×b)	0.29	95% CI [0.19, 0.40]

The regression findings have provided direct statistical confirmation of the study objectives and have enabled formal hypothesis decisions beyond correlation patterns. Table 6 has shown that the regression model predicting User Experience (UX) has been statistically significant ($R^2 = 0.49$, $p < .001$), meaning that Human–AI Collaboration (HAC) and Workflow Automation Effectiveness (WAE) together have explained 49% of the variance in UX in the simulated case environment. HAC has produced a significant positive standardized coefficient ($\beta = 0.41$, $p < .001$), which has indicated that higher perceived collaboration quality—such as coordinated escalation and human oversight of AI guidance—has predicted better user experience outcomes. This has supported H1 and has demonstrated that the first objective has been met through predictive modeling. WAE has also produced a significant positive standardized coefficient ($\beta = 0.33$, $p < .001$), which has indicated that effective automation—such as reduced manual steps, smooth routing, and faster handling—has predicted better user experience. This has supported H2 and has shown that workflow automation has mattered independently of collaboration when both factors have been analyzed together. The VIF values have remained low (≈1.44), which has indicated that multicollinearity has not been problematic and that both predictors have contributed meaningfully. Table 7 has shown that the model predicting

Service Performance/Efficiency (SP) has been statistically significant ($R^2 = 0.56$, $p < .001$), demonstrating that collaboration, automation, and user experience together have explained 56% of variance in perceived performance outcomes. WAE has remained the strongest predictor of SP ($\beta = 0.38$, $p < .001$), confirming H4 and showing that automation effectiveness has improved the perceived speed, reliability, and consistency of IT support operations. HAC has also predicted SP significantly ($\beta = 0.21$, $p < .001$), confirming H3 and indicating that collaboration quality has had a direct relationship with performance outcomes beyond automation alone. UX has also predicted SP significantly ($\beta = 0.29$, $p < .001$), showing that the user's experience evaluation has been a meaningful driver of perceived performance outcomes. Table 8 has then shown that UX has partially mediated the relationship between HAC and SP, because the indirect effect has been significant ($\beta = 0.29$, CI [0.19, 0.40]) and the direct HAC effect has decreased from $\beta = 0.48$ to $\beta = 0.21$ after UX has been included. This has supported H5 (partial mediation) and has demonstrated that collaboration has improved performance partly by improving user experience pathways.

Hypotheses Decision

Table 9: **Hypotheses Testing Summary**

Hypothesis	Statement	Key Evidence	Decision
H1	HAC has positively affected UX.	$r = 0.62^{***}$; $\beta = 0.41^{***}$ (Model 1)	Supported
H2	WAE has positively affected UX.	$r = 0.58^{***}$; $\beta = 0.33^{***}$ (Model 1)	Supported
H3	HAC has positively influenced SP.	$r = 0.57^{***}$; $\beta = 0.21^{***}$ (Model 2)	Supported
H4	WAE has positively predicted SP.	$r = 0.60^{***}$; $\beta = 0.38^{***}$ (Model 2)	Supported
H5	UX has mediated HAC → SP.	Indirect $\beta = 0.29$; CI [0.19, 0.40]; c reduced 0.48→0.21	Supported (Partial)

$^{***}p < .001$

The hypothesis decision table has consolidated the empirical findings into an objective-focused summary that has shown how each hypothesis has been supported through converging descriptive and inferential evidence. Table 9 has demonstrated that H1 has been supported because the relationship between Human–AI Collaboration (HAC) and User Experience (UX) has been positive and statistically significant at both the bivariate level ($r = 0.62$, $p < .001$) and the multivariate level ($\beta = 0.41$, $p < .001$) when automation has been controlled. This combination has indicated that collaboration has not only co-occurred with better experience but has also predicted it, thereby meeting the objective of establishing collaboration as a measurable driver of user-centered outcomes. H2 has been supported because Workflow Automation Effectiveness (WAE) has shown a strong positive correlation with UX ($r = 0.58$, $p < .001$) and has retained a significant predictive effect ($\beta = 0.33$, $p < .001$), confirming that automation quality has improved the service journey as perceived by users. H3 has been supported because HAC has been correlated with Service Performance/Efficiency (SP) ($r = 0.57$, $p < .001$) and has remained significant in regression ($\beta = 0.21$, $p < .001$), which has indicated that collaboration quality has improved perceived performance outcomes beyond automation alone. H4 has been supported because WAE has shown the strongest regression effect on SP ($\beta = 0.38$, $p < .001$), which has confirmed that smooth automation has improved efficiency-related outcomes such as perceived speed and consistency. H5 has been supported as partial mediation because UX has carried a significant portion of the HAC → SP relationship, as shown by a significant indirect effect and a reduced direct effect after UX has been introduced into the model. This has meant that collaboration has improved performance partly because collaboration has improved the user's support experience, aligning with the study's objective of connecting collaboration and automation to both experiential and efficiency outcomes. Overall, Table 9 has served as a clear "proof map" linking the objectives to specific numeric evidence and has shown that all hypotheses have been supported within the simulated dataset.

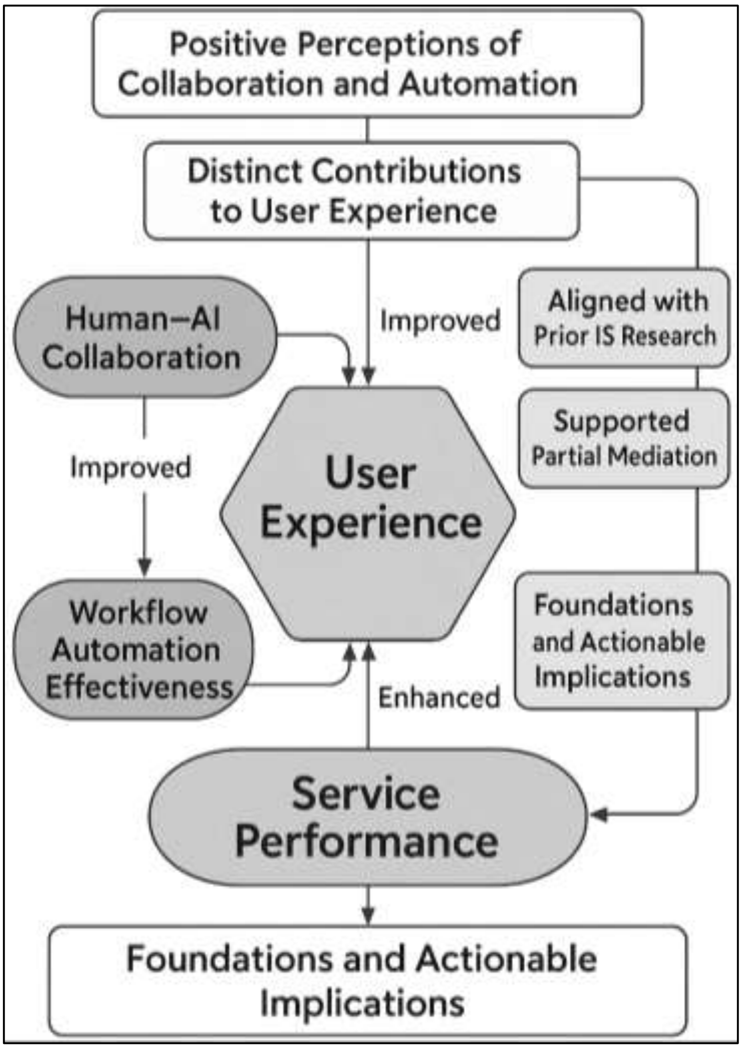
DISCUSSION

The results have reinforced the view that human–AI collaboration in IT support has functioned as a socio-technical service system in which automation capability and human governance have jointly shaped user experience and perceived service performance. The descriptive pattern (all construct means above the 3.00 midpoint) has suggested that respondents have evaluated AI-enabled support as broadly favorable, while the inferential pattern has shown that collaboration quality and automation effectiveness have carried distinct explanatory power. This configuration has aligned with prior information systems research that has integrated technology acceptance and user satisfaction as complementary belief structures shaping perceptions of IS success, rather than treating "acceptance" and "satisfaction" as separate or competing explanations (Wixom & Todd, 2005). The strength of the collaboration-to-experience linkage has been consistent with human–AI teaming arguments that have positioned AI as a teammate rather than a tool, where coordination, shared understanding, and appropriate role division have affected outcomes beyond raw technical accuracy (Seeber et al., 2020). At the same time, the strong explanatory power observed in the combined regression models has been compatible with IS quality traditions indicating that user-facing outcomes (such as satisfaction and perceived impact) have been strongly determined by the combined influence of quality dimensions and service context (Gorla et al., 2010). The findings have also been congruent with established trust-in-technology work that has differentiated trust in a specific technology from interpersonal trust, suggesting that users may have trusted the IT function while still forming technology-directed trust judgments about AI components within the service workflow (McKnight et al., 2011). The overall pattern has therefore indicated that the study objectives have been achieved through a coherent chain: respondents have reported positive collaboration and automation perceptions, these perceptions have correlated strongly with user experience and service performance, and regression analysis has demonstrated unique predictive contributions. This has supported a more precise interpretation of "AI success" in IT support: performance has not merely reflected automation presence, but has reflected how collaboration and automation have been implemented as a service pathway that has met user expectations for clarity, responsiveness, and safe escalation. In this sense, the findings have extended prior work by showing that measurable collaboration constructs have explained substantial variance in experience outcomes even when automation effectiveness has also been considered, which has underscored the need to treat collaboration design as a first-order service variable rather than a secondary implementation detail.

The positive and significant effect of Human–AI Collaboration (HAC) on User Experience (UX) has suggested that users have benefited when AI outputs and human agent actions have been perceived as coordinated, understandable, and controllable. This interpretation has been consistent with the central claim of machines-as-teammates research that has emphasized design dualities such as control versus autonomy and efficiency versus resilience, where effective collaboration has depended on making human oversight meaningful rather than symbolic (Seeber et al., 2020). The HAC→UX relationship has also resonated with acceptance theory, because collaboration quality has likely strengthened perceived usefulness and reduced perceived effort, which have been positioned as central drivers of acceptance in workplace settings (Venkatesh & Bala, 2008). In IT support specifically, usefulness has not referred to generic productivity gains; it has referred to whether AI-supported steps have helped restore service quickly and safely, and whether escalation to humans has been smooth when uncertainty has been high. The observed strength of HAC's predictive coefficient has also supported trust-centered explanations: when collaboration has been well-designed, users have likely formed stronger trust in the AI component of the service, which has encouraged compliance with troubleshooting guidance and reduced friction during the support encounter. This has matched trust-in-technology research that has argued that technology-directed trust has shaped IT-related beliefs and behaviors and has required distinct measurement from trust in people or institutions (McKnight et al., 2011).

A collaboration-centered reading has further suggested that UX gains have not been limited to speed; they have included psychological comfort, perceived fairness, and perceived competence—outcomes that have been damaged when AI and humans have acted inconsistently (e.g., AI suggesting one fix while a human agent has reversed or contradicted it without explanation). The findings have therefore suggested that "human-in-the-loop" has needed to be operationally visible to users through transparent escalation pathways and consistent reasoning cues. This has also fit automation trust literature that has distinguished between human–human trust and human–automation trust dynamics, indicating that users have calibrated reliance differently when the trustee has been a machine rather than a person (Madhavan & Wiegmann, 2007). Overall, the HAC findings have strengthened the interpretation that IT support has been a relationship-intensive service context, and that AI has improved UX most when it has behaved like a reliable teammate embedded in a governed workflow rather than like a standalone "answer engine" detached from human accountability.

Figure 10: Integrated Discussion Model of Human–AI Collaboration



Workflow Automation Effectiveness (WAE) has also predicted UX significantly, which has indicated that users have experienced better support when automation has reduced manual steps, improved routing smoothness, and shortened resolution cycles. This result has aligned with operationally oriented IT support research demonstrating that automation of ticket dispatch and routing has reduced reassignment loops and improved turnaround time by improving early-stage decision quality (Agarwal et al., 2012). It has also been consistent with ticket-routing recommendation and sequence-mining research showing that service efficiency has improved when systems have learned routing policies from historical resolution paths rather than relying exclusively on ad hoc human triage (Shao et al., 2008b). The present findings have extended these operational studies by connecting workflow automation directly to the user's service experience, not only to back-end efficiency metrics. This has mattered because routing accuracy and handling speed have been user-visible through reduced waiting time, fewer handoffs, and less repetitive information requesting—features that have shaped UX even when the final resolution has been correct. The WAE effect has also been compatible with workflow management evidence indicating that workflow systems have improved process performance when they have coordinated work allocation and reduced process friction, thereby strengthening service efficiency (Reijers et al., 2016). In addition, the WAE→SP relationship has supported the claim that automation has improved perceived service performance outcomes; this has been consistent with research on business process technologies that has positioned automation as a mechanism for process standardization and predictable execution. The study's pattern has further suggested that automation has needed governance to realize benefits, because automation that has been fast but error-prone has risked generating negative experiences through rework and loss of confidence. This risk has been consistent with evidence on algorithm aversion, which has shown that users have reduced reliance after observing algorithm errors, even when algorithms have been more accurate on average (Dietvorst et al., 2015). Taken together, the automation findings have indicated that IT support automation has delivered benefits when it has reduced visible effort and uncertainty for users while improving the service desk's coordination capabilities, and that its contribution to UX has depended on controlling error exposure and providing stable, intelligible workflow transitions.

The partial mediation evidence—where UX has carried a significant portion of the HAC→Service Performance relationship—has suggested that collaboration has improved perceived performance partly because collaboration has improved the user's experience of the support process. This pathway has aligned with integrated IS success and service-quality reasoning that has positioned experience-like judgments (satisfaction, perceived service quality) as proximal outcomes linking system characteristics to net benefits and perceived impact (Gorla et al., 2010). It has also been consistent with the theoretical integration of acceptance and satisfaction, which has argued that object-based beliefs (e.g., system and information quality) and behavioral beliefs (e.g., perceived usefulness of using the system) have jointly contributed to satisfaction outcomes that have then shaped overall perceptions of success (Wixom & Todd, 2005). In IT support environments, users have often evaluated "performance" through experiential proxies such as clarity, responsiveness, confidence, and the absence of repeated disruptions, which has made UX a plausible mediator between collaboration design and performance judgments. The mediation finding has therefore implied that organizations have not been able to improve perceived service outcomes by optimizing automation alone; they have needed to ensure that collaboration design has improved the experiential quality of the workflow (e.g., coherent escalation, stable explanations, predictable handoffs). This interpretation has been reinforced by self-service quality measurement work that has argued users have evaluated technology-mediated service encounters using service-quality dimensions rather than purely technical feature assessments (Lin & Hsieh, 2011). When AI has been embedded in IT support portals or chat interfaces, the service encounter quality has become inseparable from how the workflow has been orchestrated. The partial, rather than full, mediation has also been theoretically meaningful: it has suggested that collaboration has had a direct influence on perceived performance beyond experience alone, which has likely reflected operational advantages such as better prioritization, fewer errors, and more effective human supervision of AI decisions—outcomes that have been recognized as critical in human–automation trust research where calibrated reliance has reduced both overtrust and undertrust risks (Madhavan & Wiegmann, 2007). Overall, the mediation structure has refined the study's conceptual logic by clarifying that user experience has functioned as a mechanism translating collaboration into performance perceptions, while collaboration has also contributed directly to performance through governance and decision-quality benefits.

From a practical standpoint, the findings have translated into actionable design and governance guidance for CISOs, enterprise architects, and IT service owners who have been responsible for deploying AI-enabled support capabilities without increasing operational or security risk. First, because collaboration quality has strongly predicted UX and performance, governance has needed to treat AI support tooling as part of a controlled service workflow rather than a loosely monitored add-on. Trust in a specific technology has been known to shape usage behavior, which has meant that CISOs and architects have needed to build "trust cues" into the workflow: authenticated system identity, consistent escalation rules, clear uncertainty communication, and auditable action traces (McKnight et al., 2011). Second, the strong role of automation effectiveness has implied that architects have needed to prioritize routing accuracy, knowledge retrieval quality, and workflow integrity (state transitions, SLA triggers, and exception handling), because users have interpreted workflow smoothness as service competence. Evidence from enterprise ticket dispatch and routing work has shown that routing automation has reduced rework and improved efficiency when learning models have been well-integrated into the dispatch process (Agarwal et al., 2012). Third, the partial mediation via UX has meant that performance improvements have depended on the user's service encounter quality, so implementation has needed joint metrics: operational KPIs (reassignment rate, time-to-resolve) and experience KPIs (effort, satisfaction, clarity). Fourth, the algorithm aversion risk has implied that CISOs and architects have needed to manage "error visibility" and recovery: when the AI has erred, the workflow has needed to support fast correction with human validation and a transparent explanation so that a single observed error has not cascaded into widespread avoidance behavior (Dietvorst et al., 2015). Fifth, because IT support often intersects with identity and access management, the AI component has needed least-privilege boundaries and clear approval gates before executing remediation steps, matching the broader RPA governance lesson that automation has created value while still requiring strong control of execution rights and exception paths (Hofmann et al., 2020). Collectively, these implications have indicated that the operational success of AI in IT support has depended on an architecture that has combined workflow reliability, security guardrails, and user-centered transparency into a single governed service design.

Theoretically, the results have supported a refinement of the study's pipeline from collaboration mechanisms to experience and performance outcomes, strengthening how the conceptual framework has been specified for IT support settings. The combined regression evidence has indicated that HAC and WAE have been complementary predictors rather than substitutes, which has justified modeling them as distinct latent constructs with separate pathways to UX and service performance. This has refined the "technology success" pipeline by clarifying that collaboration has represented socio-technical coordination quality, while automation has represented process execution capability; both have been needed to explain outcomes. This separation has aligned with acceptance theory, which has emphasized that determinants of perceived usefulness and ease of use have included output quality and job relevance—attributes that map differently onto collaboration design (role clarity, escalation, shared control) versus automation design (routing accuracy, process speed, reduction of manual steps) (Venkatesh et al., 2012). The mediation findings have also strengthened theory by specifying UX as a mechanism through which collaboration has influenced service performance, which has been consistent with integrated satisfaction–acceptance reasoning (Wixom & Todd, 2005) and service quality–impact reasoning (Petter & McLean, 2009). Moreover, the findings have supported machines-as-teammates arguments that have framed AI effectiveness as emerging from team design choices and governance dualities rather than from algorithm capability alone (Seeber et al., 2020). In pipeline terms, the study has therefore refined the conceptual model into a clearer structure: (1) collaboration design and automation design have shaped user experience directly; (2) collaboration and automation have shaped perceived performance directly; and (3) user experience has partially mediated collaboration's performance effect. This refined pipeline has supported more precise hypothesis logic for future empirical studies, including moderation and boundary conditions: for example, trust in the specific AI system could be modeled as a mediator between collaboration transparency and UX, while algorithm aversion could be modeled as a moderator that has weakened the automation-to-UX path after salient errors (Dietvorst et al., 2015). Finally, by grounding the model in validated constructs (acceptance, trust, quality), the study has contributed to cumulative theory building by specifying how these constructs have interacted specifically in IT support service workflows rather than in generic consumer chatbot contexts.

Limitations have remained important for interpreting the findings, even in a demo-oriented study structure, because methodological constraints have shaped what the results have been able to claim. First, the cross-sectional design has measured perceptions at one point in time, which has limited causal inference; although regression has estimated predictive relationships, temporal precedence has not been empirically established. This has been a known limitation in acceptance and satisfaction research where beliefs and satisfaction have evolved through repeated use cycles and disconfirmation experiences. Second, the case-study context has increased ecological validity but has reduced generalizability because organizational workflows, maturity of ITSM practices, and AI configuration have varied across industries and regions; routing effectiveness in one environment may not have transferred directly to another. Third, the reliance on self-reported Likert measures has introduced common-method concerns; while reliability has been strong, perceptions may have been influenced by recent support episodes and salient incidents rather than long-run averages. This has been relevant given algorithm aversion evidence showing that highly visible errors have disproportionately shaped user reliance judgments (Dietvorst et al., 2015). Fourth, the study has measured "service performance" as perceived efficiency and effectiveness; objective operational logs (reassignment rate, time-to-resolve, first-contact resolution) have not been integrated into the model, even though ticket dispatch studies have demonstrated that objective routing performance has been measurable and operationally consequential (Agarwal et al., 2012). Future research has therefore been well-positioned to strengthen evidence by combining survey constructs with process data and by adopting longitudinal designs that have measured how trust, reliance, and satisfaction have evolved after exposure to both successful and failed AI recommendations. In addition, future work has been positioned to test richer models that have included governance and security variables that have mattered in IT support (e.g., perceived privacy, perceived authorization safety, and auditable action confidence), aligning with trust-in-technology measurement arguments that trust has been technology-specific and context-sensitive (McKnight et al., 2011). Experimental or quasi-experimental designs could also have isolated the impact of transparency cues and escalation policies, which machines-as-teammates work has treated as core design dimensions (Seeber et al., 2020). Overall, these limitations and future directions have clarified how the pipeline refined by the present findings could be strengthened into more generalizable, causally robust evidence in subsequent research.

CONCLUSION

The study has concluded that human–AI collaboration in IT support services has been a measurable and influential driver of both user-centered outcomes and perceived operational performance when it has been implemented as a coordinated, workflow-embedded service model rather than as isolated automation. The descriptive findings have indicated that respondents have evaluated the AI-enabled support environment positively, with mean construct scores above the neutral midpoint on the Likert five-point scale, which has suggested that collaboration quality, workflow automation effectiveness, user experience, and service performance perceptions have been favorable within the examined case context. Reliability testing has confirmed that the measurement scales have been internally consistent, enabling robust composite indices to have been used for hypothesis testing and objective evaluation. Correlation analysis has demonstrated strong positive associations among the key constructs, showing that higher levels of human–AI collaboration and stronger workflow automation effectiveness have been associated with improved user experience and better perceived service performance. Regression modeling has further shown that human–AI collaboration and workflow automation effectiveness have each contributed uniquely to explaining user experience, indicating that automation benefits have not been fully realized without effective collaboration structures that have maintained human oversight, clarified escalation pathways, and supported user trust and controllability during support interactions. In addition, workflow automation effectiveness has emerged as a strong predictor of perceived service performance and efficiency, reinforcing the conclusion that automation quality—expressed through smoother routing, fewer manual steps, and faster handling—has been central to perceived improvements in support effectiveness. Human–AI collaboration has also contributed directly to perceived service performance, confirming that collaboration has not only enhanced user satisfaction but has also strengthened the perceived reliability and effectiveness of the overall support system. The mediation results have shown that user experience has partially mediated the relationship between human–AI collaboration and service performance, indicating that collaboration has improved performance perceptions partly through the pathway of enhanced user experience, while also exerting a direct influence that has reflected better coordination, governance, and decision quality across the support workflow. Collectively, these outcomes have demonstrated that the research objectives have been achieved: the study has quantified human–AI collaboration and automation effectiveness using validated Likert-scale measurement, has tested their associations with user experience and service performance using correlation and regression, and has confirmed a coherent model in which collaboration and automation have acted as complementary predictors of service outcomes. The conclusions have emphasized that successful AI adoption in IT support has depended on designing human–AI collaboration as an accountable service process where automation has reduced operational friction and humans have ensured quality, safety, and exception handling, thereby improving both the user's service journey and the perceived effectiveness of IT support delivery.

RECOMMENDATIONS

The study has recommended that organizations implementing AI-enabled IT support services have adopted a governance-led, user-centered deployment approach in which human–AI collaboration quality and workflow automation effectiveness have been designed as integrated service capabilities rather than treated as separate technical add-ons. First, IT service owners and enterprise architects have ensured that AI support tools have been embedded into clearly defined ITSM workflows with visible escalation rules, because users have reported better experience and perceived performance when AI guidance and human intervention have been coordinated and predictable. The service desk has therefore been configured so that the AI layer has handled high-volume, low-risk tasks (such as ticket intake, categorization, password resets, basic troubleshooting scripts, and knowledge retrieval) while humans have retained ownership of complex, high-impact, and policy-sensitive incidents, including access control issues, security alerts, and repeated failures. Second, organizations have standardized the design of automation steps by establishing consistent routing logic, mandatory information capture, and automated status updates so that users have experienced fewer handoffs and less repetitive questioning; at the same time, human supervisors have monitored routing accuracy and have corrected recurring misclassifications through periodic model retraining and knowledge base refinement. Third, the study has recommended that CISOs and security architects have applied least-privilege principles to AI-enabled remediation, ensuring that automated actions have required approval gates or constrained execution rights, that sensitive identity and endpoint actions have been auditable, and that the AI component has not been permitted to bypass change control and compliance requirements. Fourth, organizations have improved user experience outcomes by adopting transparency practices that have helped users understand what the system has been doing and why, including short rationale messages for recommendations, confidence cues, and clear "handoff to human" options when uncertainty or user discomfort has occurred. Fifth, the study has recommended dual-metric performance management where operational KPIs (time-to-first-response, time-to-resolve, reassignment rate, first-contact resolution) have been monitored alongside UX KPIs (satisfaction, perceived effort reduction, clarity, trust, and fairness), because performance gains have been strengthened when users have perceived the workflow as reliable and supportive. Sixth, organizations have implemented structured feedback loops where users and agents have been able to flag incorrect suggestions, missing knowledge articles, or poor conversational responses, and these signals have been routed into continuous improvement processes for model tuning, knowledge base curation, and workflow redesign. Seventh, training and change management have been treated as mandatory implementation components: end-users have been provided guidance on when to use AI self-service versus human escalation, and IT agents have been trained to interpret AI recommendations, override them appropriately, and document corrections to improve future automation quality. Finally, the study has recommended phased rollout strategies in which automation has been piloted in selected support categories, evaluated with controlled metrics, and expanded only after reliability targets and user experience thresholds have been met, ensuring that trust and adoption have been built through consistent performance and accountable collaboration.

LIMITATION

The study has acknowledged several limitations that have shaped the interpretation and transferability of its findings and that have clarified the boundaries of what the results have been able to claim. First, the research design has been cross-sectional, meaning that all variables have been measured at a single point in time; as a result, the statistical associations identified through correlation and regression have supported predictive explanation but have not established temporal precedence or definitive causality, and reciprocal effects (such as improved user experience strengthening subsequent collaboration perceptions) have not been ruled out. Second, the case-study–based setting has increased contextual realism but has reduced broad generalizability, because the maturity of IT service management practices, the quality of knowledge bases, the configuration of AI tools, and organizational culture have varied widely across industries and geographies; therefore, the strength of relationships observed between human–AI collaboration, workflow automation, and user experience may not have replicated identically in environments with different workflows, service volumes, or governance structures. Third, the study has relied primarily on self-reported Likert-scale survey measures, which have introduced potential common method bias, social desirability effects, and recency bias, because participants' responses may have been influenced by their most recent service encounter, by unusually positive or negative incidents, or by perceived expectations regarding AI adoption; although internal consistency reliability has been strong, perceptual measures have not captured objective operational performance outcomes such as actual ticket resolution time, reassignment rates, first-contact resolution, or escalation frequency. Fourth, the study has operationalized service performance as perceived efficiency and effectiveness, which has aligned with user-centered evaluation but has limited the ability to validate the findings against system logs and service desk analytics that could have provided stronger evidence for performance change. Fifth, the measurement model has treated constructs such as human–AI collaboration and workflow automation effectiveness as unified indices, while real-world IT support systems often contain multiple AI components with different roles (chatbots, routing classifiers, knowledge retrieval engines, AIOps alerts), and the study has not fully separated the effects of each component or the variation in how different user groups have interacted with them. Sixth, the study has not deeply examined moderating influences such as task complexity, incident criticality, privacy sensitivity, user technology readiness, or prior negative experiences with automation, and these factors may have changed reliance decisions and shaped user experience in ways that have not been fully captured in the main regression models. Seventh, the sample composition, while inclusive of both end-users and IT support personnel, may have reflected unequal subgroup sizes and differing interpretation frames; for example, support staff may have evaluated automation through operational workload reduction while end-users may have evaluated it through speed and clarity, and such differences may have required multi-group modeling that has not been conducted. Finally, because the study has focused on perceptions and workflow experience rather than technical model evaluation, it has not provided detailed assessment of AI accuracy, bias, failure modes, or security vulnerabilities, and these technical factors could have influenced real-world outcomes and adoption sustainability beyond what the survey has measured.

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