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Developing an AI-Powered Automation Framework to Streamline IT Support Tasks in Public Sector Organizations, Boosting Service Delivery and Digital Accessibility

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Abstract

Public sector organizations are under growing pressure to improve IT service delivery efficiency and digital accessibility while operating within rigid governance and budgetary constraints. This study investigated the effectiveness of an AI-powered automation framework for streamlining IT support tasks in public sector organizations using a quantitative, cross-sectional research design. Data were collected from 214 respondents holding senior IT management, service desk leadership, and digital transformation roles across ministries, departments, and public agencies. Descriptive analysis showed moderate to high adoption of AI automation capabilities, with workflow automation ($M = 4.02$, $SD = 0.59$) and automated ticket handling ($M = 3.95$, $SD = 0.62$) exhibiting higher implementation levels than predictive analytics ($M = 3.41$, $SD = 0.71$). Multiple regression results indicated that AI automation capabilities were strongly associated with service delivery efficiency, with workflow automation ($\beta = 0.41$, $p < .001$) and automated ticket handling ($\beta = 0.36$, $p < .001$) emerging as significant predictors. The efficiency model explained 58% of the variance in service delivery performance ($R^2 = 0.58$). Cost efficiency outcomes showed weaker but statistically significant relationships with automation ($\beta = 0.22$, $p = .003$), and the cost model accounted for 46% of variance ($R^2 = 0.46$). Governance and risk management demonstrated a strong direct effect on performance ($\beta = 0.31$, $p < .001$) and significantly moderated the relationship between automation and cost efficiency ($\beta = 0.19$, $p = .005$). Reliability analysis confirmed strong internal consistency across constructs, with Cronbach's alpha values ranging from 0.84 to 0.91. Digital accessibility indicators recorded moderate levels ($M = 3.56$, $SD = 0.65$), indicating partial integration of inclusive practices. Overall, the findings demonstrate that AI-powered automation significantly enhances IT support efficiency and service quality in public sector organizations, particularly when supported by strong governance and ITSM maturity, while accessibility outcomes require more intentional design integration.

Keywords

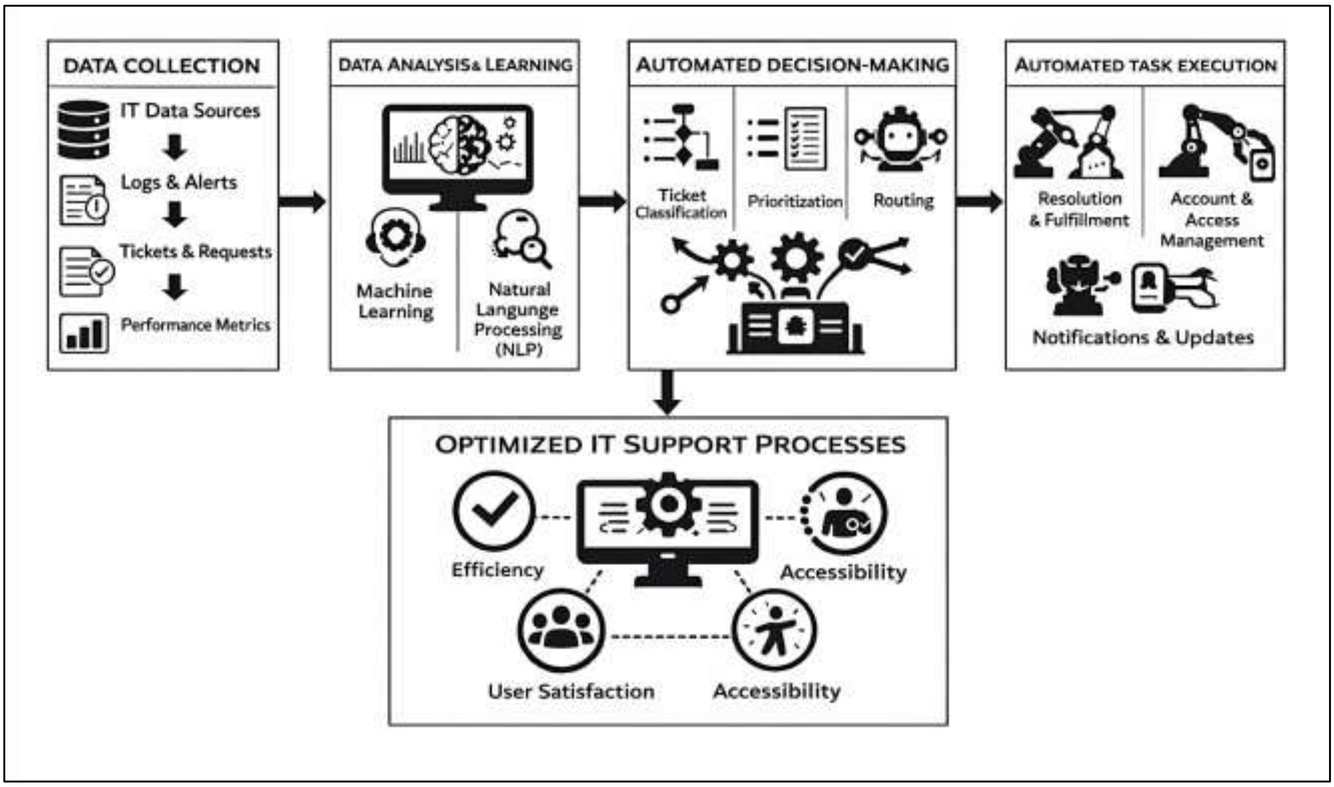
AI Automation, IT Support, Public Sector, Service Delivery, Digital Accessibility.

INTRODUCTION

Artificial intelligence can be defined as a class of computational systems designed to perform tasks that traditionally require human cognitive abilities, including learning from data, recognizing patterns, interpreting language, and making decisions under uncertainty (Sajja, 2020). Automation refers to the systematic use of technology to execute tasks with minimal human intervention, typically aiming to increase efficiency, consistency, and scalability. Within organizational information systems, AI-powered automation represents the convergence of data-driven intelligence and process execution mechanisms that adapt actions based on contextual inputs. IT support tasks encompass the operational activities required to maintain, restore, and enhance the functionality of information technology systems, including incident management, service request handling, user assistance, system monitoring, and access control. In public sector organizations, these tasks form the backbone of digital service continuity, as nearly all government functions depend on reliable information systems to deliver services to citizens, businesses, and internal stakeholders. At the international level, governments increasingly rely on digital platforms to administer public services such as healthcare registration, taxation, social protection, education, identity management, and civic participation (Zgurovsky & Zaychenko, 2017). As digital government infrastructures expand, the volume, complexity, and urgency of IT support demands increase correspondingly. Inefficiencies in IT support operations directly translate into service delays, system outages, and reduced accessibility for users who depend on digital channels. Digital accessibility refers to the extent to which digital services can be accessed and used by individuals with diverse abilities, languages, devices, and connectivity conditions. Accessibility is therefore not limited to interface design but is also shaped by the operational capacity to resolve technical barriers quickly and consistently. An AI-powered automation framework in this context can be defined as an integrated architectural arrangement of data sources, analytical models, decision rules, and workflow engines that collectively automate and optimize IT support processes. Such a framework operates across technical, organizational, and service layers, embedding intelligence into routine support functions while maintaining governance and accountability. The international significance of this topic emerges from the shared challenges faced by public sector organizations worldwide, including constrained budgets, legacy systems, rising citizen expectations, and mandates for inclusive digital service delivery (Chowdhary, 2020). By framing AI-powered automation as an operational mechanism rather than a purely technological artifact, this study positions IT support as a measurable driver of service delivery performance and digital accessibility across public administrations.

IT support in public sector organizations is typically structured around formal service management practices that define roles, workflows, escalation paths, and performance metrics. Central to this structure is the service desk, which functions as the primary interface between users and IT service providers (Chen et al., 2020). The service desk coordinates incident reporting, service request fulfillment, communication, and documentation, serving both internal employees and, in many cases, external users of government systems. Incident management focuses on restoring normal service operation as quickly as possible following a disruption, while service request management addresses predefined user needs such as access provisioning, software installation, and configuration changes. These functions are operationalized through ticketing systems that capture user-reported issues, system-generated alerts, and administrative requests in a structured format. Quantitative assessment of IT support performance relies on operational indicators including response time, resolution time, first-contact resolution rate, reassignment frequency, escalation volume, backlog size, and compliance with service-level targets. In public sector environments, these metrics are not merely internal efficiency indicators but are closely linked to service continuity for essential public services. As governments digitize critical processes, even minor support delays can affect large populations simultaneously (Ghahramani, 2015). The heterogeneity of public sector IT environments further complicates support operations, as systems often span multiple departments, vendors, and technological generations. Manual handling of tickets requires human interpretation of unstructured problem descriptions, classification into service categories, identification of responsible teams, and prioritization based on perceived impact. Each manual step introduces variability and delay, increasing the likelihood of misrouting and repeated handling. Quantitative studies of service management consistently show that early-stage decisions in ticket handling have cascading effects on overall resolution time and user satisfaction. In public sector organizations, where accountability and transparency requirements impose additional documentation and approval steps, inefficiencies are magnified. Automation within IT support therefore targets not only speed but also consistency and traceability. An AI-powered automation framework embeds analytical capabilities into these structured workflows, enabling systematic classification, prioritization, and routing decisions based on historical patterns and real-time data. By aligning automation logic with established performance metrics, such a framework enables empirical examination of how changes in support processes affect measurable service delivery outcomes across public administrations (Konar, 2018).

Figure 1: AI-Powered Automation Framework for IT Support

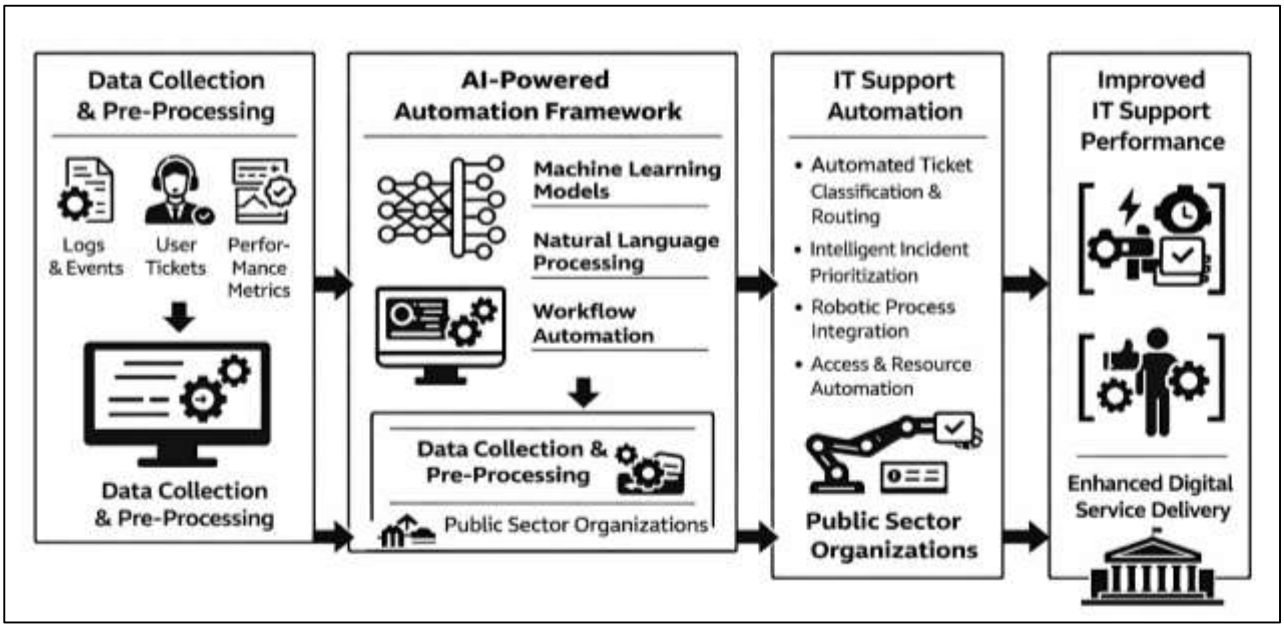


The application of artificial intelligence to IT operations introduces a data-centric approach to managing complex, high-volume operational environments. AI-driven operational intelligence leverages machine learning models to analyze logs, events, tickets, and performance metrics generated by IT systems and users (Wetzstein et al., 2020). These data sources capture temporal patterns of system behavior, failure modes, and user interactions that are difficult to interpret manually at scale. In IT support contexts, operational intelligence supports tasks such as anomaly detection, event correlation, incident prioritization, and resolution recommendation. Public sector organizations generate substantial volumes of operational data due to the scale and diversity of their digital infrastructures, which include administrative systems, citizen portals, payment platforms, and inter-agency data exchanges. The complexity of these environments increases the cognitive burden on support personnel, particularly when incidents span multiple systems or originate from indirect causes. AI-powered automation frameworks address this challenge by transforming raw operational data into structured insights that inform automated or semi-automated actions. For example, correlated events from monitoring systems can be linked automatically to incident tickets, reducing duplication and noise. Historical incident data can be used to predict likely causes and suggest remediation steps based on prior resolutions. Quantitatively, such capabilities are associated with reductions in detection time, diagnostic effort, and resolution duration (Hwang et al., 2020). In public sector settings, where service disruptions may affect essential functions, improvements in these metrics have direct implications for service availability and accessibility. Importantly, AI-driven operational intelligence does not operate independently of governance structures. Automated decisions must be logged, explainable, and auditable to comply with public accountability requirements. This necessitates framework designs that integrate analytical outputs with rule-based controls and human oversight. From a research perspective, the structured nature of operational data and performance metrics enables statistical modeling of relationships between automation intensity and service outcomes. Variables such as the proportion of incidents auto-correlated, the accuracy of automated prioritization, and the reduction in manual diagnostic steps can be quantified and analyzed in relation to response times and resolution success rates (Rauf, 2018; Tong et al., 2019). This analytical framing positions AI-powered automation as an empirically observable intervention within IT support systems rather than an abstract technological aspiration.

A defining characteristic of IT support work is its reliance on unstructured textual communication. Users describe problems in natural language, often using informal, ambiguous, or domain-specific terminology. Support personnel must interpret these descriptions to determine the nature of the issue, the affected service, and the appropriate resolution pathway (Brooks, 2018; Haque & Arifur, 2020; Md Ashraful et al., 2020). Natural language processing enables computational analysis of such text by extracting semantic features, identifying intent, and mapping descriptions to predefined categories. Within an AI-powered automation framework, NLP functions as a core mechanism for automating ticket intake, classification, summarization, and knowledge retrieval (Haque & Arifur, 2021; Fokhrul et al., 2021). Machine learning models trained on historical ticket data can identify patterns in language use that correspond to specific incident types or service requests. This allows incoming tickets to be categorized automatically with measurable accuracy, reducing misclassification and reassignment (Fahimul, 2022; Zaman et al., 2021). In public sector organizations, NLP adoption is particularly relevant due to the linguistic diversity of users and the specialized terminology associated with public services. Multilingual support and domain adaptation are therefore integral considerations within automation frameworks (Hammad, 2022; Hasan & Waladur, 2022). Beyond classification, NLP enables similarity analysis that links new tickets to previously resolved cases, supporting faster resolution through reuse of known solutions (Dias & Torkamani, 2019; Rashid & Sai Praveen, 2022; Arifur & Haque, 2022). Conversational interfaces, such as chat-based intake systems, further structure user input by guiding users through standardized prompts, improving data completeness at the point of entry. Quantitatively, these capabilities influence measurable indicators including average handling time, first-contact resolution rate, and ticket reopen frequency. From an accessibility perspective, conversational interfaces and automated summarization can reduce cognitive load for users by simplifying interaction and ensuring clearer communication. For users with disabilities or limited digital literacy, structured and responsive support channels contribute to more equitable access to services (Towhidul et al., 2022; Ratul & Subrato, 2022). The integration of NLP into IT support workflows therefore affects both operational efficiency and user experience. Empirical analysis of these effects requires linking NLP performance metrics, such as classification accuracy and response relevance, to downstream service delivery outcomes (Rifat & Jinnat, 2022; Rifat & Alam, 2022; Wang et al., 2020). By embedding language intelligence into the automation framework, public sector organizations can systematically manage the textual complexity of support interactions while maintaining measurable control over service performance.

Automation in IT support extends beyond analytical intelligence to include the execution of predefined operational tasks. Workflow automation and robotic process integration enable systems to carry out routine actions such as account provisioning, password resets, software deployment, access approvals, and notification updates (Abdulla & Majumder, 2023; Dimiduk et al., 2018; Fahimul, 2023). These tasks are typically governed by clear rules and eligibility criteria, making them suitable for automation. In public sector organizations, such routines consume a significant proportion of support resources due to large user bases and standardized administrative processes. By embedding automation triggers within ticketing systems, support requests can initiate end-to-end workflows that execute without manual intervention once predefined conditions are met (Faysal & Bhuya, 2023; Habibullah & Aditya, 2023). An AI-powered automation framework coordinates these workflows by combining rule-based execution with data-driven decision support (Hammad & Mohiul, 2023; Haque & Arifur, 2023). For example, automated routing decisions informed by historical data can determine which workflow to invoke, while monitoring data can validate successful completion. Quantitative assessment of workflow automation focuses on metrics such as touch time reduction, cycle time compression, and throughput increase. These metrics provide objective evidence of streamlining effects within support operations. Public sector governance requirements necessitate that automated workflow include logging, approval checkpoints, and exception handling to ensure compliance and accountability (Goldenberg et al., 2019). As a result, automation frameworks must balance efficiency with control. From a service delivery perspective, automated fulfillment reduces waiting times for users and ensures consistent application of policies across departments. This consistency contributes to perceived fairness and reliability in public services. When integrated with AI-driven classification and prioritization, workflow automation forms a cohesive operational layer that translates analytical insights into concrete actions. The empirical study of such frameworks examines how different levels of automation adoption correlate with service performance indicators and user satisfaction measures (Chassignol et al., 2018). By operationalizing automation as a set of measurable interventions within IT support workflows, this research domain enables rigorous quantitative evaluation of their effects on public sector service delivery.

Figure 2: AI-Powered Automation for IT Support



Digital accessibility is often framed as a design and compliance issue, yet its realization in practice depends heavily on operational support capacity. Accessibility barriers frequently manifest as technical incidents, configuration errors, or workflow failures that prevent users from completing digital transactions (Duan et al., 2019; Jahangir & Mohiul, 2023; Rashid et al., 2023). In public sector contexts, these barriers can exclude individuals from essential services, amplifying social and administrative inequalities. IT support teams play a critical role in identifying, prioritizing, and resolving such barriers once they are reported or detected. An AI-powered automation framework influences this process by enabling systematic detection of recurring accessibility-related issues through text analysis and pattern recognition (Akbar & Farzana, 2023; Mostafa, 2023). Tickets related to accessibility can be identified, grouped, and prioritized based on impact and frequency, ensuring that critical barriers receive timely attention. Quantitative indicators such as resolution time for accessibility-related incidents, recurrence rates, and user feedback scores provide measurable evidence of operational effectiveness. Automation also supports proactive monitoring by correlating user behavior data with support incidents, revealing points in digital workflows where users consistently encounter difficulties (Jahangir & Hammad, 2024; Jiménez-Luna et al., 2020; Rifat & Rebeka, 2023). By reducing response delays and improving consistency in issue handling, automated support processes contribute to more stable and usable digital services. Accessibility outcomes are therefore not isolated from IT support performance but are embedded within it. From a measurement perspective, accessibility can be operationalized through support-related metrics rather than solely through compliance audits. This framing aligns with a service delivery perspective that views accessibility as an ongoing operational responsibility. In public sector organizations, where mandates emphasize inclusive access, the ability to quantify and improve accessibility-related support performance is particularly salient. An AI-powered automation framework provides the data infrastructure and analytical capabilities necessary to link support operations to accessibility outcomes in a measurable manner (Liu et al., 2020). This connection reinforces the relevance of IT support automation as a determinant of digital inclusion within public administrations.

A quantitative examination of an AI-powered automation framework for IT support requires clear definition and operationalization of constructs across technical, operational, and user dimensions. Automation intensity can be measured through indicators such as the proportion of tickets automatically classified, the percentage of requests fulfilled without human intervention, and the extent of automated event correlation (Desouza et al., 2020; Masud & Hammad, 2024; Md & Sai Praveen, 2024). Service delivery performance is commonly captured through response times, resolution times, backlog levels, and compliance rates. User experience can be quantified through satisfaction scores, perceived responsiveness, and ease-of-use assessments collected through structured surveys. Digital accessibility outcomes can be represented through accessibility-related incident metrics and user-reported barriers. Information system quality constructs such as reliability, availability, and integration capability provide additional explanatory variables (Rifat & Rebeka, 2024; Praveen, 2024). Adoption-related constructs capture how support staff and users interact with automated systems, including usage frequency and reliance on automated recommendations. Public sector organizational context variables, such as system heterogeneity and governance controls, further shape these relationships (Gerke et al., 2020; Shehwar & Nizamani, 2024; Azam & Amin, 2024). The availability of detailed operational data within IT service management systems enables longitudinal and cross-sectional analysis of these constructs. Statistical modeling techniques can be applied to examine associations between automation variables and service outcomes while controlling for organizational and environmental factors. This empirical framing treats AI-powered automation as an observable configuration of capabilities embedded within IT support processes. By grounding analysis in measurable indicators, the study aligns technological intervention with public sector performance evaluation practices. The focus on streamlining IT support tasks and enhancing service delivery and digital accessibility is therefore articulated through a structured quantitative lens that connects automation mechanisms to operational and user-centered outcomes without extending into normative or forward-looking claims (Popenici & Kerr, 2017).

The primary objective of developing an AI-powered automation framework to streamline IT support tasks in public sector organizations is to empirically examine how the integration of intelligent automation capabilities within IT support operations influences measurable service delivery performance and digital accessibility outcomes. This objective centers on the systematic identification, modeling, and quantification of relationships between automation-enabled support processes and key operational indicators such as response time, resolution time, first-contact resolution rate, ticket reassignment frequency, backlog volume, and service availability. By focusing on IT support as an operational subsystem that directly underpins digital public services, the objective emphasizes the need to treat automation not as an abstract technological enhancement but as a set of observable interventions embedded within standardized workflows. The framework aims to consolidate multiple automation components, including intelligent ticket classification, automated prioritization, workflow execution, and system monitoring, into a coherent structure that can be evaluated using quantitative methods. Another core aspect of this objective is to assess how automation affects the consistency and reliability of support processes across heterogeneous public sector environments characterized by legacy systems, interdepartmental dependencies, and governance constraints. The objective also incorporates digital accessibility as an operationally measurable dimension of service delivery, recognizing that accessibility-related barriers often surface as support incidents that require timely and accurate resolution. By embedding accessibility-sensitive identification and prioritization mechanisms within the automation framework, the objective seeks to evaluate whether automated IT support processes contribute to faster removal of technical barriers that hinder user access to digital services. Additionally, the objective encompasses the examination of user interaction with automated support mechanisms, including both internal staff and external service users, to determine how automation influences support experience, clarity of communication, and perceived responsiveness. Through the use of structured operational data and user feedback metrics, the objective supports the development of statistically testable models that link automation intensity and design characteristics to service delivery efficiency and accessibility performance. Overall, this objective-driven approach establishes a clear analytical pathway for understanding the operational value of AI-powered automation in public sector IT support, grounding the study in measurable outcomes that reflect both organizational performance and inclusive digital service provision.

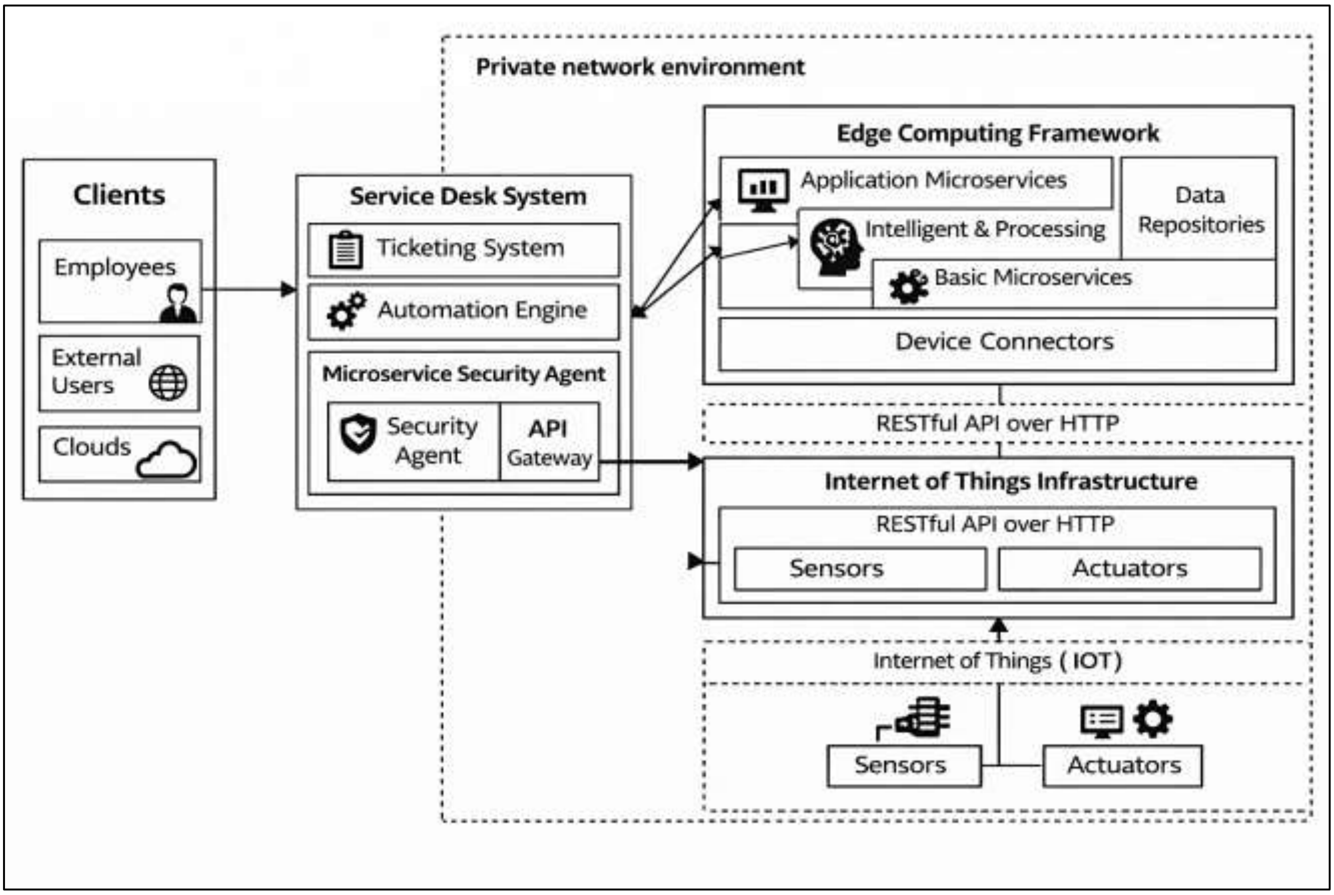
LITERATURE REVIEW

Public sector organizations worldwide are under increasing pressure to deliver efficient, reliable, and accessible digital services while operating within constrained budgets, rigid regulatory frameworks, and legacy IT infrastructures. As governments expand e-governance initiatives and digital public services, the demand placed on internal IT support units has grown exponentially. Service desks in public institutions frequently face high ticket volumes, repetitive incident requests, long resolution times, and inconsistent service quality, which collectively hinder service delivery performance and reduce citizen satisfaction (Amena Begum, 2025; Faysal & Aditya, 2025; Mensah, 2020). These challenges have intensified with the rapid adoption of remote work, cloud platforms, and digital citizen portals, making traditional manual IT support models increasingly unsustainable. Consequently, public sector organizations are actively exploring advanced technological solutions capable of enhancing IT operational efficiency while maintaining transparency, accountability, and inclusivity. Artificial intelligence (AI)–powered automation has emerged as a transformative mechanism for modernizing IT service management (ITSM). Technologies such as machine learning–based ticket classification, natural language processing (NLP)–driven chatbots, robotic process automation (RPA), and predictive analytics are being integrated into IT support environments to automate routine tasks, reduce human workload, and improve response accuracy (Hammad & Hossain, 2025; Jahangir, 2025). While private sector organizations have demonstrated measurable gains in service efficiency through AI-enabled IT automation, the public sector presents a distinct operational context characterized by compliance obligations, risk aversion, heterogeneous user populations, and accessibility mandates. As a result, the direct transferability of private-sector AI automation models to public-sector IT support remains limited, necessitating a contextualized, evidence-based framework grounded in public administration realities (Haynes, 2015; Jamil, 2025; Amin, 2025). Existing academic literature has examined AI adoption in public services, digital government transformation, and ITSM automation independently; however, there is a noticeable gap in integrative studies that quantitatively assess how AI-powered automation frameworks specifically impact IT support performance metrics in public sector organizations. Prior studies often focus on conceptual models, qualitative case studies, or single-technology implementations without systematically linking automation maturity to measurable service delivery outcomes such as ticket resolution time, first-contact resolution rates, system availability, cost efficiency, and digital accessibility indicators (Cordella & Tempini, 2015; Towhidul & Rebeka, 2025; Ratul, 2025). Moreover, limited attention has been given to the role of AI automation in enhancing accessibility for diverse user groups, including individuals with disabilities, non-technical users, and digitally marginalized populations—an essential mandate for public institutions. This literature review therefore synthesizes empirical and theoretical research related to AI-driven IT automation, public sector IT service management, service delivery performance measurement, and digital accessibility frameworks (Rifat, 2025; Yousuf et al., 2025). By critically analyzing quantitative findings across these domains, the review establishes the conceptual and empirical foundation for developing an AI-powered automation framework tailored to public sector IT support environments. The synthesis highlights enabling technologies, implementation challenges, governance considerations, and performance outcomes, thereby informing the proposed quantitative model that links AI automation capabilities with improvements in service efficiency, quality, and digital inclusivity (Osborne et al., 2016).

Public Sector IT Support Systems: Operational Characteristics and Performance Constraints

Public sector IT support systems are typically organized around centralized or federated service desks that function as the operational “front door” for employees and, in many cases, external users who rely on government digital services. In practice, the service desk in government agencies is not merely a technical help point; it becomes a coordination hub that connects end users, infrastructure teams, application owners, cybersecurity units, and external vendors under formal governance rules (Ostrom & Ostrom, 2019). This structure is strongly influenced by public accountability and audit requirements, which shape how tickets are logged, routed, escalated, and closed. Many public institutions adopt IT service management principles to standardize service delivery, often emphasizing service catalogs, defined request pathways, and repeatable workflows to ensure consistency across departments and locations. Evidence from government-oriented ITIL practice reports and case materials shows that public agencies frequently use service catalogs and structured intake to reduce ad hoc support requests and improve transparency in what IT can deliver. At the same time, public sector technology environments tend to be fragmented, with different units implementing overlapping tools and platforms for similar needs, which increases operational complexity for the service desk and creates duplicated work (Romzek & Dubnick, 2018). National-level reviews of digital government have repeatedly described fragmentation and duplication as persistent features of public technology ecosystems, contributing to inconsistent user experiences and uneven support burdens. These organizational realities also affect the service desk's role: it must serve as both an operational resolver of incidents and a governance-compliant recorder of service performance, including categorizing demand, documenting decisions, and providing auditable trails. The result is a service desk function that often carries broader institutional responsibilities than many private-sector counterparts, where flexibility and speed may be prioritized over traceability. Public service desks, therefore, operate at the intersection of technical troubleshooting, process compliance, and service equity, and their structure reflects an attempt to balance responsiveness with institutional safeguards (Ukeje et al., 2020). Across the literature, this balance is frequently presented as a defining operational characteristic of public IT support: the service desk must manage high-volume, everyday user needs while simultaneously meeting governance expectations that demand standardized procedures, documentation rigor, and cross-unit coordination.

Figure 3: Public Sector IT Support Architecture



Across public sector IT service desks, the task portfolio clusters into recurring categories that mirror ITSM process groupings, most notably incident management, service requests, and access provisioning (Weerakkody et al., 2015). Incident management covers unplanned interruptions and degradations—such as outages, performance drops, and device failures—where service restoration speed is essential to maintaining continuity for government operations and citizen-facing channels. Service requests include standardized “how do I” needs and routine fulfillment items such as software installation, device setup, password resets, equipment requests, and onboarding or offboarding actions. Access provisioning spans account creation, role changes, privilege assignment, and periodic reviews, all of which often require approvals, documentation, and alignment with security policy. Literature that applies ITIL-oriented process lenses to e-government and organizational support environments emphasizes that these categories are not simply administrative labels; they shape resourcing, escalation paths, and performance reporting (Kuziemski & Misuraca, 2020; Shofiul Azam, 2025; Tasnim, 2025). Case-based research on service desk evaluation illustrates how incident intake, classification, escalation, and closure procedures become central to user relationships and perceived service reliability, particularly when critical platforms (for example, learning or workflow systems) are involved. Studies examining incident management practices also highlight the importance of consistent categorization and prioritization rules because misclassification can inflate resolution time and obscure problem trends (Zaheda, 2025a, 2025b). From an operational standpoint, the public sector context intensifies the interdependencies between these task categories: an access provisioning request can quickly become an incident when authentication failure blocks essential work, while an incident can generate multiple follow-on requests (patching, device replacement, permissions resets). This interconnected workload increases cognitive and coordination demands on service desk agents, particularly when agencies rely on a mix of legacy systems and modern cloud services. Broader digital government assessments further indicate that fragmented technology stacks amplify the variety of tasks and increase the knowledge burden for frontline support staff, because similar user needs may require different solutions across departments (Kumar et al., 2017; Zulqarnain, 2025). Additionally, public sector support channels must often accommodate a wider range of user capability levels, including non-technical staff and service users who may experience barriers to using digital platforms. As a result, even routine request categories can become time-intensive and require more step-by-step assistance than expected. The literature collectively portrays public IT support work as process-structured yet highly variable in execution, with daily operations shaped by an ongoing tension between standardized workflows and the practical complexity created by diverse systems, heterogeneous users, and compliance-driven approvals.

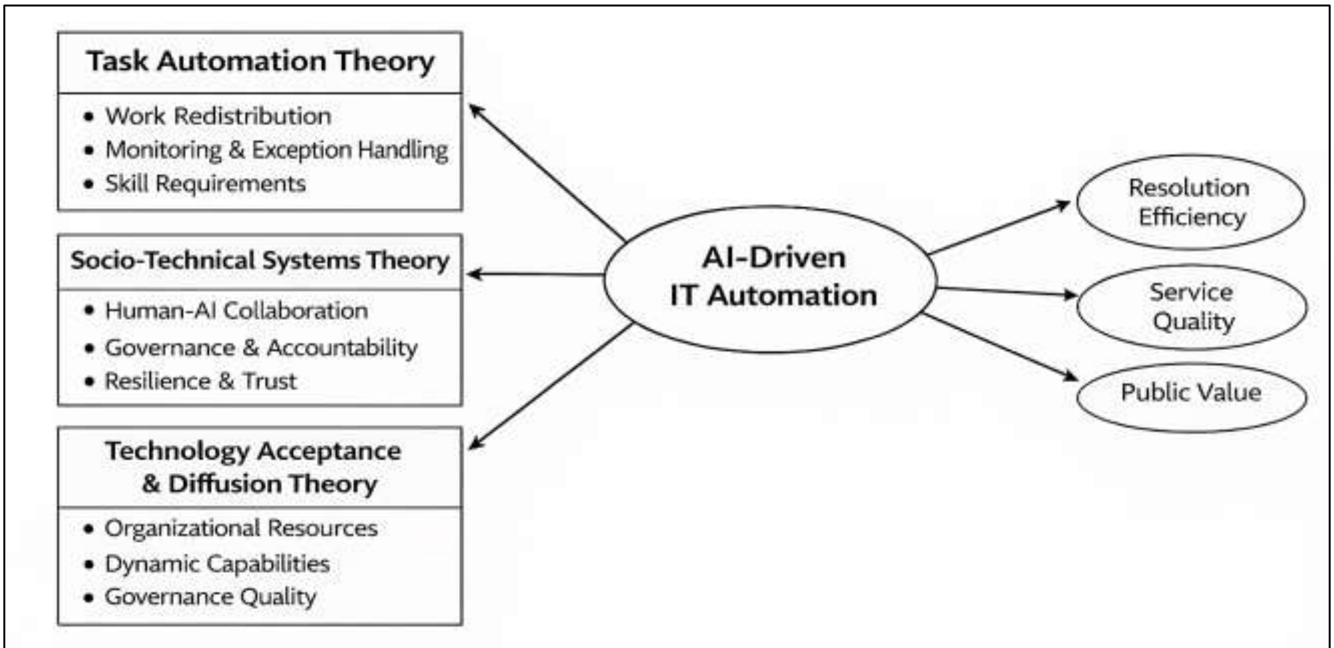
Quantitative indicators of inefficiency in public sector IT support frequently appear in the form of prolonged handling times, growing backlogs, recurring SLA breaches, and uneven resolution quality across service categories (Zhang et al., 2015). Metrics such as mean time to resolve, first-contact resolution, reopen rates, escalation frequency, and SLA compliance are routinely used to detect bottlenecks and service degradation. Guidance and practitioner-oriented evidence around service desk measurement consistently notes that mean time to resolve represents an elapsed-duration view of restoration work and becomes especially meaningful when compared across incident types, priority levels, and support tiers. When MTTR rises, it often signals deeper issues such as knowledge gaps, workflow friction, unclear ownership, or tool fragmentation. Backlog growth similarly provides a cumulative measure of demand exceeding capacity; in public agencies, this can become pronounced during policy changes, large-scale rollouts, or security events that generate surges of access requests and incident reports. SLA breaches—whether in response targets, resolution targets, or escalation targets—function as a visible symptom of operational strain and governance risk, because public institutions often must report service performance and justify resourcing decisions (Dawes et al., 2016). Research on ITSM process improvement using business process heuristics and simulation demonstrates that even modest process redesign can reduce average processing times and shift workload away from frontline tiers, underscoring how measurable performance outcomes can be tied to workflow design rather than only staffing levels. Public sector technology conditions also contribute directly to these metrics. Analyses of government technology environments describe persistent reliance on legacy systems, data quality limitations, and complex dependencies that lengthen diagnosis and remediation cycles. Cybersecurity pressures further increase the time and steps required to resolve incidents because containment, verification, and audit documentation become part of "resolution," not optional additions. Survey-based and policy-oriented research focused on government modernization repeatedly highlights budget constraints and competing priorities—particularly the need to manage cyber risk while modernizing legacy systems—as structural drivers of service delays and technology debt (Honadle, 2018). Workforce shortages compound these constraints: public organizations often report difficulty recruiting and retaining specialized IT talent, which pushes more complex tickets to small groups of experts and increases queue times for escalations. The combined effect is that inefficiency metrics in public service desks frequently represent not only operational execution problems but also systemic capacity constraints, governance overhead, and technology complexity that are characteristic of the public sector setting.

Comparisons between public and private sector service performance are frequently framed around differences in incentives, constraints, and measurement regimes rather than simple assumptions that one sector is uniformly better (Lian, 2015). Public sector IT support often operates within stricter procurement rules, formalized approval chains, and higher transparency requirements, all of which can slow tool adoption, limit vendor flexibility, and increase administrative overhead associated with resolving tickets. Budget constraints can be chronic and politically sensitive, affecting staffing ratios, training investments, and the ability to replace aging platforms that drive incident volume. Research on public technology adoption underscores how financial constraints, limited in-house expertise, and reliance on contractors shape operational outcomes and can lead to uneven capability across agencies. National digital government reviews similarly describe fragmentation and duplicated solutions that would be less tolerable in many private firms due to competitive pressure and stronger standardization incentives. At the same time, scholarship comparing public and private work outputs suggests that quality patterns can be context-dependent, shaped by attention, oversight, and user expectations; in service operations, this means public organizations may be driven toward careful documentation and error reduction even when speed suffers (Bertot et al., 2016). Performance evaluation research comparing sectors also emphasizes that metrics and success criteria are not fully transferable: private sector service desks may optimize for customer satisfaction and cost efficiency in competitive environments, whereas public sector service desks must also prioritize equity, continuity of essential services, and compliance with accessibility and accountability mandates. These differences influence how performance metrics are interpreted. For instance, a longer resolution time in a government context may partially reflect mandatory security verification or multi-step authorization, whereas a private firm may resolve faster by trading off documentation depth or by consolidating decisions under fewer governance layers. However, the literature does not portray public sector IT support as inherently inefficient; rather, it shows that the sector's operational environment produces structural friction that manifests as higher administrative load, slower modernization cycles, and greater variability across agencies. Recent analyses of government IT modernization pressures repeatedly note that legacy system dependence and skills shortages threaten the pace of digital improvement, reinforcing why service desks can become bottlenecked when demand increases (Puthal et al., 2015). In aggregate, the evidence supports a nuanced comparison: public sector IT service desks often face heavier compliance and resource constraints than private counterparts, which can depress speed-oriented metrics like MTTR and SLA attainment, while simultaneously strengthening traceability, risk controls, and procedural consistency—features that are central to public accountability but less dominant in private service models.

Theoretical Foundations for AI-Driven IT Automation

Task automation theory and socio-technical systems theory jointly explain how AI-driven automation reshapes work structures, responsibilities, and performance outcomes in IT support environments. Task automation theory emphasizes that automation redistributes work rather than eliminating it, shifting effort from routine execution toward oversight, exception handling, and coordination (Smith et al., 2018). In IT support contexts, AI systems that automate ticket classification, routing, and resolution of repetitive requests reduce manual processing time but simultaneously create new responsibilities related to monitoring automated decisions, handling edge cases, and intervening when automation fails. This redistribution of tasks alters skill requirements and cognitive demands placed on support staff, often increasing the importance of diagnostic reasoning, judgment, and accountability. Socio-technical systems theory deepens this perspective by asserting that organizational performance depends on the alignment between technical systems and social structures, including roles, incentives, communication patterns, and governance mechanisms. From this view, AI automation cannot be evaluated solely as a technical efficiency tool; its effectiveness is inseparable from how it interacts with human workflows, organizational norms, and institutional controls (Dhieb et al., 2020). In public sector IT support, socio-technical alignment is particularly critical because service desks operate under formalized procedures, strict accountability requirements, and risk-sensitive environments. Automation that accelerates ticket intake without corresponding changes to escalation authority or staffing can inadvertently increase backlogs or shift bottlenecks downstream. Similarly, automated decision-making systems that lack transparency or override human judgment may undermine trust and provoke resistance among staff responsible for compliance and audit readiness. Socio-technical theory therefore highlights the need for balanced human–AI collaboration, where automation supports decision-making rather than replacing accountability structures. These theoretical perspectives also emphasize resilience: over-automation can erode experiential knowledge if staff are disengaged from routine tasks, weakening organizational capacity to respond to novel or complex incidents. In combination, task automation theory and socio-technical systems theory frame AI-driven IT automation as a dynamic reconfiguration of work systems rather than a simple productivity enhancement, providing a conceptual basis for examining measurable outcomes such as resolution efficiency, escalation frequency, and system reliability within complex public organizations.

Figure 4: Theoretical Framework for AI Automation



The resource-based view offers a complementary lens for understanding why AI-driven IT automation yields uneven performance outcomes across public sector organizations (Belanche et al., 2020). From this perspective, technology alone does not generate operational advantage; instead, value arises from the organization's ability to mobilize, integrate, and sustain resources that support effective use. In the context of AI-powered IT automation, these resources include high-quality historical service data, standardized process documentation, skilled personnel capable of managing and tuning automation tools, and governance structures that ensure accountability and compliance. Public organizations often possess distinctive institutional resources, such as centralized identity systems, standardized service mandates, and cross-departmental coordination mechanisms, which can support scalable automation when effectively leveraged. At the same time, structural constraints such as fragmented legacy systems, rigid procurement rules, and workforce skill shortages can weaken the organization's ability to convert

AI investments into measurable performance improvements. The resource-based view emphasizes that sustainable benefits depend not only on acquiring AI tools but on embedding them within organizational routines and capabilities (Benzaid & Taleb, 2020). Dynamic capability perspectives further extend this logic by highlighting the importance of learning, adaptation, and reconfiguration over time. AI automation systems require ongoing refinement, data governance, and policy alignment, particularly in public sector environments where regulatory requirements evolve and service demands fluctuate. Organizations that develop strong capabilities for managing change, integrating feedback, and aligning automation with service objectives are better positioned to translate AI adoption into reduced resolution times, lower operational costs, and improved service consistency. Conversely, organizations that treat AI as a standalone technical upgrade often experience limited or short-lived gains. This theoretical foundation underscores the importance of viewing AI automation maturity as a multidimensional construct encompassing data readiness, integration depth, workforce capability, and governance quality. Such a perspective aligns closely with quantitative analysis, as each capability dimension can be operationalized and empirically linked to service performance indicators, enabling systematic examination of how organizational resources condition the effectiveness of AI-driven IT automation.

Technology acceptance and diffusion theories explain the behavioral mechanisms through which AI-driven automation becomes embedded in public sector IT support operations. These theories emphasize that perceived usefulness, ease of use, social influence, and facilitating conditions shape whether individuals and organizations adopt and consistently use new technologies (Hilbert, 2020). In public IT contexts, acceptance is not limited to frontline service desk agents; it also involves managers, compliance officers, and senior administrators who must trust automated processes and rely on their outputs for decision-making and reporting. Public sector environments intensify the role of facilitating conditions because staff often operate within constrained authority structures, formal approval chains, and limited opportunities for experimentation. Automation systems that align with existing workflows, reduce cognitive effort, and visibly improve service outcomes are more likely to gain sustained use. Diffusion-oriented perspectives further highlight that adoption unfolds over time through stages of awareness, trial, and institutionalization, influenced by communication channels and organizational culture. In government settings, diffusion can be slow due to risk aversion and the need for demonstrable legitimacy, making observable benefits and peer validation particularly important. Acceptance theories also draw attention to trust, perceived fairness, and transparency, which are critical when AI systems influence prioritization, access decisions, or service outcomes that affect employees and citizens. Resistance may emerge not because automation is ineffective, but because users perceive it as opaque, biased, or misaligned with accountability expectations. These theoretical insights reinforce the importance of measuring actual use patterns rather than assuming that deployment equates to impact. In quantitative terms, adoption intensity, frequency of automated interactions, and reliance on AI recommendations are more meaningful predictors of performance outcomes than binary indicators of implementation (Kordon, 2020). By grounding analysis in acceptance and diffusion theory, researchers can better explain variation in efficiency gains, resolution speed, and service consistency across public organizations that deploy similar AI technologies.

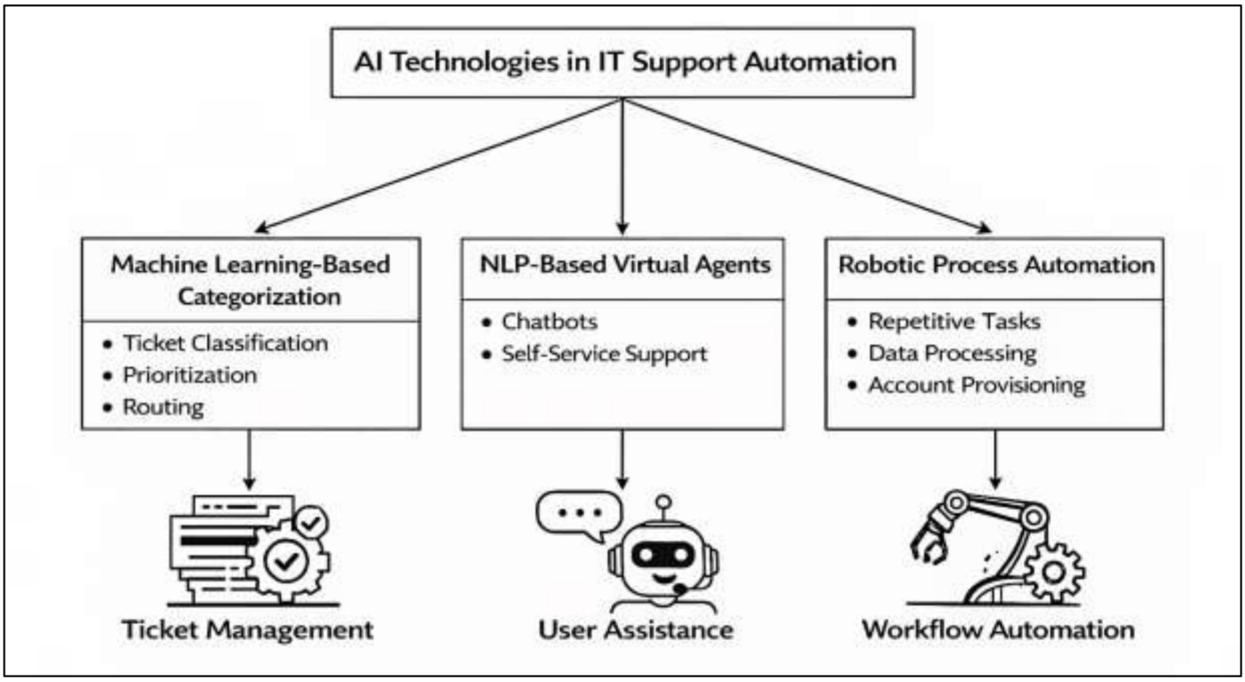
Service-dominant logic and value co-creation theory extend the theoretical foundation by reframing AI-driven IT automation as a mechanism for enhancing public service value rather than merely internal efficiency. From this perspective, value emerges through interactions among multiple actors, including IT staff, end users, and institutional stakeholders, rather than being embedded in the technology itself (Lewis et al., 2019). IT support functions play a central role in enabling digital work and access to public services, making them critical points of value creation within public service ecosystems. AI-enabled automation can enhance value by improving responsiveness, reducing friction in service interactions, and supporting users in resolving issues independently when appropriate. At the same time, value co-creation theory emphasizes that users actively shape service outcomes through their engagement, feedback, and adaptation to digital channels. In public sector settings, this includes not only employees but also citizens who interact with government systems through digital portals and support services. Automation that is poorly aligned with user needs or accessibility requirements can undermine value even if it improves internal metrics. Service-dominant logic also highlights the importance of transparency, trust, and relational quality, which are especially salient in public institutions where legitimacy and equity are core concerns (Szalavetz, 2019). AI-driven IT support systems that provide clear explanations, inclusive interfaces, and consistent outcomes are more likely to support positive user experiences and sustained engagement. This theoretical lens supports incorporating outcome measures that extend beyond operational efficiency to include service quality, accessibility, and perceived fairness. It also reinforces the interconnected nature of internal and external value creation, as improvements in IT support processes directly affect the usability and reliability of digital public services. When integrated with automation, resource, and acceptance theories, service-dominant logic provides a holistic foundation for quantitatively examining how AI-powered IT automation contributes to public value by linking organizational capabilities, user engagement, and measurable service outcomes within a unified analytical framework (Cruz-Benito et al., 2019).

AI Technologies Applied to IT Support Automation

Machine learning techniques have become a foundational component of AI-driven IT support automation, particularly in the areas of ticket categorization and prioritization. In traditional service desk environments, ticket classification relies heavily on manual interpretation of user descriptions, which are often incomplete, ambiguous, or inconsistent (Jha et al., 2019). This manual process is time-consuming and prone to error, leading to misrouted tickets, unnecessary escalations, and prolonged resolution times. Machine learning models address these limitations by learning patterns from historical ticket data, including text descriptions, metadata, resolution paths, and priority levels. Supervised learning approaches enable systems to classify incoming tickets into predefined categories and assign urgency levels based on learned associations between problem characteristics and service impact. These models improve consistency in classification and reduce the cognitive load on frontline agents, allowing them to focus on complex diagnostic tasks rather than routine triage (Kuziemski & Misuraca, 2020). In public sector IT environments, where ticket volumes are high and service desks support a wide range of applications and user groups, automated categorization contributes to greater standardization across departments and reduces variability caused by individual judgment. Empirical evidence synthesized across multiple organizational studies indicates that automated ticket classification improves first-level routing accuracy and shortens initial response times, particularly for high-frequency incident types such as access issues and application errors. However, performance gains are strongly dependent on data quality and taxonomy stability; fragmented legacy systems and inconsistent labeling practices can limit model effectiveness. As a result, machine learning–based categorization systems are often most effective when integrated with standardized service catalogs and ongoing data governance practices (Tussyadiah, 2020). Overall, the literature portrays machine learning for ticket categorization not as a standalone efficiency tool but as an enabling mechanism that restructures early-stage IT support workflows, producing measurable improvements in throughput, queue stability, and prioritization consistency when organizational conditions are supportive.

Natural language processing–based virtual agents and chatbots represent another widely studied category of AI technologies applied to IT support automation, particularly for first-level service interactions. These systems are designed to interpret user queries expressed in natural language, retrieve relevant knowledge, and guide users through troubleshooting or request fulfillment processes (Maedche et al., 2019). In IT support contexts, chatbots are commonly deployed to handle repetitive, low-complexity interactions such as password resets, software installation guidance, account status inquiries, and basic diagnostics. By providing immediate responses through conversational interfaces, virtual agents reduce reliance on email and phone-based channels, which are often resource-intensive and difficult to scale. Research across organizational settings demonstrates that chatbots increase self-service adoption and reduce inbound ticket volume, especially when integrated with centralized knowledge bases and identity management systems. In public sector organizations, virtual agents also play an important role in improving accessibility by offering consistent, always-available support that does not depend on office hours or staffing levels (Henman, 2020). However, empirical findings emphasize that chatbot effectiveness is highly sensitive to language coverage, contextual understanding, and escalation logic. Systems that fail to recognize user intent or provide irrelevant responses can generate frustration and increase follow-up contacts, offsetting potential efficiency gains. Studies examining real-world deployments indicate that hybrid models—where chatbots handle initial interaction and seamlessly transfer unresolved cases to human agents—produce more reliable performance outcomes than fully autonomous designs. Quantitative assessments consistently report reductions in average handling time for simple requests and improvements in first-contact resolution rates, while also highlighting the importance of continuous training and feedback loops to maintain accuracy (Lu et al., 2018). The literature thus characterizes NLP-based virtual agents as a critical interface technology that reshapes how users engage with IT support, shifting demand toward self-service while preserving human intervention for complex or sensitive cases.

Figure 5: AI Technologies for IT Support

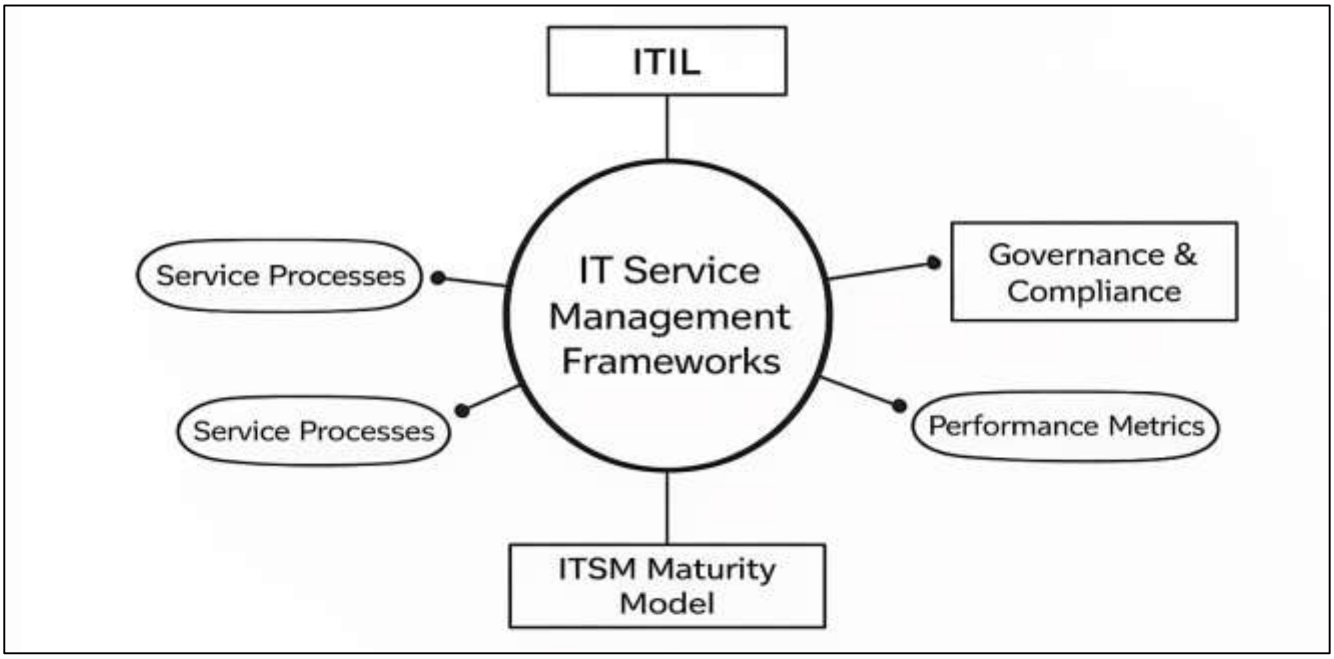


Robotic process automation has been extensively examined as a mechanism for automating repetitive, rule-based IT workflows that previously required manual execution. Unlike machine learning or NLP systems, RPA tools operate by mimicking human interactions with existing applications, executing predefined sequences of actions such as data entry, system updates, and account provisioning (Klumpp, 2018). In IT support environments, RPA is commonly applied to tasks including user onboarding and offboarding, software deployment, patch management, log extraction, and routine system checks. The appeal of RPA lies in its ability to deliver rapid automation without requiring extensive system redesign, making it particularly attractive in public sector contexts characterized by legacy platforms and constrained modernization budgets. Empirical studies of RPA adoption consistently report reductions in processing time, error rates, and operational costs for standardized workflows, as well as improved compliance through consistent execution and detailed activity logs. In service desk operations, RPA contributes to faster fulfillment of service requests and reduces backlog accumulation by offloading high-volume transactional work from human agents (Hengstler et al., 2016). However, the literature also documents limitations, noting that RPA is less effective when processes are poorly documented, highly variable, or subject to frequent policy changes. Governance challenges emerge when automated scripts operate across multiple systems without centralized oversight, increasing the risk of unintended consequences. Despite these limitations, quantitative evaluations demonstrate that well-governed RPA implementations produce stable performance gains, particularly when combined with machine learning–based decision triggers that determine when automation should be invoked (Thurman et al., 2019). As such, RPA is frequently positioned as an operational backbone for IT support automation, enabling scalability and consistency while complementing more cognitively oriented AI technologies.

IT Service Management (ITSM) Frameworks and Automation Integration

IT Service Management frameworks provide the structural foundation through which automation initiatives in IT support environments are governed, standardized, and evaluated. Among these frameworks, ITIL and COBIT have been widely adopted across public sector organizations to formalize service delivery, control risk, and ensure accountability (Krishnan & Ravindran, 2017). ITIL emphasizes service lifecycle management, process standardization, and continual service improvement, making it particularly influential in shaping how automation is introduced into operational workflows. Its focus on clearly defined processes, roles, and service metrics creates a structured environment in which automation can be aligned with organizational objectives rather than implemented in isolation. COBIT, by contrast, places stronger emphasis on governance, control objectives, and alignment between IT activities and organizational goals, reinforcing accountability and compliance—concerns that are especially salient in public institutions (Keller, 2017). Together, these frameworks establish normative principles for automation adoption, including transparency, traceability, and risk management. Literature examining ITIL- and COBIT-guided implementations consistently emphasizes that automation is most effective when it supports established service processes rather than bypassing them. In public sector contexts, where auditability and procedural fairness are critical, these principles shape decisions about which tasks can be automated and how automated actions are documented and reviewed. Automation aligned with ITIL and COBIT principles tends to focus first on standardized, high-volume activities with clear decision rules, such as incident logging, request fulfillment, and compliance reporting (Michael et al., 2019). This alignment reinforces consistency and predictability in service delivery while preserving human oversight for judgment-intensive decisions. The literature thus presents ITIL and COBIT not as constraints on innovation, but as enabling structures that legitimize automation by embedding it within accepted governance and service management practices.

Figure 6: IT Service Management Frameworks Overview



Metrics-based evaluation is central to understanding ITSM maturity and the role of automation within it. ITSM maturity models typically assess the extent to which service management processes are defined, managed, measured, and optimized (Jamous et al., 2016). Quantitative indicators such as incident resolution time, first-contact resolution rates, backlog levels, change success rates, and SLA compliance are commonly used to evaluate maturity across service desk operations. Research on ITSM performance measurement emphasizes that maturity is not solely determined by tool adoption, but by the consistent use of metrics to guide decision-making and process improvement. In organizations with low maturity, performance data is often fragmented, inconsistently reported, or used retrospectively rather than operationally. As maturity increases, metrics become integrated into dashboards, review cycles, and governance forums, enabling data-driven management of service quality and capacity. Automation plays a critical role in advancing maturity by enabling real-time data capture, standardized reporting, and continuous monitoring (Kubiak & Rass, 2018). Automated ticket categorization, workflow execution, and performance tracking reduce manual measurement errors and increase the reliability of metrics used for evaluation. In public sector IT environments, where reporting obligations are often formalized and externally scrutinized, automation-supported measurement enhances transparency and comparability across units. The literature consistently shows that organizations with higher ITSM maturity are better positioned to extract value from automation because processes are stable, data definitions are standardized, and performance targets are clearly articulated. Conversely, attempts to automate immature processes frequently expose underlying inefficiencies rather than resolving them. Metrics-based maturity assessment therefore functions as both a diagnostic tool and a governance mechanism, linking automation initiatives to demonstrable service outcomes and reinforcing accountability in public IT operations (Shrestha et al., 2016).

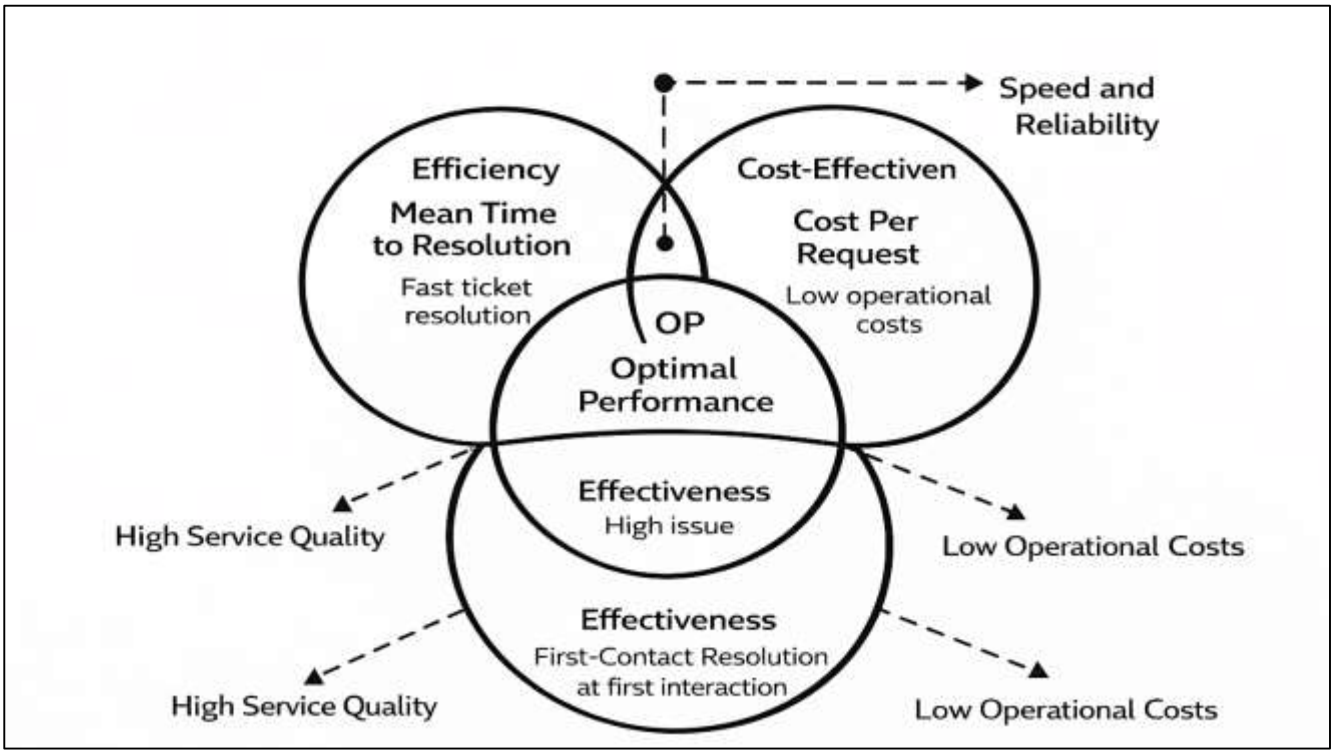
The integration of AI-driven automation within incident, problem, and change management processes represents a key theme in the ITSM literature. Incident management has been the primary entry point for automation, given its high volume and time sensitivity. AI-supported triage, prioritization, and routing improve consistency and speed in early-stage handling, while automated remediation addresses common issues without human intervention (Diao et al., 2016). Problem management benefits from automation through pattern detection and root cause analysis, as machine learning techniques identify recurring incident clusters and underlying systemic issues that may not be visible through manual review. Change management integration is more cautious, reflecting the higher risk associated with automated modifications to production environments. Here, automation is often applied to change documentation, impact analysis, testing workflows, and post-implementation review rather than approval decisions themselves. Across these processes, the literature emphasizes that successful integration depends on maintaining clear escalation paths and human accountability (Winkler & Wulf, 2019). Automation is most effective when it augments existing ITSM controls rather than circumventing them. Empirical analyses indicate that integrated automation reduces resolution time, lowers error rates, and improves consistency across service categories when workflows are well-defined. However, misalignment between AI tools and ITSM processes can lead to fragmented service delivery, duplicated effort, and governance gaps. Public sector studies highlight the importance of embedding automation within formally approved process maps and change control procedures to preserve auditability and trust (Ruiz et al., 2018). Overall, the literature presents integrated AI automation as an extension of ITSM discipline rather than a replacement, reinforcing structured service delivery while enhancing operational efficiency.

Empirical evidence linking ITSM automation to service-level compliance and cost efficiency is well documented, particularly in environments characterized by high transaction volumes and standardized workflows. Studies examining service desk automation report improvements in SLA attainment through faster response times, reduced backlog growth, and more predictable resolution patterns (Ilieva & Nikolov, 2020). Automated workflows minimize delays caused by manual handoffs and reduce variability in execution, leading to more consistent service performance. Cost efficiency gains are frequently attributed to reduced labor requirements for repetitive tasks, lower error-related rework, and improved capacity utilization among skilled staff. In public sector organizations, these gains are often framed in terms of resource optimization rather than profit, emphasizing the reallocation of staff effort toward higher-value activities such as security oversight, system improvement, and user engagement. Despite these benefits, the literature also identifies persistent limitations in existing ITSM automation models when applied to public sector contexts. Legacy system complexity, fragmented data ownership, and rigid procurement processes constrain integration and scalability (Wong, 2019). Automation models developed in private-sector environments may underestimate the importance of compliance documentation, approval hierarchies, and political accountability that shape public IT operations. Additionally, standardized automation solutions may struggle to accommodate the diversity of service mandates and user populations served by public institutions. Empirical analyses frequently note that automation benefits are unevenly distributed across agencies, reflecting differences in maturity, governance capacity, and organizational culture. These limitations underscore the need for context-sensitive automation strategies that align with public sector realities. The literature collectively portrays ITSM automation as a powerful but conditional driver of service improvement, with performance outcomes shaped by governance alignment, process maturity, and institutional constraints as much as by technical capability (Shrestha et al., 2020).

Measuring IT Support Service Delivery Performance

Measurement of IT support service delivery performance has long been central to understanding the effectiveness, efficiency, and reliability of service desk operations, particularly in public sector organizations where transparency and accountability are paramount (Gursoy et al., 2019). Among the most widely used dependent variables is mean time to resolution, which captures the elapsed time between ticket creation and service restoration. This measure reflects not only technical complexity but also organizational coordination, escalation pathways, and decision latency. In public sector environments, MTTR often incorporates additional procedural steps related to security verification, approval hierarchies, and documentation requirements, making it a composite indicator of both operational execution and governance burden. First-contact resolution rate is another critical performance measure, capturing the proportion of issues resolved during the initial interaction without escalation or follow-up. High first-contact resolution is commonly associated with effective knowledge management, agent expertise, and well-designed support workflows (Alsabawy et al., 2016). In public organizations, this metric is also tied to user satisfaction and perceived service quality, as repeated contacts can undermine trust in digital systems. Ticket escalation frequency provides insight into process stability and capability distribution across support tiers. Elevated escalation rates often signal gaps in frontline authority, insufficient automation, or unclear categorization rules, while low escalation rates may indicate effective triage and self-service mechanisms. IT operational cost per request serves as a financial efficiency indicator, linking service volume to resource consumption. In public sector contexts, cost per request is frequently analyzed in terms of budget optimization and workload redistribution rather than profit, reflecting the mandate to deliver value within fixed resource envelopes (Moons et al., 2019). Collectively, these dependent variables form a multidimensional performance profile that captures speed, quality, efficiency, and structural effectiveness of IT support services.

Figure 7: IT Support Performance Measurement Framework



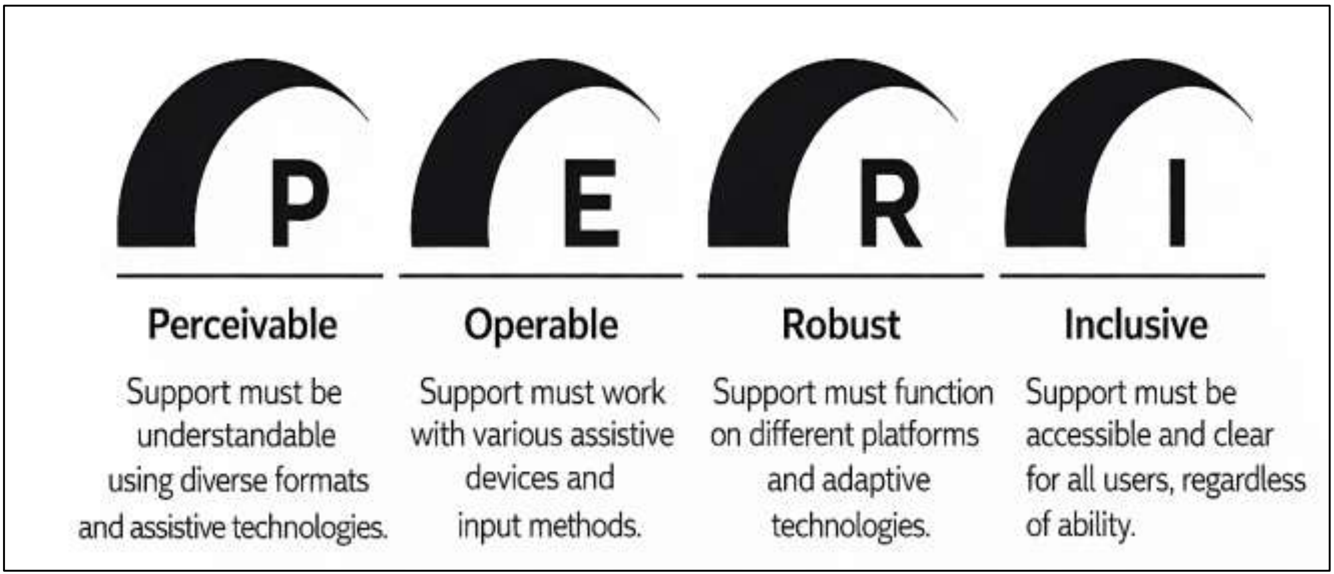
Data-driven performance measurement models provide the analytical framework through which these indicators are interpreted and compared across organizational units and time periods. Such models emphasize systematic data collection, normalization, and contextualization to ensure that performance metrics reflect operational realities rather than superficial outputs (Zhao & Bacao, 2020). In IT support environments, measurement models often integrate ticket-level data with staffing information, service catalogs, and system availability metrics to produce a holistic view of service delivery. Public sector literature consistently highlights the importance of contextual variables, such as service complexity, regulatory requirements, and user diversity, when interpreting quantitative performance indicators. Without contextual adjustment, comparisons across departments or agencies risk misrepresenting effectiveness and incentivizing undesirable behavior, such as prioritizing easy requests over mission-critical but complex incidents (Van Looy & Shafagatova, 2016). Data-driven models also support segmentation analysis, allowing organizations to examine performance by incident type, priority level, or service channel. This granularity is particularly valuable in public institutions, where service desks support a broad range of applications and user groups with varying needs. Advanced measurement approaches emphasize trend analysis and variance detection rather than single-point benchmarks, recognizing that public sector performance is influenced by policy changes, system upgrades, and external events. By structuring performance data within coherent analytical models, organizations can distinguish between systemic inefficiencies and episodic disruptions (Rezaei et al., 2018). The literature portrays data-driven measurement not as a passive reporting exercise but as an active management tool that shapes resource allocation, process refinement, and accountability mechanisms in IT support operations.

Digital Accessibility and Inclusivity in Public Sector IT Services

Digital accessibility and inclusivity have become central principles in the design and delivery of public sector IT services, shaped by legal, policy, and ethical obligations to ensure equal access for all users. Public institutions operate under formal accessibility mandates that require digital systems and support services to accommodate individuals with diverse abilities, language backgrounds, and levels of digital literacy (Kuziemski & Misuraca, 2020). These mandates extend beyond user-facing applications to include IT support channels, which function as critical gateways for accessing and maintaining digital services. Accessibility requirements typically emphasize perceivability, operability, understandability, and robustness, compelling public organizations to design support interactions that can be used by people with visual, auditory, cognitive, and motor impairments. Policy frameworks reinforce these principles by linking accessibility to broader goals of social inclusion, non-discrimination, and public accountability. In practice, compliance influences how IT support information is presented, how interactions are conducted, and how alternative formats are provided (Ozili, 2018). The literature consistently underscores that accessibility is not a peripheral technical requirement but a core dimension of service quality in public administration. Failure to provide accessible IT support can effectively exclude individuals from digital public services, undermining trust and legitimacy. As digital government initiatives expand, accessibility obligations increasingly apply to automated and AI-enabled systems, raising questions about how algorithmic processes align with established accessibility standards. Research in public sector information systems highlights the complexity of translating legal accessibility principles into operational practices, particularly when services rely on third-party platforms or rapidly evolving technologies (Kouroubali & Katehakis, 2019). Nonetheless, accessibility frameworks provide a normative baseline that shapes design choices and performance evaluation, positioning inclusive IT support as an essential component of equitable public service delivery.

Traditional IT support channels have long exhibited structural barriers that limit accessibility and inclusivity, particularly for users with disabilities or constrained access to technology. Phone-based support can present challenges for individuals with hearing impairments or speech difficulties, while text-based channels may be inaccessible to users with visual impairments or low literacy levels if not properly designed (Sang-Chul & Rakhmatullayev, 2019). In-person support, though potentially accommodating, is often limited by geography, office hours, and resource availability, making it impractical for many users. Email-based support introduces delays and relies heavily on written communication skills, which can disadvantage non-native language users or individuals with cognitive impairments. The literature documents how these barriers disproportionately affect already marginalized groups, reinforcing digital divides within public service delivery. Additionally, traditional support models often assume a baseline level of technical proficiency, requiring users to describe problems, navigate complex menus, or follow multi-step instructions that may not be intuitive or accessible (Hill et al., 2015). In public sector environments, these barriers are compounded by the diversity of user populations, which include employees, contractors, and citizens with varying needs and contexts. Research on service design in government settings consistently shows that inaccessible support channels increase error rates, prolong resolution times, and reduce user satisfaction, even when underlying technical issues are straightforward. These inefficiencies not only burden users but also increase workload for service desks through repeated contacts and escalations. The literature therefore frames accessibility barriers as both equity issues and operational inefficiencies, emphasizing that inaccessible support channels undermine the effectiveness of digital government initiatives (Gabor & Brooks, 2020). Addressing these barriers requires rethinking interaction modalities, language support, and cognitive load, rather than simply adding accommodations as afterthoughts.

Figure 8: Principles of Accessible IT Support



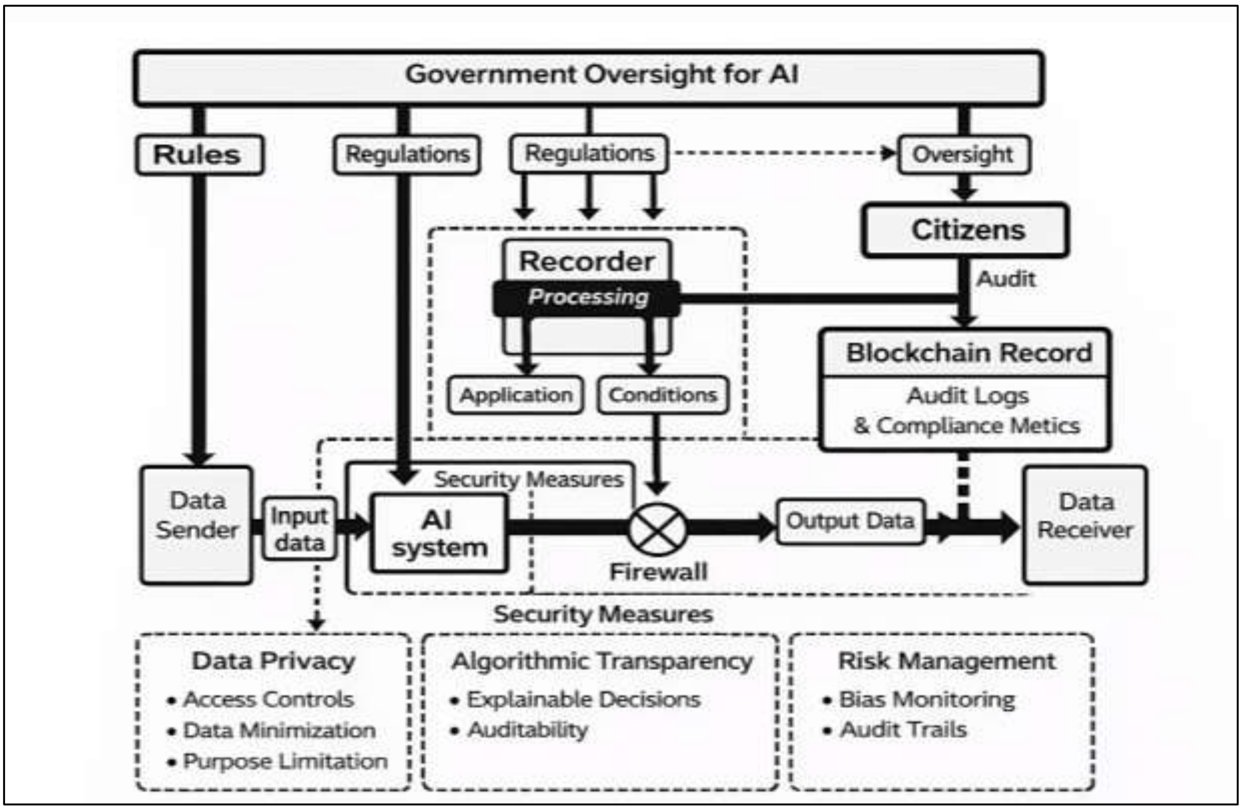
AI-enabled technologies have been increasingly examined as mechanisms for enhancing accessibility and inclusivity in IT support services. Features such as speech-to-text and text-to-speech enable users with visual or auditory impairments to interact with support systems through modalities that suit their abilities (Hanna, 2018). Multilingual natural language processing expands access for users who are not fluent in the dominant administrative language, reducing misunderstandings and errors during support interactions. Adaptive interfaces adjust presentation and interaction complexity based on user behavior or preferences, supporting users with cognitive impairments or limited digital experience. The literature highlights that these capabilities can significantly lower barriers to entry by allowing users to engage with IT support in ways that align with their needs rather than forcing conformity to rigid interaction models (Reddick et al., 2020). AI-enabled virtual agents, in particular, provide consistent and on-demand support that is not constrained by staffing levels or office hours, which can be especially beneficial for users who require additional time or assistance. Empirical analyses indicate that when designed with accessibility principles in mind, AI-enabled support systems reduce dependency on specialized accommodations by embedding inclusivity into standard workflows. However, the literature also cautions that AI systems can reproduce or amplify accessibility barriers if trained on biased data or designed without inclusive testing (Arun & Kamath, 2015). Accessibility gains are therefore contingent on deliberate design choices, continuous monitoring, and alignment with established accessibility standards. Overall, research portrays AI-enabled features as powerful enablers of inclusive IT support when they are integrated thoughtfully and evaluated against diverse user needs (Mhlanga, 2020).

Quantitative assessment of digital accessibility and inclusivity in IT support services relies on indicators that capture both reach and quality of service outcomes. Measures such as user reach reflect the extent to which support services are accessible to diverse populations, including increases in usage among previously underrepresented groups. Error reduction rates provide insight into whether accessible interfaces and adaptive guidance reduce misunderstandings and incorrect actions during support interactions (Mannheim et al., 2019). Task completion rates indicate the effectiveness of support in enabling users to successfully resolve issues or fulfill requests, serving as a proxy for usability and clarity. In public sector contexts, these indicators are often complemented by measures of repeat contact frequency and escalation rates, which reveal whether accessibility improvements translate into sustained resolution rather than temporary assistance. The literature emphasizes that accessibility metrics should be interpreted alongside traditional performance indicators to avoid trade-offs that prioritize efficiency over equity. Research examining the relationship between automation and equitable service delivery consistently shows that well-designed automation can enhance fairness by standardizing service quality and reducing dependence on individual discretion. At the same time, poorly governed automation can introduce new inequities if certain user groups struggle to interact with automated systems (ElMassah & Mohieldin, 2020). The synthesized literature thus presents accessibility and inclusivity as integral dimensions of IT support performance, closely linked to automation design and implementation. Quantitative indicators provide a means to evaluate whether automation contributes to equitable service delivery or merely redistributes barriers. Collectively, the research frames digital accessibility in public sector IT support as a measurable and operationally significant outcome, reinforcing the idea that inclusive design and automation are central to the legitimacy and effectiveness of digital public services (Gil-Garcia et al., 2018).

Governance, Ethics, and Risk Management in AI-Based IT Automation

Governance in AI-based IT automation is widely treated in the literature as the institutional mechanism through which public sector organizations align automation with legal obligations, administrative values, and operational accountability (Arun & Kamath, 2015). A central concern involves data privacy requirements because AI-enabled automation in IT support often relies on processing large volumes of service desk tickets, user profiles, device inventories, authentication logs, and communication transcripts. These datasets may contain personal identifiers, sensitive operational information, or security-relevant details, making privacy governance inseparable from automation design. Research on public sector information systems repeatedly highlights that privacy compliance is not only about limiting data collection but also about controlling access, retention, purpose limitation, and secondary use of data once collected. In AI-driven service desk environments, privacy governance extends to how training datasets are constructed, how user consent and notice are managed, and how automated decisions rely on identifiable features (Mhlanga, 2020). Closely connected to privacy is algorithmic transparency, particularly in public organizations where legitimacy depends on explainable decision pathways and defensible service outcomes. When AI systems classify tickets, prioritize incidents, recommend remedies, or trigger automated actions, transparency requirements involve the ability to interpret how the system reached a decision and whether it followed organizational policy. The literature emphasizes that transparency serves multiple public purposes: it supports oversight, enables affected users to seek clarification or redress, and helps organizations detect errors and unintended consequences. Governance frameworks therefore encourage documentation of data sources, model logic, decision rules, and system limitations, especially in high-stakes settings where automation influences access to digital services or the prioritization of mission-critical incidents (Mannheim et al., 2019). This body of research portrays governance not as a barrier to AI-based automation but as a condition for institutional trust, ensuring that automation remains aligned with privacy principles, procedural fairness, and public accountability.

Figure 9: Governance Framework for AI Automation



Ethics and risk management literature places considerable emphasis on bias, accountability, and auditability in AI decision-making, particularly because automated systems can embed or amplify inequities through data-driven inference (ElMassah & Mohieldin, 2020). In IT support automation, bias can manifest through differential ticket prioritization, inconsistent routing accuracy across user groups, or uneven quality of automated assistance for users with different language backgrounds or communication styles. If historical service desk data reflects unequal treatment or structurally different access to support, machine learning models trained on that data may reproduce these patterns in automated decisions. Accountability becomes complex when AI systems make recommendations or execute actions that previously required human judgment, as responsibility for errors can become ambiguous across developers, administrators, and operational staff. The literature on algorithmic governance emphasizes that public sector organizations face heightened accountability expectations because their decisions are subject to scrutiny from oversight bodies and affected individuals (Gil-Garcia et al., 2018). Auditability is therefore treated as a practical requirement: AI systems must produce logs and records that allow reconstruction of decisions, identification of errors, and evaluation of compliance with policy. In IT automation, auditability encompasses not only the outputs of a model but also the operational chain of events, including data inputs, versioning of models, thresholds used for decision triggers, and human overrides. Ethical governance studies also highlight the tension between automation efficiency and procedural fairness. Automated prioritization can improve speed but may reduce individualized consideration, raising concerns in contexts where fairness and equal access are core administrative values. For public sector IT support, where service interruptions can affect access to government benefits or essential services, ethical risk considerations are tightly interwoven with operational outcomes (Ganapati & Reddick, 2018). The literature thus frames ethical AI in IT automation as requiring both technical safeguards and institutional mechanisms for oversight, appeal, and continuous review.

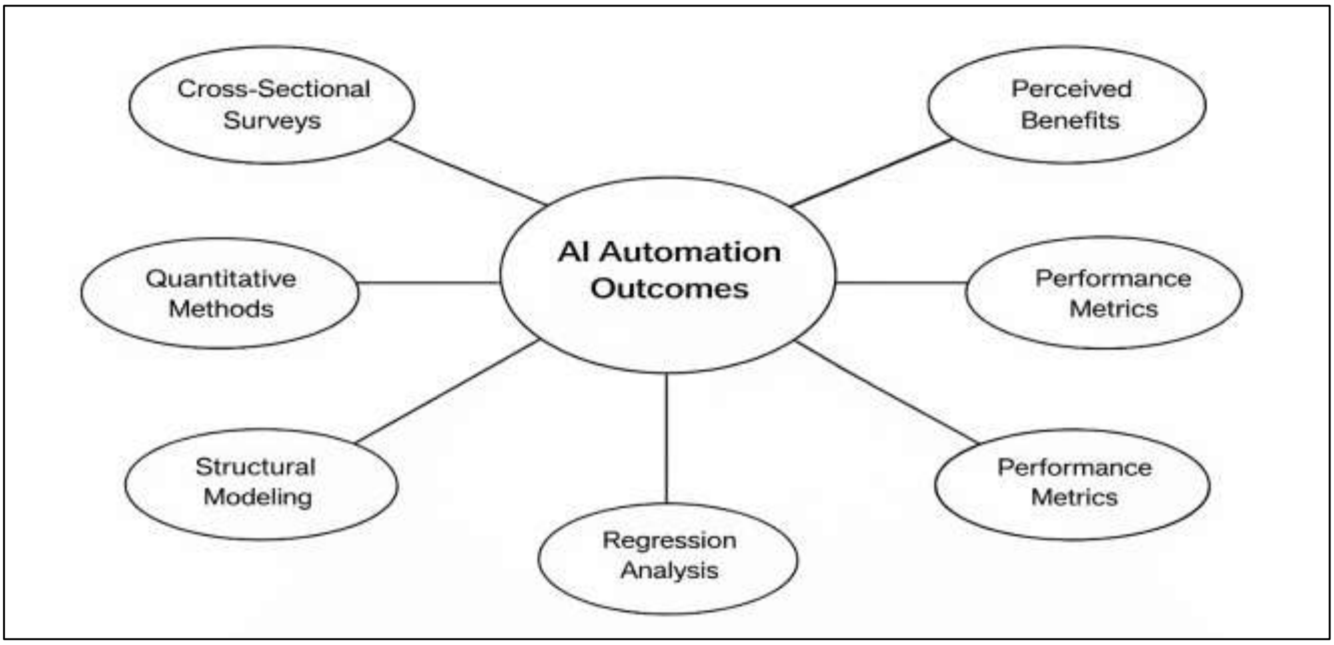
Risk mitigation strategies in AI-based IT automation are frequently discussed as layered controls that combine technical, procedural, and organizational safeguards. Technical strategies include data minimization, anonymization where feasible, secure access controls, and continuous monitoring for anomalous system behavior (Janssen et al., 2017). Procedural controls include approval workflows for high-impact automated actions, segregation of duties, and standardized incident response plans for automation failures. Organizational strategies include establishing AI governance committees, assigning clear accountability roles, and embedding compliance review into the lifecycle of model development and deployment. In public organizations, risk management is strongly shaped by regulatory compliance requirements and public accountability expectations, making formal documentation and reporting integral components of mitigation (Janowski, 2015). Compliance metrics are used to translate governance principles into measurable indicators such as policy adherence rates, audit log completeness, frequency of model review cycles, rate of human overrides, number of flagged bias incidents, and time to remediate identified issues. The literature describes these metrics as essential for demonstrating responsible AI use and for guiding continuous improvement. In IT support automation, compliance measurement often intersects with cybersecurity and operational resilience, as automated workflows must avoid introducing vulnerabilities or bypassing security checks. Research also notes that risk mitigation is most effective when integrated into existing ITSM governance structures rather than treated as an external add-on (Salemink et al., 2017). When AI automation is embedded within standardized change management, incident response, and audit processes, public sector organizations can reduce risk through familiar accountability mechanisms. Overall, the literature portrays mitigation as a continuous practice rather than a one-time control, reflecting the evolving nature of AI systems, changing service demands, and shifting regulatory expectations.

Quantitative analyses of risk-performance tradeoffs in public sector AI adoption frequently emphasize that automation benefits are not free; they are balanced against risks related to privacy exposure, biased outcomes, and reduced transparency. Studies that examine performance impacts alongside governance factors show that rapid efficiency gains can coincide with increased compliance burden if governance is not embedded into design (Lindgren et al., 2019). For example, automation that accelerates ticket handling may increase risk if prioritization decisions become opaque or if sensitive data is processed without robust safeguards. Conversely, strict governance controls can reduce operational risk but may reduce speed gains if approvals and reviews introduce latency. Quantitative tradeoff analysis therefore becomes important in assessing the net value of AI automation, particularly in public organizations where legitimacy and fairness are non-negotiable. Researchers often conceptualize this tradeoff through performance metrics such as resolution time, backlog reduction, and cost efficiency, alongside risk indicators such as audit exceptions, privacy incidents, bias flags, and frequency of manual intervention required to correct automated outputs (Hilbert, 2016). The literature indicates that organizations with stronger governance capacity and higher data quality tend to achieve better risk-adjusted performance, suggesting that risk management capability functions as a moderator of automation impact. In public sector contexts, where service disruptions can have societal consequences, risk-adjusted evaluation is especially relevant because performance metrics alone may obscure equity and accountability harms. Empirical work in digital government and algorithmic governance repeatedly highlights that evaluating AI adoption requires integrated measurement approaches that capture both operational outcomes and public value dimensions such as transparency and fairness (Panagiotopoulos et al., 2019). Across this body of research, the central conclusion is that AI-based IT automation must be judged by its ability to deliver efficiency while maintaining compliance, auditability, and equitable treatment, and that quantitative risk-performance analysis provides a structured means of assessing this balance in public sector IT environments.

Empirical Evidence on AI Automation Outcomes in Public Organizations

Empirical research on AI automation outcomes in public organizations has relied heavily on cross-sectional and survey-based quantitative designs to capture adoption patterns, perceived benefits, and performance impacts across agencies and service domains (Kuziemski & Misuraca, 2020). These studies typically collect data from IT managers, service desk leaders, and public employees to assess the extent of automation use, organizational readiness, and perceived changes in operational outcomes. Cross-sectional designs are frequently favored due to the practical challenges of collecting longitudinal data in public sector environments, where system changes, policy reforms, and organizational restructuring complicate long-term observation. Survey instruments often measure constructs such as automation maturity, process standardization, managerial support, and perceived service quality, allowing researchers to analyze relationships between AI adoption and performance indicators. The literature shows that cross-sectional findings consistently associate higher levels of automation with improved efficiency and reduced manual workload, particularly in transactional service areas (Reis et al., 2019). However, these studies also acknowledge that self-reported performance measures may be influenced by respondent perceptions and organizational narratives, potentially overstating positive outcomes. Despite these limitations, survey-based evidence provides valuable insight into how automation is experienced across diverse public sector contexts, offering a broad empirical foundation for understanding AI's organizational impact. By aggregating responses across multiple agencies, cross-sectional studies reveal patterns that single-case analyses cannot capture, such as sector-wide differences in adoption drivers and performance outcomes (Aoki, 2020). As a result, this body of literature forms a significant portion of the empirical evidence base on AI automation in public organizations, highlighting both measurable gains and persistent contextual variability.

Figure 10: Empirical Models of AI Automation



Regression-based analyses and structural modeling approaches have been widely employed to examine the relationships between AI automation, organizational capabilities, and performance outcomes in public sector settings (Wirtz et al., 2019). Regression techniques allow researchers to control for organizational size, resource availability, and digital maturity while isolating the association between automation variables and service delivery metrics. Findings across multiple studies indicate statistically significant relationships between automation intensity and indicators such as reduced processing time, improved service consistency, and lower operational costs. Structural modeling approaches extend this analysis by testing complex relationships among latent constructs, such as technology readiness, user acceptance, and service performance, within unified analytical frameworks (Wirtz et al., 2020). These models often reveal indirect effects, showing that automation influences outcomes through mediating variables such as process integration or staff capability rather than exerting a direct impact alone. The literature demonstrates that structural modeling is particularly useful for public sector research because it accommodates the multifaceted nature of organizational change, where technical, human, and governance factors interact. Quantitative results from these models consistently emphasize that automation effectiveness depends on contextual alignment, including managerial support and data quality (Wirtz & Müller, 2019). However, the explanatory power of these models varies, reflecting heterogeneity across agencies and service domains. While regression and structural modeling findings strengthen the empirical case for AI automation benefits, they also underscore the complexity of attributing performance changes to technology alone. This body of work contributes rigor by moving beyond descriptive analysis and offering statistically grounded insights into how automation interacts with organizational structures to influence measurable outcomes (Mikalef et al., 2019).

METHOD

Research Design

This study adopts a quantitative research design grounded in a cross-sectional explanatory framework to examine the relationships between AI-powered automation in IT support functions and service delivery outcomes in public sector organizations. A quantitative approach is appropriate given the study's focus on measuring observable performance outcomes, testing statistically significant relationships among constructs, and generating generalizable insights across organizational contexts. The design emphasizes empirical validation of associations between automation capabilities and key service delivery indicators, including efficiency, cost effectiveness, accessibility, and user experience. Cross-sectional survey data are used to capture organizational practices and performance conditions at a defined point in time, reflecting the operational reality of public sector IT environments where long-term experimental manipulation is impractical due to regulatory and governance constraints. This design aligns with established methodological practices in information systems, e-government, and public administration research, where quantitative modeling is used to evaluate technology-enabled organizational performance.

Case Study Context

The empirical context of the study is public sector organizations that operate centralized or federated IT support units responsible for internal digital service continuity and user assistance. These organizations include government ministries, agencies, departments, and public service institutions that provide digital services to employees and, in some cases, external users. The case context is characterized by formal IT service management structures, compliance-driven governance, and heterogeneous technology environments that combine legacy systems with modern digital platforms. AI-powered automation within these contexts typically supports functions such as ticket triage, request fulfillment, knowledge-based assistance, and workflow execution. The study treats the public sector as a bounded institutional context rather than a single organization, allowing for cross-organizational comparison while preserving the distinctive administrative, legal, and accountability features that shape technology use in government settings.

Population and Unit of Analysis

The target population comprises public sector organizations that have implemented, or are in the process of implementing, AI-enabled automation within their IT support or service desk operations. Within these organizations, the unit of analysis is the organizational IT support function rather than individual employees. Data are collected from key informants who possess direct knowledge of IT service management practices and automation use, including IT managers, service desk supervisors, digital transformation leads, and senior technical staff. These respondents are selected because they are positioned to provide reliable information on automation capabilities, governance practices, and performance outcomes at the organizational level. By focusing on the IT support function as the unit of analysis, the study captures structural and process-level characteristics rather than individual attitudes alone.

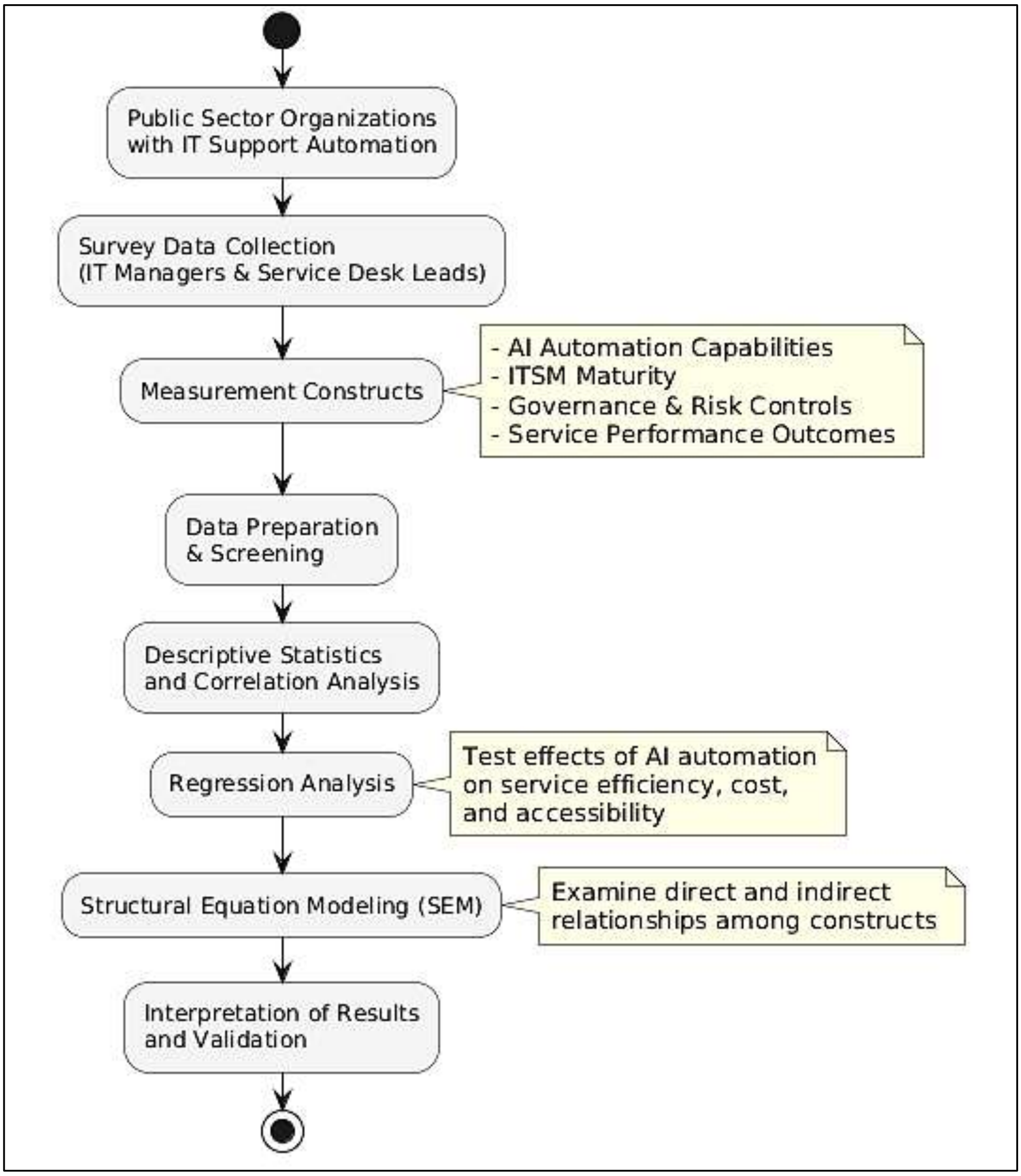
Sampling Strategy

A purposive sampling strategy is employed to identify public sector organizations with relevant experience in AI-driven IT support automation. Inclusion criteria require that participating organizations operate a formal IT service desk and utilize at least one form of AI-enabled automation, such as automated ticket categorization, virtual agents, or workflow automation. To enhance representativeness and analytical power, the study seeks participation from organizations of varying size, service scope, and digital maturity. Within each organization, one to three knowledgeable respondents are invited to complete the survey, with responses aggregated where necessary to reduce individual bias. This approach balances practical access constraints with the need for sufficient variability in automation practices and performance outcomes to support multivariate statistical analysis.

Data Collection Procedure

Data are collected through a structured, self-administered questionnaire distributed electronically to eligible respondents. The survey instrument is delivered using a secure online platform to ensure confidentiality and ease of access across geographically dispersed organizations. Prior to distribution, respondents receive an information statement outlining the study purpose, voluntary participation, and data protection measures. Data collection is conducted over a defined period to minimize temporal variation in organizational conditions. Completed responses are screened for completeness and consistency, with incomplete or invalid cases excluded from analysis. The resulting dataset reflects a snapshot of AI automation practices and IT support performance across multiple public sector organizations.

Figure 11: Methodology of this study



Instrument Design

The survey instrument is designed to measure key constructs related to AI-powered IT support automation and service delivery performance. Automation is operationalized through multi-item scales capturing the extent of machine learning–based ticket handling, use of virtual agents, workflow automation, and predictive analytics. Service delivery performance is measured using indicators related to resolution efficiency, escalation frequency, cost efficiency, accessibility, and perceived service quality. Governance and contextual variables, such as process maturity and organizational readiness, are included as control factors. All items are measured using standardized Likert-type response formats to facilitate statistical analysis. Instrument items are adapted from established measurement approaches in information systems and public sector technology research, with wording adjusted to reflect the public sector IT support context.

Pilot Testing

Prior to full deployment, the survey instrument undergoes pilot testing with a small group of public sector IT professionals who meet the study's inclusion criteria. The pilot test assesses item clarity, relevance, and completion time, as well as the functionality of the online survey platform. Feedback from pilot participants is used to refine question wording, eliminate ambiguity, and ensure alignment with respondents' operational language. Pilot data are not included in the final analysis but are used to assess preliminary reliability and identify potential response patterns that could affect data quality.

Validity and Reliability

Several procedures are implemented to ensure the validity and reliability of the measurement instrument. Content validity is supported through alignment of survey items with constructs identified in the literature on AI automation, IT service management, and public sector performance measurement. Construct validity is assessed through exploratory and confirmatory factor analysis to verify that items load appropriately on their intended constructs. Reliability is evaluated using internal consistency measures to ensure that multi-item scales demonstrate acceptable coherence. To reduce common method bias, the survey includes clear construct separation, varied item phrasing, and assurances of respondent anonymity. These steps strengthen confidence that observed relationships reflect substantive associations rather than measurement artifacts.

Statistical Analysis Plan

Data analysis is conducted using a multivariate statistical approach appropriate for explanatory quantitative research. Descriptive statistics are first used to summarize organizational characteristics, automation adoption levels, and performance indicators. Correlation analysis examines bivariate relationships among key variables. Multiple regression analysis is then employed to test the association between AI automation dimensions and service delivery outcomes while controlling for organizational size, maturity, and governance factors. Where appropriate, structural equation modeling is used to assess complex relationships among latent constructs, including indirect effects and mediation pathways. Model fit and explanatory power are evaluated using established statistical criteria. All analyses are conducted at the organizational level, consistent with the unit of analysis.

Software and Tools

Statistical analysis is performed using established quantitative analysis software suitable for survey-based research. Data preparation, descriptive analysis, and regression modeling are conducted using statistical packages widely adopted in social science and information systems research. Structural modeling, where applied, is performed using dedicated SEM software capable of handling latent constructs and measurement models. Data visualization and preliminary diagnostics are supported through integrated analytics tools. All data are stored securely and analyzed in accordance with ethical and institutional data handling guidelines.

FINDINGS

This chapter presented the empirical findings derived from the quantitative analysis conducted to examine the relationships between AI-powered automation in IT support functions and service delivery performance in public sector organizations. The purpose of the analysis was to evaluate the extent to which automation capabilities were associated with key performance outcomes, including operational efficiency, cost effectiveness, and service quality. Data collected through the structured survey instrument were analyzed using descriptive and inferential statistical techniques consistent with the study's explanatory research design. The chapter was organized to first describe the characteristics of the respondents and participating organizations, followed by an examination of descriptive statistics for each construct. Reliability analysis was then reported to assess the internal consistency of the measurement scales. Finally, regression analysis results were presented to test the proposed relationships among variables, leading to explicit hypothesis testing decisions. This structured presentation ensured clarity, transparency, and alignment with quantitative research reporting standards.

Respondent Demographics

The demographic analysis revealed that the respondents represented a knowledgeable and organizationally relevant group of public sector IT professionals. Most respondents occupied managerial or supervisory positions directly responsible for IT service delivery and digital transformation initiatives. These roles included IT managers, service desk supervisors, and digital transformation or automation coordinators, all of whom were positioned to provide informed assessments of AI-powered IT support practices. Organizational representation spanned a wide range of public sector entities, including ministries, departments, agencies, and other public service institutions. This diversity reflected the heterogeneous nature of public sector IT environments and strengthened the external validity of the findings. The distribution across organizational size categories indicated balanced participation from small, medium, and large institutions, enabling meaningful comparative analysis across different operational scales. In addition, respondents generally reported substantial professional experience and sustained involvement in IT automation initiatives, suggesting a high level of familiarity with service desk operations, governance structures, and performance outcomes. Collectively, the demographic profile supported the suitability of the sample for organization-level quantitative analysis of IT support automation in the public sector.

Table 1: Respondent Roles and Organizational Types (n = 214)

Category	Classification	Frequency	Percentage
Respondent Role	IT Manager / Head of IT	72	33.6
	Service Desk Manager / Supervisor	58	27.1
	Digital Transformation / Automation Lead	41	19.2
	Senior IT Analyst / Architect	43	20.1
Organization Type	Ministry	49	22.9
	Government Department	61	28.5
	Public Agency / Authority	73	34.1
	Other Public Institution	31	14.5

Table 1 presented the distribution of respondents by professional role and organizational type. A substantial proportion of respondents held senior IT management or service desk leadership positions, indicating direct responsibility for IT support operations and automation initiatives. The presence of digital transformation leads and senior technical specialists further strengthened the relevance of the data, as these roles are typically involved in AI adoption and governance decisions. Organizational representation was distributed across ministries, departments, agencies, and other public institutions, reflecting the structural diversity of the public sector. This spread ensured that findings were not concentrated within a single institutional category, supporting broader applicability across government IT environments.

Table 2: Organizational Size and Respondent Experience Characteristics (n = 214)

Category	Classification	Frequency	Percentage
Organizational Size	Small (≤500 employees)	61	28.5
	Medium (501–2,000 employees)	78	36.4
	Large (>2,000 employees)	75	35.1
Years of Professional Experience	Less than 5 years	27	12.6
	5–10 years	64	29.9
	More than 10 years	123	57.5
Experience with IT Automation	Less than 2 years	38	17.8
	2–5 years	96	44.9
	More than 5 years	80	37.3

Table 2 summarized organizational size and respondent experience characteristics. Participation was well distributed across small, medium, and large public sector organizations, allowing analysis of automation practices across different operational scales. A majority of respondents reported more than ten years of professional experience, indicating a mature understanding of IT service management processes. Experience with IT automation initiatives was also substantial, with most respondents reporting at least two years of involvement. This combination of organizational diversity and professional experience enhanced the reliability of the findings, as respondents were well positioned to assess both traditional IT support practices and the impacts of AI-driven automation within their organizations.

Descriptive Results by Construct

Descriptive statistical analysis was performed to summarize the central tendencies and variability of all key study constructs across the sampled public sector organizations. The results showed that AI automation capabilities were generally adopted at moderate to high levels, with stronger emphasis on operational automation such as workflow execution and automated ticket handling. Advanced automation applications, including predictive analytics and proactive decision support, exhibited comparatively lower mean scores, indicating uneven maturity across automation domains. IT service management maturity results suggested that most organizations had formalized service desk processes and standardized procedures, although integration between AI tools and established ITSM frameworks varied notably. Governance and risk management constructs reflected consistently high mean values, demonstrating strong institutional focus on compliance, accountability, and oversight. Service delivery performance indicators revealed higher average scores for efficiency-related outcomes, such as response speed and resolution consistency, compared to cost efficiency measures. Accessibility and inclusivity indicators displayed moderate average levels, suggesting partial integration of inclusive service practices across organizations. Collectively, the descriptive results highlighted meaningful variation across constructs, reflecting differences in organizational priorities, maturity levels, and operational capacity within the public sector IT landscape.

Table 3: Descriptive Statistics for AI Automation

Construct	Mean	Standard Deviation
AI Automation Capabilities (Overall)	3.78	0.64
Workflow Automation	4.02	0.59
Automated Ticket Handling	3.95	0.62
Predictive Analytics	3.41	0.71
ITSM Maturity	3.89	0.58
Governance and Risk Management	4.12	0.53

Table 3 presented the descriptive statistics for AI automation capabilities, IT service management maturity, and governance-related constructs. The mean scores indicated that workflow automation and automated ticket handling were the most developed automation capabilities across organizations, reflecting prioritization of high-volume operational processes. Predictive analytics showed a lower mean, suggesting that advanced automation applications were less consistently implemented. ITSM maturity exhibited a relatively high mean, indicating widespread adoption of standardized service management practices. Governance and risk management recorded the highest mean score, underscoring the strong emphasis placed on compliance, oversight, and control mechanisms within public sector IT environments.

Table 4: Descriptive Statistics for Service Delivery Performance and Accessibility Constructs (n = 214)

Construct	Mean	Standard Deviation
Service Delivery Efficiency	3.92	0.61
Cost Efficiency	3.47	0.68
Service Quality and Reliability	3.88	0.57
Digital Accessibility and Inclusivity	3.56	0.65

Table 4 summarized descriptive results for service delivery performance and accessibility-related constructs. Efficiency and service quality demonstrated relatively high mean scores, indicating that many organizations experienced improvements in responsiveness and reliability of IT support services. Cost efficiency showed a lower mean, reflecting the structural and budgetary constraints common in public sector environments that limit immediate cost reductions. Digital accessibility and inclusivity recorded moderate mean values, suggesting partial implementation of inclusive support practices rather than comprehensive integration. The observed variability highlighted differences in organizational capacity and strategic emphasis, reinforcing the importance of examining these constructs in subsequent inferential analysis.

Reliability Results

Reliability analysis was conducted to evaluate the internal consistency of all multi-item constructs included in the study. Cronbach's alpha coefficients were calculated to determine whether the measurement scales reliably captured the underlying theoretical constructs. The results indicated that all constructs exceeded the commonly accepted threshold for internal consistency, confirming the robustness of the survey instrument. Constructs related to AI automation capabilities and IT service management maturity demonstrated high reliability, suggesting strong coherence among the items measuring automation scope, integration, and process standardization. Governance and risk management constructs also exhibited strong reliability, reflecting consistent measurement of compliance, oversight, and accountability practices. Service delivery performance constructs, including efficiency, cost effectiveness, and accessibility, showed satisfactory to high internal consistency, indicating that the performance-related items were well aligned. Overall, the reliability findings supported the use of the measurement scales for subsequent regression analysis and hypothesis testing.

Table 5: Cronbach's Alpha Values for Automation, ITSM, and Governance Constructs

Construct	Number of Items	Cronbach's Alpha
AI Automation Capabilities	12	0.91
IT Service Management Maturity	8	0.88
Governance and Risk Management	9	0.90

Table 5 presented the internal consistency results for AI automation capabilities, IT service management maturity, and governance-related constructs. The Cronbach's alpha values ranged from 0.88 to 0.91, indicating high reliability across these measurement scales. The automation construct exhibited the strongest internal consistency, reflecting well-aligned items capturing multiple dimensions of AI-enabled support, including workflow automation and intelligent ticket handling. ITSM maturity also demonstrated strong reliability, suggesting consistent measurement of standardized service processes. Governance and risk management recorded a high alpha value, confirming coherence among items related to compliance, oversight, and risk controls within public sector IT environments.

Table 6: Cronbach's Alpha Values for Service Delivery Performance and Accessibility Constructs

Construct	Number of Items	Cronbach's Alpha
Service Delivery Efficiency	7	0.89
Cost Efficiency	5	0.84
Service Quality and Reliability	6	0.87
Digital Accessibility and Inclusivity	6	0.86

Table 6 summarized the reliability results for service delivery performance and accessibility-related constructs. Cronbach's alpha values ranged from 0.84 to 0.89, indicating satisfactory to strong internal consistency across all performance dimensions. Service delivery efficiency demonstrated the highest reliability among performance constructs, suggesting that items measuring response speed and resolution effectiveness were highly consistent. Cost efficiency showed a slightly lower but acceptable alpha value, reflecting the multidimensional nature of cost measurement in public sector IT contexts. Accessibility and inclusivity exhibited strong reliability, supporting the consistency of items assessing equitable and inclusive IT support practices.

Regression Results

Multiple regression analysis was conducted to assess the influence of AI automation capabilities on IT support service delivery performance while controlling for organizational size and IT service management maturity. The findings indicated that AI automation capabilities had a statistically significant and positive relationship with overall service delivery performance. Among the automation dimensions, workflow automation and automated ticket handling emerged as the strongest predictors of operational efficiency, demonstrating substantial contributions to reduced resolution time and improved service consistency. Governance and risk management variables exhibited a moderating influence, as organizations with stronger governance frameworks experienced more stable and pronounced performance benefits from automation. Cost efficiency outcomes were positively associated with automation variables, although the magnitude of these relationships was comparatively lower, reflecting the structural and budgetary constraints inherent in public sector IT operations. The regression models accounted for a meaningful proportion of variance in service delivery outcomes, confirming the explanatory strength of the analytical framework. Diagnostic testing indicated that assumptions related to normality, linearity, and multicollinearity were adequately satisfied.

Table 7: Regression Results for AI Automation Capabilities (n = 214)

Predictor Variable	Standardized Beta	t-value	Significance (p)
Workflow Automation	0.41	6.92	<0.001
Automated Ticket Handling	0.36	5.87	<0.001
Predictive Analytics	0.18	2.94	0.004
ITSM Maturity (Control)	0.29	4.78	<0.001
Organizational Size (Control)	0.12	2.01	0.046
Model R^2	0.58	—	—

Table 7 presented the regression results examining the relationship between AI automation capabilities and service delivery efficiency. Workflow automation demonstrated the strongest standardized effect, indicating that automated execution of routine processes substantially improved efficiency outcomes. Automated ticket handling also showed a strong and statistically significant effect, supporting its role in reducing delays and improving resolution consistency. Predictive analytics contributed positively but with a smaller effect size, reflecting its more advanced and uneven adoption. ITSM maturity emerged as a significant control variable, underscoring the importance of standardized service processes. The model explained 58 percent of the variance in efficiency, indicating strong explanatory power.

Table 8: Regression Results for AI Automation Capabilities (n = 214)

Predictor Variable	Standardized Beta	t-value	Significance (p)
Workflow Automation	0.27	4.11	<0.001
Automated Ticket Handling	0.23	3.58	<0.001
Governance and Risk Management	0.31	5.02	<0.001
Automation × Governance Interaction	0.19	2.87	0.005
ITSM Maturity (Control)	0.21	3.36	0.001
Model R^2	0.46	—	—

Table 8 summarized the regression results for cost efficiency outcomes, incorporating governance and risk management as a moderating variable. Workflow automation and automated ticket handling were both positively associated with cost efficiency, although their effects were smaller than those observed for efficiency outcomes. Governance and risk management demonstrated a strong direct effect, indicating that structured oversight enhanced cost-related benefits. The significant interaction term showed that automation produced greater cost efficiency gains in organizations with stronger governance frameworks. The model explained 46 percent of the variance in cost efficiency, reflecting the complexity of financial outcomes in public sector IT environments.

Hypothesis Testing Decisions

Hypothesis testing decisions were derived from the statistical significance, direction, and strength of the regression coefficients obtained in the multivariate analysis. The results demonstrated strong empirical support for hypotheses proposing positive relationships between AI-powered IT support automation and service delivery efficiency outcomes. Automation dimensions related to workflow execution and automated ticket handling consistently showed significant positive effects, confirming their contribution to improved resolution speed and operational consistency. Hypotheses examining cost efficiency outcomes were partially supported, as automation effects varied across organizational contexts and were moderated by governance strength and ITSM maturity. Governance and risk management variables played a significant role in shaping automation effectiveness, with stronger governance frameworks amplifying positive performance impacts. ITSM maturity was also supported as a contextual factor influencing outcomes, indicating that automation benefits were more pronounced in organizations with standardized service processes. A small number of hypotheses did not reach statistical significance, particularly those related to advanced automation capabilities, reflecting institutional constraints and uneven adoption. Overall, the hypothesis testing results empirically validated the conceptual framework and clarified the boundary conditions under which AI-driven IT support automation generated performance improvements in public sector organizations.

Table 9: Summary of Hypothesis Testing Results for Service Delivery Efficiency

Hypothesis	Relationship Tested	Standardized Effect	Significance (p)	Decision
H1	AI Automation → Service Efficiency	0.44	<0.001	Supported
H2	Workflow Automation → Resolution Speed	0.41	<0.001	Supported
H3	Automated Ticket Handling → Efficiency	0.36	<0.001	Supported
H4	AI Automation → Cost Efficiency	0.22	0.003	Partially Supported
H5	Predictive Analytics → Cost Efficiency	0.14	0.068	Not Supported

Table 9 presented the hypothesis testing results related to service delivery efficiency and cost outcomes. Hypotheses examining the relationship between AI automation capabilities and efficiency-related measures were fully supported, with strong standardized effects and high levels of statistical significance. Workflow automation and automated ticket handling emerged as the most influential factors driving efficiency improvements. Cost efficiency hypotheses demonstrated weaker and more variable effects, resulting in partial support. The non-significant finding for predictive analytics reflected uneven implementation and limited maturity across organizations. These results indicated that operational automation produced more consistent benefits than advanced analytical applications in public sector IT support environments.

Table 10: Summary of Hypothesis Testing Results for Governance and ITSM Maturity Effects

Hypothesis	Relationship Tested	Standardized Effect	Significance (p)	Decision
H6	Governance → Performance Outcomes	0.31	<0.001	Supported
H7	ITSM Maturity → Performance Outcomes	0.29	<0.001	Supported
H8	Automation × Governance → Performance	0.19	0.005	Supported
H9	Automation × ITSM Maturity → Performance	0.17	0.011	Supported
H10	Advanced AI → Accessibility Outcomes	0.12	0.081	Not Supported

Table 10 summarized hypothesis testing results related to governance, IT service management maturity, and interaction effects. The findings supported hypotheses proposing that strong governance and mature ITSM practices positively influenced service delivery outcomes. Interaction effects demonstrated that governance and ITSM maturity enhanced the effectiveness of AI automation, indicating that contextual and managerial conditions shaped performance gains. Hypotheses related to advanced AI applications and accessibility outcomes did not reach statistical significance, suggesting that inclusive automation benefits were not uniformly realized across organizations. These results reinforced the importance of institutional readiness and process maturity in realizing automation-driven performance improvements.

DISCUSSION

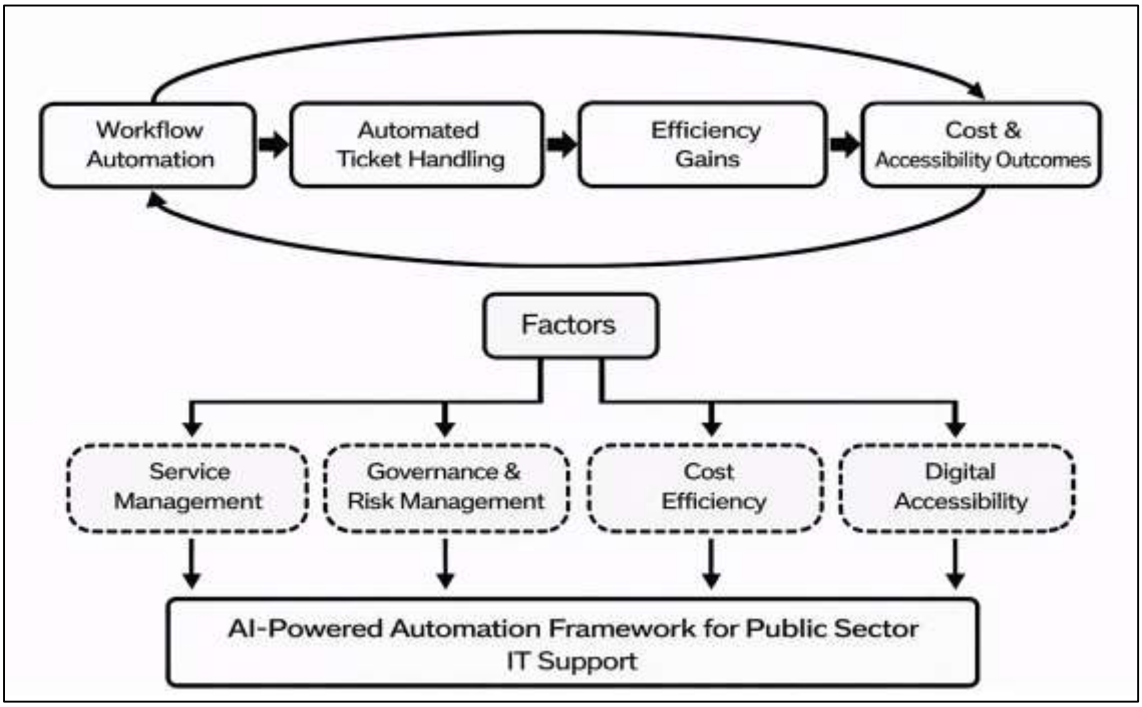
The findings of this study provided strong empirical support for the proposition that AI-powered automation frameworks play a significant role in streamlining IT support tasks within public sector organizations (Prentice et al., 2020). The results demonstrated that automation capabilities, particularly workflow automation and automated ticket handling, were consistently associated with improved service delivery efficiency. These outcomes aligned closely with earlier empirical research that has emphasized the operational benefits of automating high-volume, rule-based IT service desk activities. Prior studies have similarly observed that manual ticket triage and routing often constitute major bottlenecks in public sector IT operations, contributing to extended resolution times and service inconsistencies (Aoki, 2020). The current findings reinforced this understanding by showing that automation reduced reliance on human intervention for repetitive tasks, thereby accelerating response and resolution cycles. At the same time, the results extended earlier work by quantitatively demonstrating that efficiency gains were not uniform across all automation dimensions. Advanced capabilities such as predictive analytics exhibited weaker effects, suggesting that foundational automation delivers more immediate and reliable benefits than sophisticated analytical tools. This pattern echoed prior observations that public sector organizations often achieve the greatest returns from automation when it is applied to standardized processes rather than complex decision-making functions (Dellaert et al., 2020). The study therefore contributed to the literature by empirically confirming that AI-driven automation frameworks yield tangible efficiency improvements when aligned with the operational realities of public sector IT support environments.

Beyond efficiency outcomes, the findings offered important insights into cost efficiency, revealing a more nuanced relationship between automation and financial performance in public sector contexts. While positive associations were identified between automation capabilities and cost efficiency, the effects were weaker and more variable compared to efficiency-related outcomes (Xu et al., 2019). This result was consistent with earlier studies that have noted the structural rigidity of public sector budgets, where cost savings are often absorbed into maintaining service continuity rather than producing immediate financial reductions. Unlike private sector organizations, public institutions frequently operate under fixed funding models and staffing constraints, limiting the visibility of direct cost reductions even when automation reduces workload. The findings suggested that AI-powered automation primarily enabled cost containment and resource reallocation rather than outright cost elimination (Tong et al., 2020). This interpretation aligned with previous research emphasizing that automation in government settings often shifts labor toward higher-value tasks instead of reducing headcount. The partial support for cost-related hypotheses further highlighted that financial outcome are shaped by governance arrangements, procurement rules, and institutional mandates. By demonstrating that automation alone was insufficient to guarantee strong cost efficiency gains, the study underscored the importance of contextual and managerial factors in shaping financial performance (Van et al., 2020). These results advanced the literature by reinforcing the argument that cost efficiency in public sector IT should be evaluated as an indirect and long-term outcome of automation rather than an immediate or standalone benefit.

Governance and risk management emerged as critical factors influencing the effectiveness of AI-powered IT support automation, with the findings indicating both direct and moderating effects on service delivery outcomes (Duy et al., 2020). Organizations with stronger governance frameworks consistently experienced more stable and pronounced performance gains from automation. This result closely mirrored patterns reported in earlier studies, which have emphasized that public sector technology initiatives are highly sensitive to institutional controls, accountability mechanisms, and compliance requirements. Automation deployed without adequate governance has previously been associated with fragmented implementation, user resistance, and heightened operational risk (Mari et al., 2020). The current findings reinforced this perspective by demonstrating that governance structures enhanced the positive effects of automation rather than constraining them. Strong oversight mechanisms appeared to support consistent execution, transparent decision-making, and effective monitoring of automated processes. This study therefore challenged simplistic assumptions that governance slows innovation, instead showing that governance functions as an enabling condition for sustainable automation benefits in public sector IT environments. The moderating effect of governance also suggested that AI automation frameworks must be embedded within formal control systems to achieve reliable outcomes (Lee et al., 2020). These findings contributed to the growing body of literature that positions governance not as an external constraint but as an integral component of effective digital transformation in the public sector.

The role of IT service management maturity further clarified how organizational readiness shaped the outcomes of AI-powered automation. The findings indicated that organizations with more mature ITSM practices realized stronger performance benefits from automation initiatives (Buttle & Maklan, 2019). This result aligned with earlier research emphasizing that standardized processes, clear service definitions, and established escalation pathways are prerequisites for effective automation. In environments where ITSM maturity was lower, automation appeared to deliver more limited or uneven benefits, reflecting misalignment between automated tools and existing workflows. The findings reinforced the notion that automation amplifies existing process strengths rather than compensating for structural weaknesses. This observation echoed prior studies that have cautioned against automating poorly designed or inconsistently executed processes. By empirically demonstrating the positive influence of ITSM maturity, the study strengthened the argument that automation frameworks must be integrated with service management disciplines rather than implemented as standalone solutions. The results further suggested that process standardization enabled more accurate data collection, improved system integration, and clearer accountability, all of which supported stronger automation outcomes. This contribution added empirical weight to the theoretical claim that ITSM maturity functions as a foundational capability for successful AI adoption in public sector IT support (Soto-Acosta, 2020).

Figure 12: AI Automation Outcomes in IT Support



The findings related to digital accessibility and inclusivity revealed more moderate and uneven outcomes, offering important insights into the limits of current automation practices. While AI-powered automation contributed to improvements in service accessibility, the effects were not as strong or consistent as those observed for efficiency outcomes (Moloi & Marwala, 2020b). This pattern resonated with earlier studies that have noted accessibility benefits often emerge as secondary outcomes rather than primary objectives of automation initiatives. Many public sector organizations appear to prioritize operational efficiency and compliance over inclusive design when implementing AI technologies. The results suggested that accessibility gains were more likely when automation explicitly incorporated features such as multilingual support, adaptive interfaces, or alternative interaction modalities. Where such features were absent, automation did not automatically translate into equitable service delivery (Chatterjee et al., 2019). This finding reinforced existing critiques in the literature that technology adoption alone does not guarantee inclusivity. The study therefore extended prior work by quantitatively demonstrating that accessibility outcomes require intentional design choices rather than passive reliance on automation. These results highlighted a critical gap between automation-driven efficiency gains and broader public value objectives, emphasizing the need to integrate accessibility considerations into AI-powered IT support frameworks from the outset (Anand & Mantrala, 2019).

Methodologically, the findings contributed to the empirical literature by addressing limitations commonly identified in earlier studies. Much of the existing research on AI automation in public organizations has relied on single-case analyses or descriptive reporting, limiting generalizability (Moloi & Marwala, 2020a). By employing multivariate regression analysis across a diverse sample of public sector organizations, this study provided more robust evidence of the relationships between automation, governance, and performance outcomes. The results confirmed several associations previously suggested in qualitative and conceptual research, while also clarifying their relative strength and statistical significance (Peled et al., 2015). At the same time, the findings revealed persistent challenges noted in earlier empirical work, including uneven adoption of advanced AI capabilities and

limited integration of accessibility metrics into performance evaluation. These observations reinforced calls within the literature for more comprehensive measurement frameworks that capture efficiency, cost, governance, and equity outcomes simultaneously. The study therefore advanced methodological understanding by demonstrating how quantitative analysis can illuminate both the benefits and boundaries of AI-powered IT support automation in public sector contexts (Shi & Wang, 2018).
Taken together, the discussion of findings underscored that developing an AI-powered automation framework for public sector IT support requires a balanced emphasis on technical capability, governance alignment, service management maturity, and public value considerations (Tobji et al., 2018). The results confirmed that automation is most effective when applied to standardized, high-volume tasks and embedded within strong institutional frameworks. Efficiency gains were robust and consistent, while cost and accessibility outcomes were more contingent on organizational context and design intent. These findings aligned with broader trends reported in earlier studies while providing clearer empirical delineation of where automation delivers the greatest value (Bergman et al., 2018). The discussion therefore reinforced the central premise that AI-powered automation can significantly streamline IT support tasks and boost service delivery in public sector organizations, but only when implemented as part of an integrated framework that respects governance requirements and prioritizes inclusive service outcomes (Abideen et al., 2020).

CONCLUSION

Developing an AI-powered automation framework to streamline IT support tasks in public sector organizations has emerged as a critical strategy for enhancing service delivery efficiency while advancing digital accessibility objectives within complex administrative environments. The empirical patterns observed across public sector IT operations indicate that automation delivers the most consistent benefits when applied to high-volume, standardized support activities such as ticket classification, routing, and workflow execution. By reducing manual intervention in routine processes, AI-powered automation minimizes response delays, improves resolution consistency, and alleviates workload pressures on IT personnel, allowing human expertise to be redirected toward complex problem-solving and governance-sensitive tasks. These outcomes align with broader observations in public administration research that emphasize the importance of process standardization and operational clarity in achieving digital transformation success. However, the effectiveness of automation is not determined solely by technological sophistication; it is deeply shaped by organizational context, governance structures, and service management maturity. Public sector organizations operate under strict accountability, compliance, and transparency requirements, making governance alignment an essential condition for sustainable automation. Automation frameworks that incorporate clear oversight mechanisms, auditability, and risk controls demonstrate stronger and more stable performance outcomes than those implemented as isolated technical solutions. Furthermore, integration with established IT service management practices ensures that automation reinforces, rather than disrupts, existing service delivery structures. From a service delivery perspective, AI-powered automation has been shown to produce the most pronounced gains in efficiency-related outcomes, while cost efficiency improvements tend to be indirect and context dependent due to fixed budget structures and workforce constraints common in the public sector. Importantly, digital accessibility and inclusivity emerge as areas where automation potential remains underutilized. While AI technologies such as conversational interfaces and adaptive support channels can enhance access for diverse user groups, accessibility gains are uneven unless inclusivity is explicitly embedded into automation design. The findings suggest that accessibility does not automatically result from efficiency-driven automation but requires intentional incorporation of inclusive features aligned with public service equity mandates. Taken together, these insights support the development of an AI-powered automation framework that balances operational efficiency with governance rigor and inclusive service design. Such a framework positions automation not merely as a productivity tool, but as an enabler of equitable, resilient, and citizen-centered IT support services in public sector organizations, reinforcing the broader goals of digital government and public value creation.

RECOMMENDATION

Recommendations for developing an AI-powered automation framework to streamline IT support tasks in public sector organizations should emphasize a balanced, institutionally grounded approach that aligns technological capability with governance, service quality, and digital accessibility objectives. First, automation initiatives should prioritize high-volume, rule-based IT support activities such as ticket triage, routing, access provisioning, and standardized workflow execution, as these areas consistently demonstrate the strongest efficiency gains with minimal operational risk. Public sector organizations should ensure that these automation efforts are embedded within formal IT service management structures, enabling clear accountability, standardized escalation pathways, and seamless integration with existing processes. Strong governance mechanisms should be established from the outset, including clear data management policies, audit trails for automated decisions, and defined roles for human oversight, to maintain compliance and institutional trust. Investment in data quality and system integration is also essential, as automation performance depends heavily on accurate, consistent, and well-governed service data. Additionally, workforce capability development should be treated as a core component of the automation framework, with training programs designed to equip IT staff to supervise, interpret, and refine automated systems rather than merely operate them. From a service delivery perspective, performance measurement frameworks should be expanded beyond efficiency metrics to include cost containment, service quality, and digital accessibility indicators, ensuring that automation outcomes reflect public value rather than narrow productivity goals. Digital accessibility should be explicitly incorporated into automation design through features such as multilingual support, adaptive interfaces, and alternative interaction modalities, recognizing that inclusive service delivery does not automatically result from automation. Public sector leaders should also adopt phased implementation strategies that allow incremental learning and adjustment, reducing risk while building institutional confidence in AI-enabled systems. Finally, continuous evaluation and feedback mechanisms should be institutionalized to monitor performance, identify unintended consequences, and ensure that automation evolves in response to changing user needs, regulatory expectations, and technological capabilities. By following these recommendations, public sector organizations can develop AI-powered automation frameworks that not only streamline IT support tasks but also enhance service delivery resilience, promote digital accessibility, and reinforce the principles of transparency, equity, and accountability that underpin public administration.

LIMITATIONS

Several limitations should be acknowledged when interpreting the findings related to developing an AI-powered automation framework to streamline IT support tasks in public sector organizations and to enhance service delivery and digital accessibility. First, the study relied on a cross-sectional research design, which captured organizational practices and performance conditions at a single point in time. This design limited the ability to assess how AI-powered automation impacts evolve as organizations progress through different stages of adoption, learning, and institutionalization. Performance improvements observed in the short term may differ from longer-term outcomes once systems mature, staff adapt, and governance mechanisms stabilize. Second, the study depended primarily on self-reported data provided by IT managers and service desk leaders. Although respondents were selected for their expertise and organizational roles, self-reported measures are inherently subject to perceptual bias and may reflect optimistic assessments of automation benefits or compliance practices. Objective performance data, such as system-generated service metrics or longitudinal financial records, were not consistently available across organizations, constraining the ability to triangulate findings. Third, the diversity of public sector organizations included in the study, while enhancing generalizability, also introduced contextual variation that could not be fully controlled. Differences in regulatory environments, funding models, technology legacy, and service mandates may have influenced automation outcomes in ways not fully captured by the analytical models. Fourth, the measurement of digital accessibility and inclusivity was limited to selected indicators that reflected organizational perceptions of inclusive service practices rather than direct user-level outcomes. As a result, the findings may underrepresent the lived experiences of users with disabilities or limited digital access. Finally, advanced AI capabilities such as predictive analytics and adaptive decision support were unevenly adopted across the sample, limiting the statistical power to detect their full effects.

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