



AI-Enabled Decision Support Systems for Service Operations and Analytical Modeling and IT Strategy Framework

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Abstract

This study examined the quantitative relationships among AI-enabled decision support system (AI-DSS) capability, IT strategy alignment, and measurable service operations performance using unit-level data from a data-intensive service organization. A cross-sectional explanatory design was applied with structured retrospective extraction of operational KPIs and AI-DSS system log indicators, combined with survey-based measurement of IT strategy alignment dimensions. The final dataset included 52 operational service units and 198 valid survey responses retained after screening from an initial pool of 214 responses (92.5% retention). AI-DSS capability was operationalized as a composite index (0–100) supported by indicators such as system-use frequency, recommendation viewing rate, decision latency, and forecasting accuracy. IT strategy alignment was measured using a composite index (1–5) based on data integration maturity, interoperability, governance strength, and workflow embedding. Service operations performance was measured through unit-level KPIs including average waiting time, service-level attainment, cost per transaction, and abandonment rate. Descriptive results indicated relatively high AI-DSS capability ($M = 71.6$, $SD = 11.4$) and moderate-to-high IT strategy alignment ($M = 3.84$, $SD = 0.52$), with the greatest dispersion observed in decision latency ($M = 26.4$ minutes, $SD = 13.2$). Regression analysis showed that AI-DSS capability was significantly associated with lower waiting time ($B = -0.021$, $p = 0.001$), higher service-level attainment ($B = 0.142$, $p = 0.005$), lower cost per transaction ($B = -0.016$, $p = 0.002$), and lower abandonment rate ($B = -0.071$, $p = 0.001$). IT strategy alignment demonstrated significant direct effects on waiting time ($B = -0.118$, $p = 0.025$), service-level attainment ($B = 1.87$, $p = 0.004$), and cost per transaction ($B = -0.091$, $p = 0.044$). Moderation analysis indicated significant interaction effects for waiting time ($B = -0.0062$, $p = 0.005$), service-level attainment ($B = 0.041$, $p = 0.020$), and cost per transaction ($B = -0.0049$, $p = 0.009$), confirming that IT strategy alignment strengthened the operational impact of AI-DSS capability. Overall, the findings supported an integrated analytical modeling and IT strategy framework in which AI-DSS capability functioned as a direct performance driver and IT strategy alignment acted as both an independent predictor and an amplifying condition for operational outcomes.

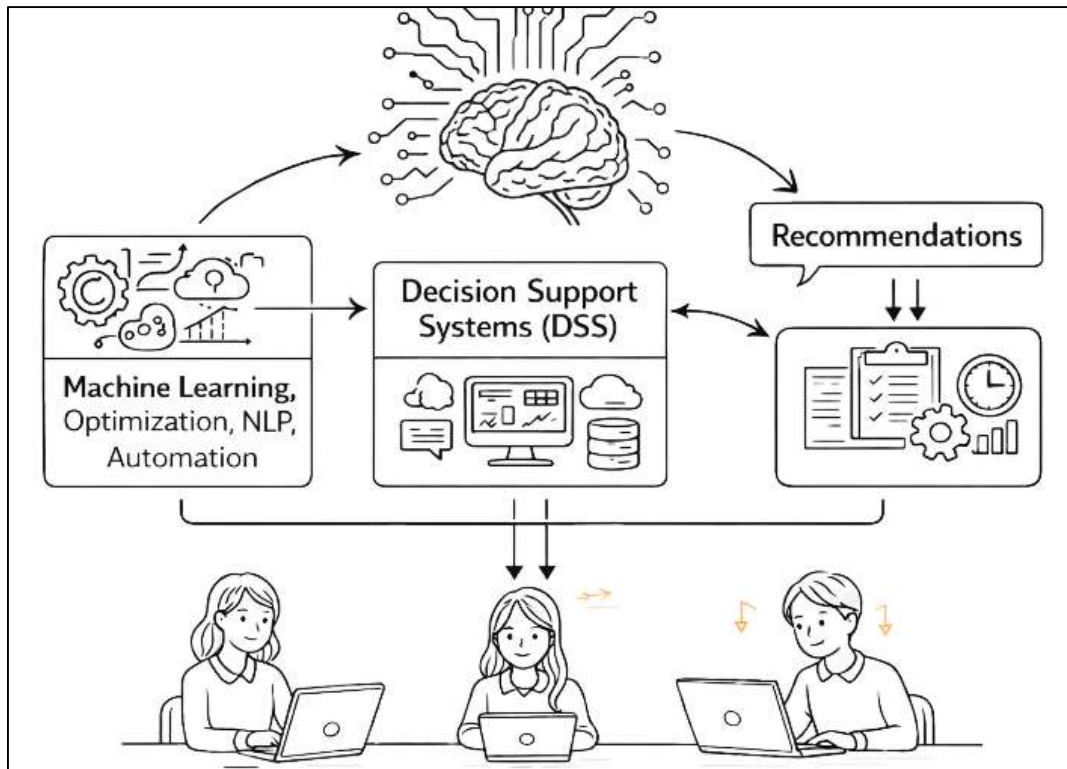
Keywords

AI-Enabled Decision Support, Service Operations Performance, IT Strategy Alignment, Operational Analytics Modeling, Quantitative Regression Analysis;

INTRODUCTION

Artificial intelligence (AI) is generally defined as the ability of computational systems to perform tasks that require human-like intelligence, including learning from data, recognizing patterns, reasoning under uncertainty, and producing recommendations for action (Sai Praveen, 2024). In organizational environments, AI is commonly operationalized through machine learning, optimization, natural language processing, and intelligent automation, all of which contribute to improved analytical capacity and faster interpretation of complex information (Arora, Vats, et al., 2023).

Figure 1: AI-Enabled DSS in Service Operations

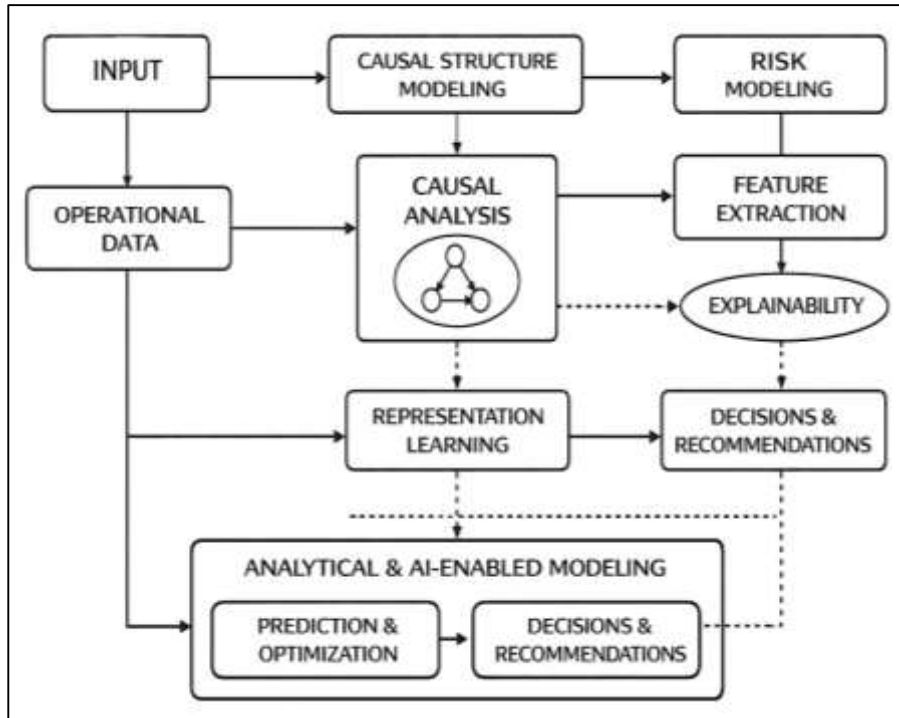


Decision support systems (DSS) are computerized information systems designed to assist managers and operational decision-makers in analyzing problems, evaluating alternatives, and selecting appropriate courses of action. DSS typically combine data management, analytical modeling, and user-oriented interfaces to support decision processes, particularly in semi-structured contexts where human judgment and quantitative evidence must be integrated. Service operations refer to the design and management of processes that deliver intangible value to customers, including scheduling, queue management, workforce allocation, service capacity planning, customer interaction management, and performance monitoring. Unlike manufacturing systems, service operations are characterized by customer involvement in the production process, variability in demand and service time, and the difficulty of storing service capacity (Ward, 2023). These features create operational complexity and elevate the importance of timely, data-driven decisions. AI-enabled decision support systems extend traditional DSS by incorporating adaptive learning, predictive analytics, and intelligent decision logic that can update recommendations based on changing operational conditions. In quantitative research, AI-enabled DSS are treated not only as technological tools but also as measurable systems whose performance can be evaluated through statistical testing, model estimation, and operations research metrics. The relevance of definitions is foundational because the title emphasizes both analytical modeling and IT strategy, requiring conceptual clarity about how algorithms, decision structures, and service delivery processes connect (Zdravković et al., 2022). A rigorous introduction begins by defining these constructs in measurable terms so that variables, modeling assumptions, and operational metrics can later be formalized. This framing also establishes the scope of service operations as a domain where

operational efficiency, responsiveness, and customer outcomes depend heavily on decision quality. The integration of AI into DSS introduces a shift from static reporting toward dynamic recommendation systems, where decision logic becomes partially automated and evidence-driven. Such systems are increasingly studied as socio-technical mechanisms where models, data, users, and organizational structures interact. A quantitative study in this area therefore needs to treat AI-enabled DSS as both an analytical artifact and an operational capability embedded in service systems (Loftus et al., 2022). Service operations frequently involve decision-making under uncertainty, with demand variability, time sensitivity, and customer behavior shaping outcomes. Decisions such as staffing levels, routing, appointment scheduling, capacity reservation, and service recovery require balancing efficiency with service quality. The complexity is intensified by the fact that service demand often fluctuates across hours, days, and seasons, while customer expectations remain consistently high (Wu & Shang, 2020). In many service industries, operational performance is evaluated through measurable indicators such as waiting time, throughput, service-level compliance, customer satisfaction, abandonment rate, and cost per transaction. These indicators are interdependent, meaning that improving one metric may create trade-offs in another. Quantitative decision-making approaches provide structured methods for analyzing such trade-offs through models, optimization routines, simulation, and statistical inference. Traditional decision support systems contributed to service operations by enabling reporting, what-if analysis, and rule-based planning (Ouanes & Farhah, 2024). However, the increasing scale and speed of service systems, including digital service platforms and omnichannel environments, require decision tools that can learn from historical patterns and respond to real-time signals. AI-enabled DSS address this requirement by combining predictive modeling with optimization and automated recommendation logic. For example, predictive models can estimate arrival rates, customer churn likelihood, or expected service times, while optimization models translate these estimates into actionable staffing plans or scheduling decisions. Quantitative modeling becomes essential because service environments produce large volumes of operational data, including transaction logs, customer interactions, sensor-based operational signals, and digital trace data (Schmitt, 2023). These data sources enable the estimation of models that connect operational inputs to outcomes, allowing organizations to evaluate whether AI-enabled DSS improves performance relative to baseline decision methods. The analytical emphasis in service operations also arises from the cost of poor decisions. Understaffing increases waiting time and abandonment, while overstaffing increases labor cost and reduces productivity. Poor routing increases travel time and reduces service coverage, while inaccurate forecasting leads to resource shortages or idle capacity. These consequences are measurable and thus align naturally with quantitative evaluation (Kim & Seo, 2023). The integration of AI into DSS further expands the decision space by introducing automated learning and adaptation, which can improve accuracy and reduce the time required for human decision cycles. A quantitative introduction must therefore position AI-enabled DSS as a response to measurable operational complexity, not merely as a technological innovation. The focus on analytical modeling implies that the paper will examine how models represent service processes and how decision rules derived from models affect operational outcomes. This approach aligns with the idea that service operations performance is not improved by data alone but by the transformation of data into structured decision logic (Finkelstein et al., 2024). As service systems grow in scale and customer expectations intensify, quantitative decision support becomes a central mechanism for ensuring consistency, efficiency, and operational resilience. Analytical modeling refers to the development of mathematical, statistical, and computational representations of real-world systems to explain behavior, estimate relationships, and optimize outcomes. In service operations, analytical models commonly include queuing theory, stochastic process modeling, forecasting models, simulation, linear and nonlinear optimization, and multi-criteria decision analysis (Arora, Gupta, et al., 2023). These models provide a formal structure for representing service demand, service capacity, customer flow, and operational constraints. Decision support systems traditionally relied on deterministic models and managerial rules to guide operational decisions. AI-enabled DSS expand analytical modeling by incorporating learning-based approaches such as regression-based prediction, classification models, probabilistic estimation, reinforcement learning, and hybrid model architectures. A key concept is that AI does not replace analytical modeling but

becomes part of a broader modeling ecosystem. Predictive models estimate uncertain inputs, and optimization models convert these estimates into recommended actions. This integration is especially relevant in service operations where uncertainty is a defining feature. For example, forecasting demand for call centers, hospitals, and logistics services involves estimating arrival patterns, service time distributions, and cancellation behavior (Khalifa et al., 2024).

Figure 2: Analytical AI Decision Support Framework



AI-based forecasting methods can improve accuracy by incorporating nonlinear relationships, high-dimensional features, and real-time signals. Once demand is estimated, optimization models allocate resources, schedule staff, and manage capacity to satisfy service-level constraints. Another modeling function of AI-enabled DSS is anomaly detection and operational monitoring. Service systems generate continuous performance signals, and AI models can detect deviations from normal conditions, enabling timely corrective decisions. Analytical modeling also supports decision evaluation by enabling counterfactual analysis, where alternative policies are tested through simulation or statistical inference (Khalid et al., 2024). In quantitative research, the effectiveness of AI-enabled DSS can be evaluated using measurable outcomes such as reduction in waiting time, improvement in forecasting accuracy, reduction in cost, or improvement in service compliance. The modeling foundation must therefore be framed as a measurable system of inputs, transformations, and outputs. Inputs include operational data, customer data, and contextual signals. Transformations include predictive modeling, optimization, and decision logic. Outputs include recommended actions, decision explanations, and performance impacts. The analytical modeling dimension in the title signals that the study will not treat AI as a black box but will emphasize the measurable mechanisms through which decision support is generated (Kovari, 2024). This matters because service organizations require transparency and reliability, especially in regulated environments such as healthcare, finance, and public services. Analytical modeling also enables generalization: models can be tested across service contexts, compared using statistical metrics, and validated through performance evaluation. In quantitative studies, model performance is assessed through accuracy, precision, recall, error metrics, robustness measures, and operational utility metrics. The analytical modeling component thus becomes the bridge between AI capabilities and operational decision-making, allowing researchers to formalize how AI-enabled DSS contributes to service efficiency and customer outcomes (Leoni et al., 2024).

IT strategy refers to the set of organizational decisions and governance structures that align information

technology resources with business objectives, operational needs, and competitive positioning. In service operations, IT strategy shapes how data is collected, stored, integrated, secured, and transformed into operational intelligence (Huang et al., 2023). AI-enabled decision support systems require more than algorithm development; they depend on the strategic design of data pipelines, enterprise architecture, system interoperability, and governance. Without a coherent IT strategy, AI-enabled DSS may produce fragmented insights that cannot be operationalized at scale. Service organizations often operate across multiple systems, including customer relationship management platforms, enterprise resource planning systems, workforce management tools, ticketing systems, and digital channels. AI-enabled DSS must integrate these sources to generate accurate recommendations. IT strategy determines whether data standards exist, whether system interfaces are available, and whether real-time processing is feasible (Sarcia, 2023). Another critical element is data governance, which defines roles, responsibilities, access controls, data quality standards, and compliance mechanisms. Service industries frequently handle sensitive customer data, making privacy and security essential operational requirements. AI-enabled DSS also raises issues of accountability and auditability, particularly when recommendations influence customer outcomes. IT strategy therefore provides the organizational infrastructure for responsible decision support deployment. In addition, service organizations require scalable computing resources for model training, inference, and real-time analytics. IT strategy determines whether these capabilities are developed internally, outsourced, or implemented through cloud-based services (Antoniadi et al., 2021). This affects cost, flexibility, and performance reliability. Another strategic factor is change management and user adoption. Decision support systems succeed when managers and frontline staff trust recommendations and integrate them into workflows. IT strategy influences training programs, user interface design, and organizational readiness for AI-based decision support. From a quantitative research perspective, IT strategy can be conceptualized as a measurable construct reflected in system maturity, integration level, governance strength, and operational alignment. The title's emphasis on an IT strategy framework implies that the paper will formalize how strategic technology alignment supports or conditions the performance of AI-enabled DSS (Vold, 2024). In service operations, where decisions are executed rapidly and customer experiences are immediate, the operationalization of AI-enabled DSS depends on the stability and responsiveness of IT infrastructure. System downtime, poor integration, or delayed data flows can degrade decision accuracy and reduce operational effectiveness. Therefore, IT strategy becomes a foundational layer that determines whether analytical models can be translated into practical decision support. This makes IT strategy an essential element of the framework, not as a managerial abstraction but as a measurable determinant of system performance. The introduction must therefore position IT strategy as a core enabler that shapes the reliability, scalability, and operational value of AI-enabled decision support in service contexts (Gudigantala et al., 2023).

The international significance of AI-enabled decision support systems in service operations arises from the global expansion of service economies, the digitization of customer interaction, and the increasing reliance on data-driven operational management. Services account for a dominant share of economic activity in many regions, including North America, Europe, Asia, and emerging markets. In this global context, service operations have become central to national productivity, public welfare, and organizational competitiveness (Danish & Senju, 2023). AI-enabled DSS is relevant internationally because service organizations face similar operational challenges across countries: fluctuating demand, labor constraints, cost pressures, customer expectations, and the need for operational transparency. In healthcare services, decision support influences patient flow, resource allocation, and scheduling. In financial services, decision support influences risk monitoring, fraud detection, and customer service efficiency. In logistics and transportation, decision support influences routing, delivery scheduling, and capacity planning. In hospitality and tourism, decision support influences pricing, staffing, and service personalization. In public services, decision support influences resource allocation, queue management, and citizen engagement. The global relevance of AI-enabled DSS also stems from the internationalization of service delivery through digital platforms (Johnson, 2023). Many services are now delivered across borders through remote support centers, digital banking, telemedicine, and online customer service. These systems generate large-scale operational data, enabling AI-enabled DSS

to improve performance through analytics and automated decision logic. International service operations also involve multilingual and culturally diverse customer interactions, increasing the complexity of operational decision-making. AI-enabled DSS can support such complexity by integrating customer segmentation, behavioral analytics, and service customization into operational models (Haque & Arifur, 2021; Hu & You, 2024; Rauf, 2018). From a quantitative research standpoint, the international significance of AI-enabled DSS can be reflected in measurable improvements in operational performance, service equity, and resource utilization across diverse contexts. However, the global adoption of AI-enabled DSS is not uniform, making cross-context analysis relevant. Differences in IT infrastructure, regulatory requirements, workforce skills, and data availability influence how AI-enabled DSS is implemented (Rashid & Sai Praveen, 2022; Zaman et al., 2021). This creates a strong rationale for analytical modeling and IT strategy frameworks that can generalize across settings while remaining adaptable. Service operations in developing economies often operate under resource constraints and may benefit from efficient decision support systems that reduce waste and improve service access. Service operations in advanced economies may focus on real-time optimization, customer experience, and service differentiation. Across both contexts, decision support remains a measurable driver of performance (Omoge et al., 2022; Ratul & Subrato, 2022; Rifat & Jinnat, 2022). The international significance therefore lies in the ability of AI-enabled DSS to serve as a structured operational capability applicable across multiple service sectors and geographic regions. The study's framing must therefore reflect global relevance by treating service operations as a universal domain of measurable decision challenges and by positioning AI-enabled DSS as a system that can be evaluated quantitatively across varied service environments (Faysal & Bhuya, 2023; Habibullah & Aditya, 2023). A quantitative paper in this domain requires explicit attention to measurement, operationalization, and statistical evaluation. AI-enabled decision support systems in service operations can be evaluated through measurable outcomes, including operational efficiency metrics, service quality indicators, and decision accuracy measures. Efficiency metrics may include throughput, average handling time, service completion time, utilization rates, and cost per service unit (Mukhopadhyay et al., 2024). Service quality metrics may include waiting time, service-level compliance, customer satisfaction scores, complaint rates, and customer retention. Decision accuracy measures may include forecasting error, classification accuracy, detection rates, and optimization objective improvements. Quantitative evaluation also requires comparing AI-enabled DSS performance to baseline decision approaches, such as manual planning, rule-based systems, or traditional DSS models. This comparison can be structured through experimental designs, quasi-experimental designs, statistical modeling, or simulation-based evaluation. Analytical modeling plays a central role in establishing measurable relationships between decision inputs and outcomes (Iyer, 2021; Jahangir & Mohiul, 2023; Rashid et al., 2023). For example, statistical models can estimate the relationship between demand forecasts and staffing decisions, while optimization models can quantify how recommended decisions influence cost and service quality. In addition, AI-enabled DSS can be evaluated based on system-level characteristics such as latency, scalability, stability, and interpretability. In service operations, latency is critical because decisions often need to be made in real time (Khaled & Mosheur, 2023; Mostafa, 2023). Scalability matters because service organizations may operate across multiple locations, channels, and customer segments. Stability matters because model performance must remain reliable under changing conditions. Interpretability matters because service decisions often involve accountability and require decision-makers to understand why recommendations are generated (Amiri, 2024; Md & Sai Praveen, 2024; Rifat & Rebeka, 2023). A quantitative framework must also consider the interaction between system recommendations and human decision-making. AI-enabled DSS may generate recommendations, but managers may override them based on experience or contextual knowledge. This introduces a measurable human-in-the-loop dynamic where decision outcomes depend on both algorithmic suggestions and human judgment. Such interactions can be modeled statistically, for example through moderation or mediation frameworks, or evaluated through adoption and compliance metrics. The IT strategy component also becomes measurable in quantitative research (Begum, 2025; Kuziemski & Misuraca, 2020; Sai Praveen, 2024). Variables such as data integration maturity, governance strength, system interoperability, and user training intensity can be measured through surveys, maturity indices,

or organizational indicators. These variables can then be tested as predictors of AI-enabled DSS effectiveness. The title's emphasis on an analytical modeling and IT strategy framework implies that the paper will treat decision support as a multi-layer system where operational outcomes depend on both model performance and organizational capability. Therefore, the introduction must establish a measurement logic where constructs can later be translated into variables, hypotheses, and statistical tests. The value of this framing is that it enables objective evaluation, replication, and generalization (Jiang et al., 2023). A quantitative introduction must therefore position AI-enabled DSS not as a conceptual promise but as a measurable operational system whose performance can be assessed through rigorous empirical methods.

The combined focus on analytical modeling and IT strategy indicates a need for an integrated framework that explains how AI-enabled decision support systems operate within service organizations. Analytical modeling represents the technical core of decision support, including forecasting, optimization, simulation, and machine learning (Alshahrani et al., 2024). IT strategy represents the organizational and infrastructural layer that enables models to function reliably at scale. Service operations represent the application domain where decisions translate into measurable outcomes affecting efficiency and customer experience. An integrated framework must therefore connect these elements into a coherent structure that supports quantitative analysis. At the analytical level, decision support systems can be conceptualized as pipelines where data inputs are transformed into predictions, recommendations, and decision rules. At the operational level, these recommendations influence staffing, scheduling, capacity planning, and service recovery decisions. At the strategic IT level, the quality of data pipelines, integration architecture, governance, and deployment infrastructure determines whether analytical outputs can be delivered to decision-makers in usable form (Hannah et al., 2021). The framework must also incorporate feedback loops. Service operations generate performance data, which can be used to update predictive models and refine decision rules. This creates a measurable learning cycle where system performance improves or degrades depending on data quality, operational changes, and user adoption. The framework orientation is essential because service operations are complex systems where outcomes are influenced by multiple interacting factors. For example, a highly accurate forecasting model may not improve service outcomes if staffing policies are rigid or if system recommendations are not implemented. Similarly, a strong IT infrastructure may not yield operational improvements if analytical models are poorly specified or not aligned with service process realities (Groesser & Jovy, 2016). An integrated framework enables quantitative testing of these relationships by defining measurable constructs and specifying how they interact. For example, model accuracy can be tested as a predictor of operational performance, while IT integration maturity can be tested as a moderating factor. Workforce adoption can be tested as a mediator between system recommendations and operational outcomes. Such a framework supports a quantitative research design that is capable of explaining not only whether AI-enabled DSS improves service performance but also how and under what organizational conditions improvements occur. International significance strengthens the relevance of such a framework because service organizations across regions differ in infrastructure, governance, and operational constraints. A generalizable framework provides a structured way to evaluate AI-enabled DSS across diverse contexts while maintaining analytical rigor (Van Calster et al., 2019). The introduction therefore establishes the conceptual foundation for a quantitative study by defining key constructs, clarifying measurement logic, and positioning the framework as a structured integration of analytical modeling and IT strategy within service operations. This creates a coherent basis for later sections of the paper, including model development, variable specification, and empirical testing, while remaining aligned with the constraints of the introduction format (Si et al., 2018).

The objective of this quantitative study is to develop and empirically operationalize a structured framework that explains how AI-enabled decision support systems improve measurable performance in service operations through the combined influence of analytical modeling capability and IT strategy alignment. The study aims to translate the broad concept of AI-enabled decision support into a set of quantifiable components that can be tested using statistical and analytical methods, focusing on the measurable pathways through which data-driven recommendations are generated, delivered, and

executed within service environments. A primary objective is to specify the analytical modeling layer of AI-enabled decision support by identifying measurable indicators of predictive accuracy, optimization effectiveness, model responsiveness, and decision rule quality as they relate to operational outcomes such as waiting time, throughput, service-level compliance, utilization, and operating cost. A second objective is to define and measure the IT strategy layer as a set of organizational and infrastructural capabilities, including data integration maturity, system interoperability, governance strength, computational readiness, and workflow embedding, and to assess how these capabilities condition the effectiveness of AI-enabled decision support in real operational settings. A third objective is to test the statistical relationships between AI-DSS analytical performance and service operations performance, using quantitative modeling approaches that allow estimation of effect sizes, significance levels, and explanatory power across service contexts. A fourth objective is to examine the implementation pathway from AI-generated recommendations to operational execution by measuring decision adoption rates, human override patterns, decision latency, and alignment between recommended and executed actions, treating these as quantifiable mechanisms that influence observed outcomes. A fifth objective is to construct a coherent analytical modeling and IT strategy framework that is suitable for quantitative validation across multiple service sectors, allowing consistent measurement of constructs and enabling comparative evaluation of AI-enabled decision support effectiveness under different operational conditions. Collectively, these objectives position the study to produce a measurable account of how AI-enabled decision support functions as an operational system, how its analytical outputs are shaped by IT strategy, and how these combined factors relate to observable performance in service operations using quantitative evidence and statistically testable relationships.

LITERATURE REVIEW

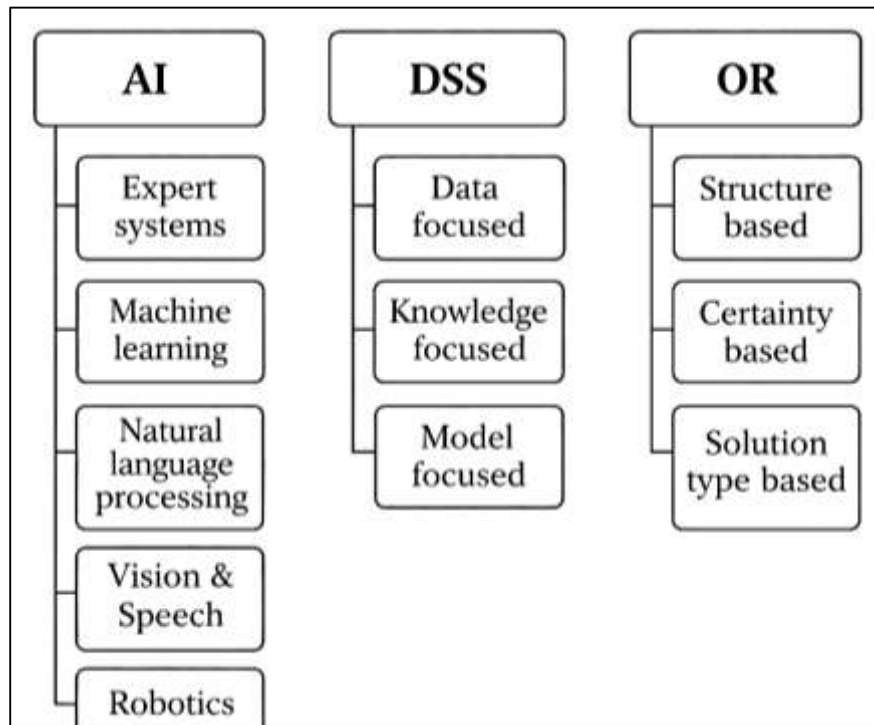
This literature review synthesizes quantitative research on AI-enabled decision support systems (AI-DSS) in service operations with a specific focus on measurable performance effects, analytical modeling structures, and the enabling role of IT strategy. The section is organized to support a quantitative paper by mapping prior studies into testable constructs, measurable variables, and model-driven relationships that can be statistically evaluated. Rather than presenting broad thematic commentary, the review is structured around empirical evidence on how AI-based prediction, optimization, simulation, and algorithmic recommendation systems influence operational metrics such as waiting time, throughput, capacity utilization, service-level attainment, cost efficiency, and decision accuracy. The review also clarifies how IT strategy components—data integration, interoperability, governance, digital infrastructure maturity, and workflow embedding—function as measurable conditions that shape the effectiveness of AI-DSS in real service settings. By organizing the literature into analytically distinct clusters, the section creates a logical foundation for hypothesis development, variable operationalization, and the selection of quantitative methods suitable for model testing, including regression-based inference, structural modeling, quasi-experimental evaluation, and simulation-optimization validation. The scope includes service sectors with high decision frequency and high data intensity, such as healthcare, contact centers, banking, logistics, hospitality, and public services, emphasizing studies that report quantifiable effects and replicable evaluation metrics.

AI-Enabled Decision Support Systems in Service Operations

The quantitative foundations of AI-enabled decision support systems (AI-DSS) in service operations are grounded in a systems-based perspective that defines these technologies as structured, measurable pipelines transforming inputs into operational outcomes. In service environments, AI-DSS can be operationally defined as integrated analytical systems that collect data from multiple sources, apply predictive or prescriptive models, generate structured recommendations, and influence measurable performance outcomes (Alsolbi et al., 2023; Jahangir, 2025; Md Syeedur, 2025). This input–model–recommendation–outcome configuration reflects a process-oriented understanding of decision support, where each stage of the system can be evaluated in terms of observable metrics. Rather than conceptualizing AI as an abstract technological capability, contemporary service operations research frames AI-DSS as performance-linked infrastructures embedded within operational workflows. In sectors such as healthcare, banking, hospitality, and logistics, AI-DSS platforms influence queue management, demand forecasting, workforce allocation, and service personalization. Their

effectiveness is therefore assessed through operational improvements such as reduced waiting times, improved capacity utilization, enhanced service accuracy, and greater responsiveness (Funda & Francke, 2024). This quantitative framing aligns AI-DSS with broader operations management theory, positioning it as a decision augmentation mechanism that enhances managerial judgment through structured analytics. By emphasizing measurable transformations between data inputs and service outcomes, the literature increasingly treats AI-DSS as a socio-technical system whose value is demonstrated through operational efficiency gains, consistency improvements, and decision traceability across service environments (Zdravković et al., 2022).

Figure 3: AI DSS OR Conceptual Framework



To enable rigorous empirical analysis, AI-DSS in service operations is increasingly dimensionalized into quantifiable components that capture distinct aspects of system performance. Four core dimensions frequently emerge in the literature: prediction quality, optimization quality, decision latency, and recommendation reliability. Prediction quality refers to the accuracy and robustness of forecasting or classification outputs generated by machine learning models, particularly in demand estimation, risk assessment, or customer behavior prediction (Amin, 2025; Towhidul & Rebeka, 2025; Qinxia et al., 2021). Optimization quality captures the effectiveness of prescriptive algorithms in allocating resources, scheduling services, or balancing workloads to achieve operational objectives such as cost minimization or throughput maximization (Ratul, 2025; Rifat, 2025). Decision latency represents the time interval between data acquisition and actionable recommendation delivery, which is particularly critical in high-velocity service environments such as emergency care or digital banking. Recommendation reliability reflects the consistency and stability of AI-generated advice across different operational contexts and time periods. By decomposing AI-DSS into these measurable components, researchers can distinguish between analytical precision and operational responsiveness (Kondapaka et al., 2023; Azam, 2025; Tasnim, 2025). This multidimensional approach prevents oversimplification and allows scholars to isolate which aspects of AI-DSS performance most strongly influence service efficiency, customer satisfaction, and decision-maker trust. Such dimensionalization also facilitates cross-industry comparisons by providing standardized constructs that can be empirically validated across diverse service settings.

Quantitative research on AI-DSS effectiveness employs a layered measurement strategy that integrates model-level, operational-level, and decision-level indicators. At the model level, performance is assessed using established evaluation metrics such as mean absolute error, root mean square error, classification accuracy, precision-recall balance, and area under the receiver operating characteristic curve (Russell et al., 2023; Zaheda, 2025a, 2025b). These indicators quantify the predictive or classification strength of AI models but do not, on their own, capture operational value. Consequently, service operations research links model performance to operational metrics such as waiting time, service cycle time, throughput, capacity utilization, staff workload balance, and resource idle rates. These indicators reflect tangible improvements in system efficiency attributable to AI-guided decisions. Beyond operational outputs, decision-level metrics are increasingly incorporated to evaluate behavioral responses to AI recommendations. Override rates measure how frequently managers or frontline staff reject algorithmic advice, while adoption rates assess the degree of reliance on AI-generated recommendations. Additional measures such as compliance rates, intervention frequency, and escalation rates provide insight into the interaction between human decision-makers and AI systems (Loftus et al., 2022). By integrating these three measurement layers, researchers construct comprehensive evaluation frameworks that capture both technical performance and organizational impact. This multi-level measurement strategy strengthens causal inference by connecting algorithmic accuracy to operational improvements and behavioral acceptance within service systems.

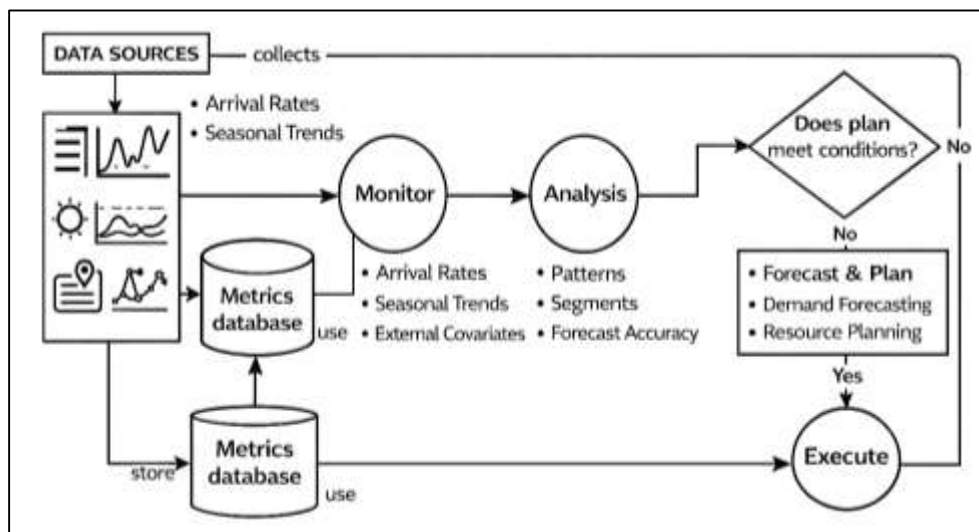
The empirical study of AI-DSS in service operations requires careful specification of the unit of analysis, as system impacts may vary across organizational and temporal scales. Research commonly adopts branch-level or facility-level units when examining multi-site service organizations such as banks, hospitals, or retail chains. In such contexts, performance comparisons across branches enable assessment of AI-DSS-driven efficiency gains in localized operational environments. Facility-level analysis is particularly relevant for capacity planning, workforce scheduling, and demand forecasting applications (Molina et al., 2024). Team-level units are employed when AI-DSS influences collaborative decision processes, such as call center staffing teams or medical triage groups. At a more granular level, transaction-level analysis captures individual service encounters, allowing researchers to measure AI-driven variations in response time, accuracy, or customer satisfaction per interaction. Time-window analysis, such as hourly, daily, or weekly intervals, is used to evaluate temporal stability and responsiveness of AI systems under fluctuating demand conditions. Selecting an appropriate unit of analysis enhances measurement validity and ensures that performance outcomes align with the scope of AI intervention (Ward, 2023). By explicitly defining analytical levels, quantitative studies can more accurately attribute performance changes to AI-DSS implementation, control for contextual heterogeneity, and strengthen the reliability of empirical conclusions in service operations research.

Service Demand and Workload Forecasting

Predictive analytics for service demand and workload forecasting is widely positioned in the literature as a foundational capability for improving operational stability in high-variability service systems. Empirical studies consistently emphasize that demand forecasting accuracy depends on the inclusion of both classical time-dependent signals and context-sensitive drivers. Core variables frequently used in service forecasting include arrival rate patterns, intra-day and intra-week seasonality, holiday effects, and long-run trend shifts (Zdravković & Panetto, 2022). Beyond these baseline signals, many service industries incorporate promotional activity, marketing campaigns, pricing changes, and product bundling effects because they can create short-lived demand surges that traditional models fail to capture. Another widely supported stream of evidence highlights the value of customer segmentation variables, including service type, customer class, channel (in-person, phone, mobile), and behavioral history. These segmentation signals are especially relevant in banking, healthcare, and ride-hailing, where demand is not only seasonal but also shaped by heterogeneous customer groups and service urgency levels. In operational terms, forecasting is treated not simply as predicting volume but as anticipating workload, which depends on service complexity, average handling time, and the distribution of service categories. The literature also notes that service demand is often influenced by external covariates such as weather, traffic conditions, local events, or epidemiological trends, particularly in transportation and hospital admissions forecasting (Amiri, 2024). Collectively, these findings show that modern service forecasting increasingly relies on rich, multi-source variables rather

than single-series historical counts, reflecting a shift toward context-aware predictive analytics embedded within operational decision systems.

Figure 4: Predictive Service Demand Forecasting



The literature on service demand forecasting shows an evolution from classical time-series methods toward machine learning and hybrid modeling approaches. Traditional time-series models remain widely applied in service operations because of their interpretability and strong baseline performance under stable seasonality (Ouanes & Farhah, 2024). However, empirical comparisons repeatedly show that supervised machine learning models often outperform purely statistical methods when demand patterns are shaped by nonlinear interactions among covariates, customer segments, and short-term operational disruptions. Supervised learning approaches such as tree-based models, kernel-based regression, and neural network architectures are frequently applied in call center forecasting, ride-hailing demand estimation, and hospital workload prediction because they can incorporate high-dimensional inputs and automatically detect complex patterns. Hybrid models, which combine time-series decomposition with machine learning components, are also strongly represented in the literature because they preserve seasonality modeling while enabling nonlinear learning for irregular demand drivers (Khalifa et al., 2024). A notable trend in recent service forecasting research is the adoption of probabilistic forecasting, where models generate uncertainty estimates rather than single-point predictions. This approach is particularly valued in staffing and scheduling decisions because operational risk depends not only on expected demand but also on variance and tail outcomes. By shifting from deterministic forecasting toward probabilistic outputs, service operations research increasingly aligns forecasting models with decision-making under uncertainty, strengthening the link between predictive analytics and operational planning quality (Kovari, 2024).

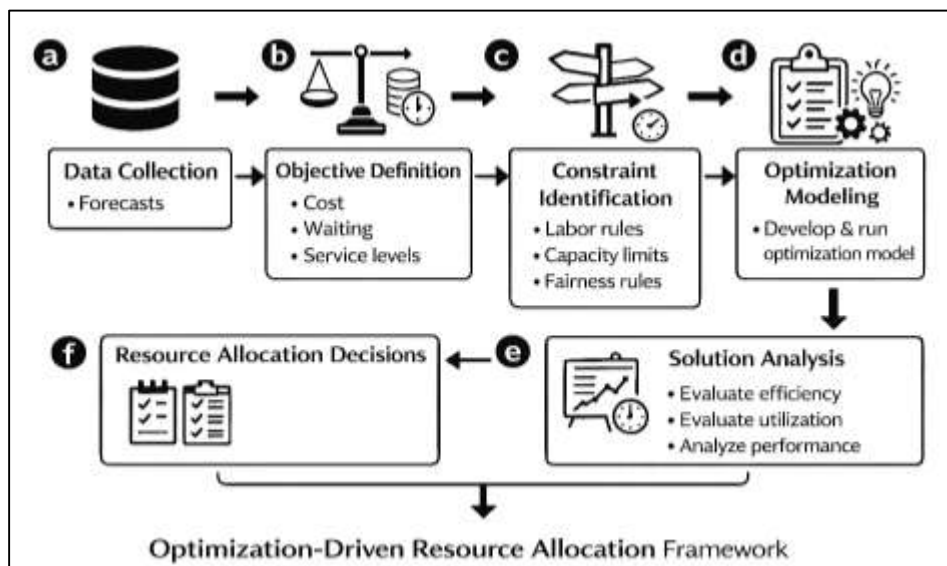
Quantitative evidence on the benefits of AI-based forecasting in services is largely derived from comparative evaluation designs that benchmark machine learning models against traditional forecasting baselines. Across service industries, studies commonly evaluate performance using structured experimental protocols that include train-test splits across time, rolling forecasting origins, and cross-validation approaches adapted for time-dependent data. Benchmark comparisons typically include naïve seasonal baselines, classical time-series models, and operational heuristics, which serve as reference points for evaluating AI models (Mhapsekar et al., 2024). Many studies report that supervised machine learning and hybrid approaches produce measurable accuracy gains, especially in environments with high volatility, complex segmentation, or strong covariate effects such as promotions and weather. Importantly, recent literature also emphasizes that forecasting accuracy should not be evaluated only through average error but also through error distributions, because service operations are sensitive to peak underestimation and extreme demand shocks. As a result, researchers increasingly analyze bias, variance, tail errors, and asymmetric costs of under-forecasting

versus over-forecasting. Another key insight is that evaluation design strongly affects reported performance, and rigorous studies often include multiple forecasting horizons and multi-level aggregation (hourly, daily, weekly) to reflect operational planning needs (Chaturvedi & Verma, 2023). Overall, the literature provides consistent quantitative evidence that AI-driven forecasting improves predictive accuracy under realistic evaluation settings, but it also highlights that the credibility of reported gains depends on robust benchmarking, time-aware validation protocols, and transparent error distribution analysis.

Optimization-Driven Resource Allocation in Services

Optimization-driven resource allocation is widely documented in the service operations literature as a central mechanism for converting limited capacity into reliable, cost-efficient service delivery. Across empirical and model-based studies, the optimization scope typically spans workforce scheduling, appointment allocation, routing, and capacity reservation, each addressing a distinct but connected source of operational inefficiency (Sarcia, 2023).

Figure 5: Optimization-Driven Resources Allocation Framework



Workforce scheduling research shows how optimization improves coverage alignment with time-varying demand while managing shift structures and break policies that are common in call centers, hospitals, retail branches, and field services. Appointment allocation studies, often grounded in healthcare and professional services, treat time slots as scarce capacity and allocate them to balance throughput, waiting time, and access targets while accounting for service-time variability and no-show behavior. Routing optimization is prominent in last-mile services, home healthcare, and field maintenance, where travel time, dynamic requests, and geographic dispersion create high operating costs and performance variability. Capacity reservation models extend these ideas to settings where demand arrives before service is delivered and customers or clients must be assigned to limited “reservable” capacity, including outpatient capacity planning and revenue management contexts (Sarcia, 2023). The common empirical theme across these areas is that optimization does not only reduce cost; it restructures how capacity is exposed to demand, often improving utilization without sacrificing service levels. As a result, the literature frequently treats optimization as a measurable operational intervention whose value is assessed through efficiency, utilization, and customer-facing performance indicators rather than only through mathematical elegance (Al-Doghman et al., 2022).

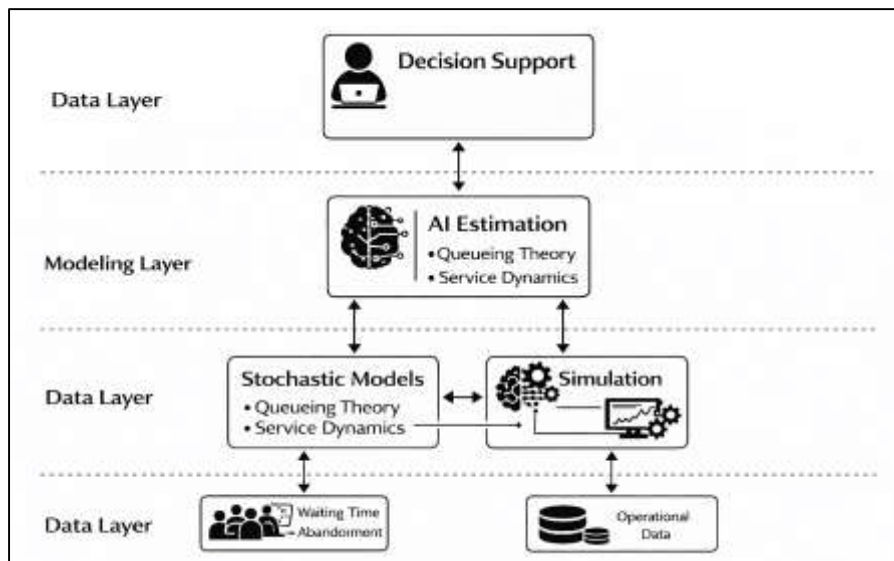
A consistent finding across service optimization research is that objective structures are rarely single-minded; instead, they formalize operational trade-offs among cost, waiting, and service-level targets. Cost-focused formulations typically represent labor, overtime, outsourcing, travel, and capacity-expansion penalties, reflecting the controllable expense categories that service managers monitor. Waiting-time minimization is common in appointment systems and queueing-driven environments because delays directly impact customer experience, abandonment, and perceived quality (Gizelis et

al., 2023). Service-level maximization objectives translate organizational commitments into measurable targets such as response-time compliance, fill-rate-like service thresholds, or time-window adherence in routing. What the literature demonstrates most clearly is that these objectives interact: minimizing cost can increase delay risk during demand peaks; minimizing waiting can require higher staffing buffers; maximizing service levels may increase travel costs or reduce fairness if the system “chases” performance at the expense of equitable allocation. To reconcile these tensions, many studies adopt multi-criteria structures, weighted penalties, or hierarchical priorities that reflect how service organizations make decisions in practice. Another recurring insight is that objective choice shapes implementation success: models aligned with operational scorecards and frontline realities are more likely to be accepted and sustained (Mejia & Rawat, 2024). Thus, optimization research in services increasingly reports not only the objective used, but also the managerial rationale, the performance indicators affected, and the operational conditions under which the objective produces stable benefits. Service optimization studies repeatedly emphasize that constraints often dominate model design because feasibility and legitimacy depend on respecting operational rules and human considerations. Labor rules and contracts impose limits on hours, rest times, overtime, weekend allocations, and break patterns, making workforce scheduling a constraint-rich problem where feasible solutions must reflect policy and compliance requirements (Kim & Seo, 2023). Skill-mix constraints are also critical: service systems frequently require coverage by competency type, licensing level, language, or specialization, and ignoring these dimensions can inflate theoretical utilization while degrading real performance. Shift structures and task interdependencies further restrict flexibility, particularly in hospitals and multi-skill contact centers where teams must be simultaneously staffed across roles. Capacity limits appear across appointment systems and reservation settings, where physical rooms, equipment, and provider time create hard caps; these caps are often intertwined with stochastic service durations, creating practical “soft” limits that must be buffered. Importantly, fairness constraints have gained attention as service organizations face retention pressures and reputational expectations; constraints that balance undesirable shifts, distribute overtime equitably, or prevent systematic disadvantage to certain customer groups are used to avoid hidden harms even when they reduce the theoretical optimum (Manser Payne et al., 2021). The literature treats these constraints as more than technical details: they operationalize trust, workforce sustainability, and policy adherence. Consequently, many studies report how constraint choices affect solution quality, utilization, and stakeholder acceptance, highlighting that implementable optimization is frequently a negotiation between efficiency and organizational legitimacy.

Modeling and Simulation in AI-DSS

Queueing theory provides a quantitative lens for understanding congestion dynamics in service systems and remains central to how AI-enabled decision support systems model operational uncertainty (Gupta et al., 2022). The literature consistently treats expected waiting time as a primary indicator of congestion because it captures both customer experience and the operational burden created by demand exceeding instantaneous capacity. Service time distribution is another foundational element, since variability in handling time strongly shapes queue length growth, idle time, and the stability of staffing plans. In many service settings, the distributional form of service time matters as much as its average because long-tail service durations can generate persistent congestion even when average load appears manageable. Abandonment probability is widely used in call centers, emergency departments, and digital service queues where customers may leave when delays exceed tolerance thresholds; this measure is important because it links congestion to lost demand, revenue leakage, and perceived service quality (Gupta et al., 2022). Studies across applied queueing research emphasize that these metrics are interdependent: changes in service variability influence waiting time, and waiting time influences abandonment, which in turn alters effective arrival rates and observed congestion. Within AI-DSS contexts, these queueing measures become actionable performance targets and diagnostic signals, guiding decisions such as staffing adjustments, dynamic prioritization rules, and capacity reservation policies. Overall, the literature shows that queueing metrics remain a core quantitative interface between uncertainty in demand and observable service performance, providing a structured foundation for decision support in congested systems (Kovari, 2024).

Figure 6: AI Queuing Decision Support Framework



Stochastic modeling research in services frequently relies on process assumptions that make uncertainty mathematically tractable while retaining operational realism. Markov models are commonly used to represent service systems where state transitions capture customer progression through stages such as waiting, service, transfer, and exit, enabling analysis of stability, congestion, and policy impacts. Poisson process assumptions remain prominent for modeling arrivals, particularly in foundational work on telephony, call centers, and transaction-based services, because they provide a workable baseline for random demand in large populations (Tyler & Jacobs, 2020). However, applied research also emphasizes that many service environments are characterized by nonstationary arrivals, where demand intensity changes predictably across hours, days, and seasons, and unpredictably under shocks such as promotions, outages, or disease outbreaks. This has led to a broad literature on time-varying or nonstationary queueing models that better reflect real-world service demand patterns. Additionally, service systems often include time-dependent service rates due to fatigue, learning, shift changes, and multitasking, which further complicates classical assumptions. The literature therefore treats stochastic modeling as an empirical modeling exercise rather than a purely theoretical one, encouraging parameter estimation, diagnostic checks, and sensitivity analysis to ensure assumptions remain defensible (Zhang et al., 2024). In AI-DSS, these stochastic representations are especially valuable because they provide interpretable structures linking operational policies to performance under uncertainty, enabling decision-makers to explore trade-offs between efficiency, delay risk, and service stability.

Simulation has long been used in service operations to evaluate queueing and stochastic models when analytical solutions are infeasible or when system complexity exceeds closed-form tractability. Discrete-event simulation is the most common design, representing arrivals, queue formation, service starts, service completions, and abandonments as event sequences that evolve over time. This approach is particularly effective for multi-stage service systems, priority queues, appointment systems, and environments with time-varying arrivals, where interactions among resources and customers produce emergent congestion patterns (Amann et al., 2020). Monte Carlo experiments are widely used to quantify uncertainty by repeatedly sampling stochastic processes and estimating distributions of outcomes such as waiting time, queue length, utilization, and abandonment. Scenario testing is also strongly represented, allowing researchers to assess performance under alternative staffing levels, routing rules, appointment allocation strategies, and prioritization policies. The literature shows that simulation is often used not just for prediction but for policy evaluation, enabling “what-if” experiments that estimate operational impacts before real-world implementation. In AI-DSS contexts, simulation supports decision-making by translating uncertain inputs into operational risk profiles,

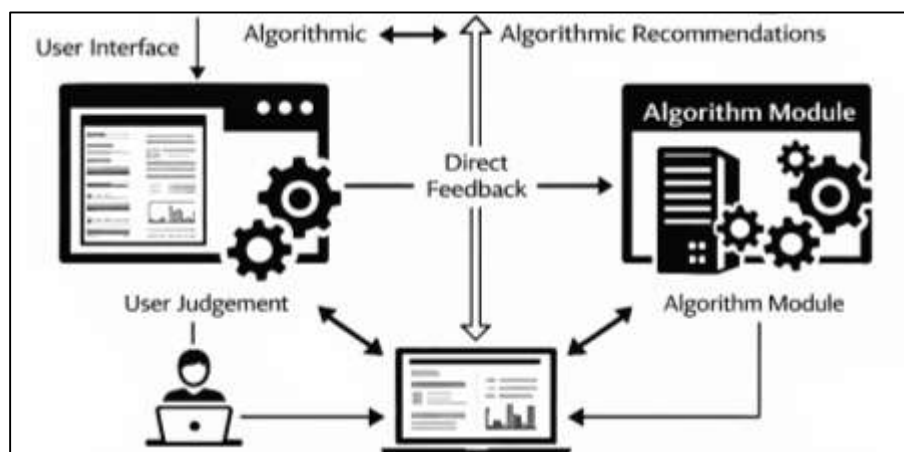
highlighting the probability of service-level violations, the frequency of extreme congestion events, and the expected cost of mitigation strategies (Amann et al., 2020). Thus, simulation is treated as a quantitative experimentation environment, bridging theoretical queueing insights with complex operational realities and supporting evidence-based resource planning.

A recurring emphasis in the literature is that queueing and simulation models are only as credible as their calibration and validation procedures. Goodness-of-fit testing is commonly applied to validate distributional assumptions for service times, interarrival processes, and abandonment behavior, particularly when empirical data exhibit overdispersion, burstiness, or heavy tails (Gadewadikar & Marshall, 2024). Calibration procedures typically involve estimating parameters from operational datasets and tuning models to reproduce observed patterns such as time-of-day congestion, average wait times, service completion rates, and queue length distributions. Confidence intervals and uncertainty bounds are used to express the reliability of simulation outputs, especially when results are used for staffing or capacity decisions that carry cost and service risks. In AI-DSS, a prominent integration pathway involves using AI-based estimation to feed queueing or simulation models with more accurate parameters, such as time-varying arrival intensities, customer patience distributions, or conditional service-time predictions based on customer segment and service type. This integration allows queueing models to remain interpretable while benefiting from AI’s ability to learn nonlinear patterns and context effects (Chung et al., 2019). The literature increasingly positions this combined approach as a practical compromise: AI improves parameter realism, while queueing and simulation provide transparent operational reasoning and policy evaluation under uncertainty. As a result, validated hybrid pipelines that couple machine learning estimation with stochastic modeling are frequently presented as robust quantitative foundations for AI-enabled decision support in congested service systems.

Human-in-the-Loop Decision Support in Services

Human-in-the-loop decision support in services is increasingly studied as a measurable interaction system in which algorithmic recommendations and human judgment jointly shape operational outcomes. The literature operationalizes adoption behavior through variables such as adoption rate, compliance, override rate, and time-to-decision, treating these as observable indicators of how decision support is used in practice rather than how it is intended to function (Sanikhani et al., 2019). Adoption rate is commonly measured as the proportion of eligible decisions in which users accept and act on system recommendations, while compliance is treated as the extent to which recommended actions are followed without modification. Override behavior is analyzed as an active rejection or alteration of algorithmic advice and is often interpreted as a signal of mistrust, contextual mismatch, or expertise-based correction. Time-to-decision is used to quantify decision latency, reflecting the cognitive and workflow impact of decision support tools on frontline or managerial work.

Figure 7: Human-in-the-Loop Service Decision Support



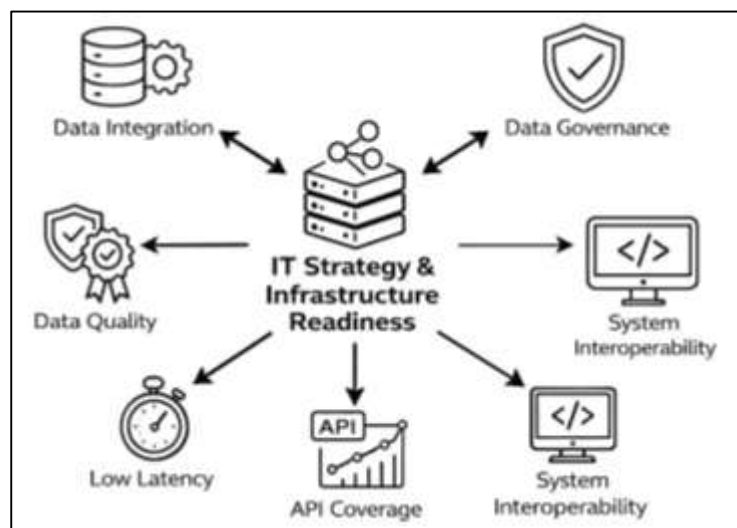
Across service settings such as call centers, healthcare triage, retail operations, and banking approvals, these variables enable researchers to connect the presence of decision support to measurable behavioral responses (Ali et al., 2022). Importantly, studies highlight that these measures are interdependent: high adoption may coexist with high override in environments where recommendations are used as starting points rather than final actions, while low latency may reflect either efficiency gains or superficial compliance. This quantitative framing supports a more realistic evaluation of human-in-the-loop systems by shifting attention from algorithmic performance alone to how decision support changes operational behavior under real service constraints (de Hond et al., 2022).

The evidence base for human-in-the-loop decision support is strongly shaped by experimental and quasi-experimental research designs that estimate causal effects under operational conditions. A/B testing is frequently used in digital service environments, where algorithmic interfaces or recommendation formats can be randomized across users, teams, or time windows. This approach supports measurement of how changes in recommendation presentation, confidence cues, or explanation detail affect adoption, overrides, and decision speed (Gadewadikar & Marshall, 2024). In settings where randomization is impractical, difference-in-differences designs are used to compare outcome changes across treated and untreated service units before and after decision support deployment, allowing researchers to control for common temporal shocks. Interrupted time series methods are also prominent, particularly in healthcare and public service systems, because they can detect structural shifts in productivity or error rates coinciding with the introduction of decision support while accounting for pre-existing trends. Across these designs, studies emphasize the importance of separating immediate novelty effects from sustained behavioral change, as adoption may initially rise due to attention and training but later stabilize or decline when workflow pressures increase (Chung et al., 2019). Moreover, research often reports heterogeneity of effects across teams and contexts, showing that measured improvements depend on baseline performance, decision complexity, and organizational readiness. Overall, these quantitative designs provide a structured foundation for evaluating whether observed improvements in service performance reflect the decision support tool itself, complementary process changes, or broader operational variation (Elkiran et al., 2019).

Digital Infrastructure as Quantitative Moderators

The literature increasingly frames IT strategy and digital infrastructure not merely as background conditions for analytics adoption, but as measurable moderators that shape whether data-driven systems translate into operational performance gains. In quantitative studies of digital transformation, infrastructure readiness is often treated as a capability layer that determines the speed, reliability, and scalability with which decision-support outputs can be embedded into workflows (Sanikhani et al., 2019).

Figure 8: IT Infrastructure and Governance Framework



This strand of research argues that organizations with mature integration architectures tend to achieve more stable performance improvements because data can move across service units with fewer delays and fewer reconciliation errors. In service environments, the performance effects of advanced analytics and AI are frequently contingent on the ability to combine operational, customer, and transactional data into unified datasets that support timely recommendations. Rather than attributing performance changes solely to model quality, the literature documents that infrastructure variables influence the completeness of input signals, the timeliness of decision cycles, and the consistency of deployment across units (de Hond et al., 2022). As a result, IT strategy is conceptualized as a measurable alignment of governance, architecture, and investment priorities that enables operational performance through standardized data pipelines and interoperable systems. Empirical research commonly compares outcomes across organizations and sites with different levels of infrastructure maturity and finds that higher readiness is associated with stronger and more reliable performance effects, whereas low readiness can produce fragmented adoption, inconsistent recommendations, and slower decision latencies that erode operational impact (Ai et al., 2017).

Quantitative research operationalizes IT maturity through variables that capture data integration maturity, system interoperability, and technical responsiveness. Studies frequently use integration indices reflecting the degree to which core systems are linked across departments, service channels, and customer touchpoints. Data quality scores are used to quantify accuracy, completeness, consistency, and timeliness of data, with many studies treating data quality as a necessary condition for reliable analytics-driven decisions (Mohammadi et al., 2021). API coverage is increasingly measured as a proxy for interoperability and modularity, reflecting how many internal and external systems can exchange data through standardized interfaces.

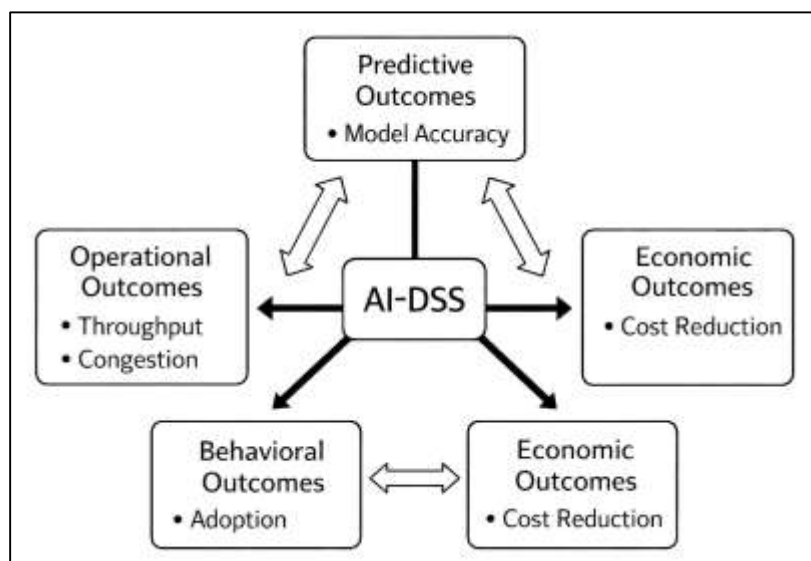
Latency is treated as an infrastructure performance variable because it captures the delay between data generation and its availability for decision making, which is particularly important in high-velocity service settings. Measurement approaches often combine survey-based constructs with system telemetry indicators, recognizing that managerial perceptions alone may not reflect actual integration performance. Telemetry indicators such as data refresh frequency, pipeline failure rates, processing time, and system uptime provide observable evidence of infrastructure functioning. The literature also notes that integration readiness is multi-dimensional: an organization may have high API coverage but low data quality, or strong internal integration but weak external interoperability (Aster et al., 2018). These empirical distinctions help explain why analytics outcomes vary across organizations even when similar predictive or optimization tools are deployed.

Data governance strength is consistently presented in the literature as a critical moderator of performance effects in digital systems, particularly where AI-enabled decision support depends on sensitive customer and operational data. Quantitative studies measure governance through variables such as access control rigor, stewardship role clarity, auditability of data flows, and compliance readiness for regulatory standards (Li & Huang, 2020). Access control maturity is often measured by the degree of role-based permissions, authentication strength, and consistency of enforcement across systems. Stewardship roles are assessed through whether accountable owners exist for datasets, definitions, and quality remediation processes, which directly affects whether data inconsistencies are corrected or allowed to persist. Auditability is measured through the presence of traceable logs, lineage tracking, and documented decision pathways, all of which increase reliability and reduce operational risk when automated recommendations are questioned. Compliance readiness is often quantified through policy adherence scores, frequency of audits, incident reporting maturity, or certification indicators, reflecting how well the organization can maintain lawful and ethical data practices (Li & Huang, 2020). The literature suggests that governance is not simply a constraint; it is also an enabling mechanism that increases stakeholder trust, reduces friction in data sharing, and supports scale-out of analytics across multiple service units. Where governance is weak, studies report higher risk of data silos, inconsistent definitions, and operational resistance, which can dilute the measurable performance benefits of advanced decision systems.

AI-DSS in Service Operations

Quantitative evaluation designs for AI-enabled decision support systems in service operations are increasingly organized around a multi-domain metrics taxonomy that separates predictive, operational, economic, and behavioral outcomes (Celik, 2023). The literature shows that predictive metrics are often treated as necessary but insufficient evidence because they capture model accuracy without demonstrating operational value. Operational outcomes are therefore emphasized to reflect how AI-DSS changes service performance, using indicators such as waiting time, throughput, utilization stability, service-level compliance, and congestion reduction. Economic outcomes extend evaluation into cost and value domains, including staffing cost variance, overtime exposure, capacity waste, revenue protection, and cost-to-serve reduction. Behavioral outcomes represent the human interaction layer, measuring adoption, override behavior, compliance, decision latency, and consistency across staff or teams (Chen & Lei, 2018). This taxonomy supports a layered view of evaluation in which AI-DSS can succeed technically but fail operationally if workflows resist adoption, or succeed operationally but deliver weak economic value if implementation costs outweigh gains. Across service sectors, research increasingly argues that strong evaluations link these outcome categories rather than reporting them separately, because service operations outcomes are shaped by complex interactions between model signals, operational constraints, and human choices. Moreover, studies highlight the importance of matching metric definitions to the operational setting, since identical indicators can represent different meanings across call centers, hospitals, banks, and platform-based services (Akhavan & Jalali, 2024). Overall, the literature positions metrics taxonomy as the backbone of credible AI-DSS evaluation, ensuring that claims of “improvement” are measurable across technical, operational, economic, and behavioral dimensions.

Figure 9: AI-DSS Multi-Domain Evaluation Framework



Validity concerns occupy a central position in the quantitative evaluation literature because service operations environments rarely allow clean experimentation without bias risks. Selection bias is frequently identified when AI-DSS is rolled out first to high-performing sites, digitally mature branches, or teams with stronger leadership, creating inflated estimates of system impact. Confounding is also common because AI-DSS adoption often coincides with training programs, staffing changes, policy updates, or process redesign, making it difficult to attribute observed performance changes to the system alone (Gupta et al., 2022). Temporal drift and nonstationarity further complicate inference because service demand patterns evolve over time due to seasonality, promotions, competitor actions, macroeconomic conditions, or public health shocks. This creates evaluation instability where a model that appears effective in one period performs differently later, and where operational KPIs shift due to

external conditions rather than system use. The literature emphasizes that service datasets are typically time-dependent, autocorrelated, and influenced by feedback loops, such as staffing changes affecting waiting time and abandonment, which then alter demand patterns (Magaya et al., 2024). As a result, rigorous evaluation designs often require explicit handling of temporal structure, drift detection, and pre-trend diagnostics. These validity threats explain why AI-DSS evaluation is increasingly treated as a causal inference problem rather than a simple performance comparison, pushing researchers to adopt methods that better isolate system effects from contextual variation (Higgins et al., 2023).

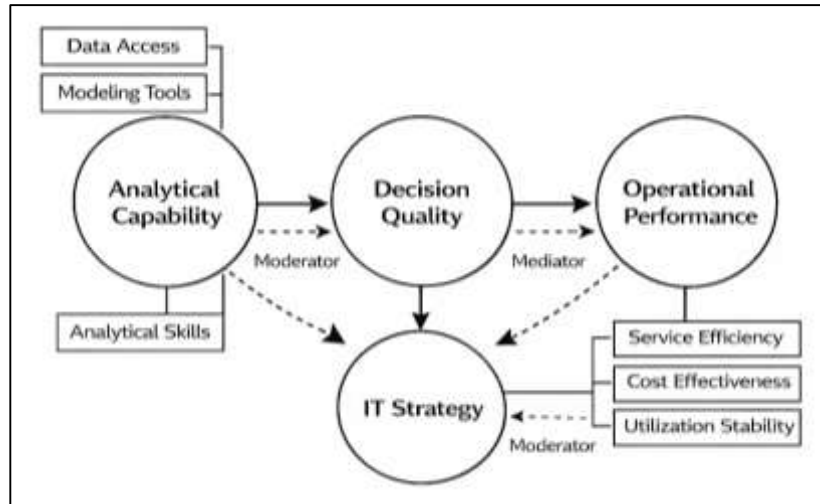
The literature highlights several preferred quantitative methods for evaluating AI-DSS in services, selected based on data structure and deployment constraints. Panel regression is widely used when multi-site service data are available across time, allowing analysts to control for unobserved site heterogeneity and estimate the relationship between AI-DSS adoption and service outcomes under repeated observations. Structural equation modeling and variance-based approaches such as PLS-SEM are frequently used when researchers evaluate latent constructs like perceived usefulness, trust, explainability, governance strength, and adoption intention alongside operational outcomes (Nimri et al., 2020). Causal inference methods are strongly represented in field evaluations where randomization is infeasible, including quasi-experimental approaches that leverage natural experiments, staggered rollouts, policy discontinuities, or matched comparisons across treated and untreated units. Time-series modeling is also prominent because service operations data often show strong seasonality, autocorrelation, and regime shifts, requiring models that can account for temporal dependencies when estimating impact. Across these methods, robust statistical testing is emphasized through careful model specification, diagnostics for multicollinearity and autocorrelation, and transparent reporting of uncertainty (Amann et al., 2020). The literature shows an increasing tendency to combine approaches, such as using causal inference to estimate operational impact while applying SEM to explain behavioral adoption mechanisms, thereby capturing both performance change and the human-technology drivers that produce it.

Robustness checks are presented in the literature as essential safeguards against overclaiming impact in AI-DSS evaluations. Placebo tests are commonly used to verify that estimated effects do not appear in periods before deployment or in outcomes that should not logically be affected, strengthening causal credibility (Cubric, 2020). Sensitivity analyses test whether conclusions hold under different assumptions, alternative control groups, missing data treatments, or definitions of adoption intensity. Alternative specifications are used to assess whether results depend on a particular functional form, time window, or exclusion rule, which is particularly important in service systems with volatile demand. Reporting standards increasingly emphasize effect sizes rather than relying solely on statistical significance, because small p-values may reflect large datasets rather than meaningful operational impact. Confidence intervals and uncertainty bounds are used to communicate practical risk, especially when decisions involve staffing budgets, service guarantees, or regulatory compliance (Smirnov et al., 2023). Replicability considerations appear as stronger expectations for transparent documentation of data preprocessing, variable definitions, validation protocols, and model selection criteria. The literature also encourages sharing evaluation code, reporting pre-trends and diagnostics, and clarifying deployment context to help others interpret generalizability. Taken together, these practices reflect a maturation of the AI-DSS evaluation field, where credible evidence is defined by rigorous validity controls, robust testing, and transparent reporting that supports replication across service contexts (Liu et al., 2021).

Integrated Analytical Modeling and IT Strategy Frameworks

The literature on integrated analytical modeling and IT strategy increasingly specifies causal frameworks that connect analytical capability to decision quality and, in turn, to operational performance outcomes. This structure is widely used in quantitative hypothesis-driven studies because it offers a clear sequence for modeling how analytics creates value in organizations, particularly in service operations where performance is sensitive to demand volatility and execution quality (Li & Little, 2023).

Figure 10: Integrated Analytical and IT framework



Analytical capability is commonly conceptualized as the organization’s ability to acquire data, transform it into usable information, and deploy advanced analytical techniques that produce actionable insights. Decision quality is treated as a measurable intermediate mechanism capturing whether decisions become more accurate, consistent, timely, and aligned with operational targets when analytics is embedded into workflows. Operational performance represents downstream outcomes such as service-level compliance, waiting time reduction, utilization stability, throughput improvement, and cost efficiency. The literature emphasizes that this chain is not purely technical: the transition from analytical capability to decision quality requires adoption and integration into decision routines, while the translation from decision quality to performance requires implementation consistency and alignment with operational constraints (Berniak-Woźny & Szelągowski, 2024). Quantitative research therefore uses integrated frameworks to test whether analytics improves performance indirectly through decision quality rather than assuming direct performance effects. By structuring models around this sequence, the literature provides a practical approach for hypothesis testing that allows researchers to isolate where value is created or lost, distinguishing between strong analytical outputs that fail to change decisions and decision improvements that do not translate into operational gains due to capacity, governance, or process limitations (Grossman, 2018).

IT strategy is frequently modeled as both a moderator and mediator within integrated analytical frameworks, reflecting evidence that infrastructure and governance conditions shape how effectively analytics-based systems are implemented and used. As a moderator, IT strategy is conceptualized as an enabling environment that strengthens or weakens the relationship between analytical capability and decision quality, or between decision quality and operational performance (Hannah et al., 2021). Organizations with higher infrastructure readiness, stronger interoperability, and more mature data governance tend to experience more consistent performance effects because decision support can be deployed at scale with fewer delays and fewer data inconsistencies. As a mediator, IT strategy is treated as a pathway through which analytical capability influences implementation effectiveness, such as system reliability, data availability, and integration into workflow tools. In this view, organizations may invest in analytics but realize performance gains only if those investments translate into improved digital infrastructure that supports real-time data flow, traceability, and controlled access (Mahmood et al., 2019). The literature also suggests that IT strategy can shape decision quality by enabling transparency and auditability, which increases trust and reduces resistance to analytics-driven recommendations. Quantitative studies frequently show that implementation effectiveness is not only a technical outcome but also a managerial one, affected by governance clarity, stewardship roles, training, and alignment between IT priorities and operational goals. By integrating IT strategy into analytical frameworks as moderator and mediator, the literature provides a more realistic model of how analytics produces value in service organizations under varying levels of digital readiness (Nalchigar et al., 2016).

A major methodological emphasis in quantitative framework literature is the explicit specification of measurable constructs and their indicators, often presented in variable dictionary style to support replicability and hypothesis testing. Analytical capability is typically operationalized through indicators such as data accessibility, integration maturity, tool availability, analytical skill resources, and model deployment frequency. Decision quality is frequently measured using indicators that capture accuracy improvements, consistency across decision-makers, reduced decision cycle time, reduced error rates, and alignment with service targets or policies (Nalchigar & Yu, 2018). Operational performance is measured through objective service KPIs such as waiting time, throughput, utilization rates, service-level attainment, customer satisfaction proxies, and cost variance indicators. For IT strategy and infrastructure readiness, measurable indicators include system integration indices, API coverage, data quality scores, latency measures, governance maturity ratings, and compliance readiness markers. The literature stresses that construct specification must match both theoretical meaning and empirical observability, avoiding overly abstract measures that cannot be reliably captured in operational data. Many studies combine survey-based indices for latent constructs such as perceived usefulness and governance clarity with telemetry indicators such as uptime, refresh frequency, and data pipeline stability to reduce common-method bias (Argelaguet et al., 2020). This alignment approach strengthens measurement validity by ensuring constructs are supported by multiple indicators and are consistent across contexts. As a result, the literature positions variable dictionary-style alignment as a key step in translating conceptual frameworks into testable models, especially when integrating analytics, human decision processes, and IT strategy conditions (Gray et al., 2019).

METHOD

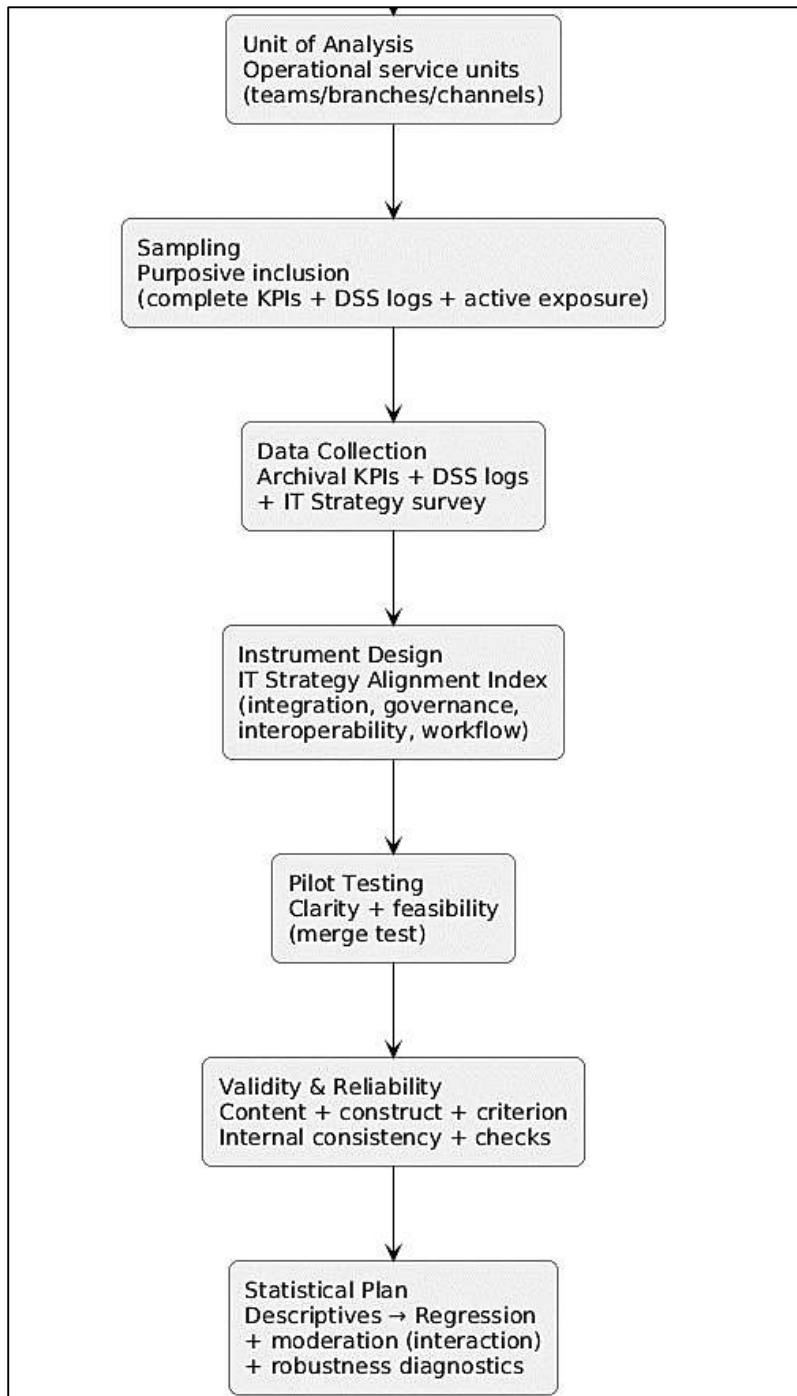
Research Design

This study was designed as a quantitative, explanatory research project that tested statistically specified relationships among AI-enabled decision support system capability, IT strategy alignment, and measurable service operations performance. The design was cross-sectional with structured retrospective extraction of operational metrics from organizational records over a fixed observation window, allowing the variables to be quantified consistently and modeled using inferential statistics. The study treated AI-enabled decision support as an organizational capability that could be measured through system use indicators and model performance outputs, while service operations outcomes were measured using objective operational KPIs routinely captured by service systems. The research design emphasized analytical modeling and IT strategy as complementary layers, where the analytical layer represented the performance of predictive and optimization components, and the strategy layer represented the maturity of integration, governance, and deployment readiness. The relationships were modeled using statistical estimation procedures to determine the magnitude and significance of direct effects and interaction effects, with explicit control variables included to reduce confounding. All methodological decisions were documented in a structured protocol so that measurement procedures, data cleaning, and statistical tests could be replicated.

Case Study Context

The empirical context was a data-intensive service organization operating standardized service delivery processes supported by digital transaction systems and workforce scheduling tools. The organization used an AI-enabled decision support system to generate operational recommendations such as workload forecasts, staffing plans, and service prioritization rules that were embedded into routine service management. The case setting included consistent operational definitions of service demand, service completion, queue states, and customer interaction events, enabling the extraction of objective performance indicators. The service environment experienced time-based demand fluctuations and operational constraints linked to staffing, capacity, and service-level requirements, which provided a suitable context for evaluating whether AI-enabled decision support outputs were associated with measurable improvements in operational performance. The organization maintained system logs for decision support usage and operational databases for service outcomes, which supported the integration of decision system indicators with KPI records. The context was treated as a bounded case for measurement consistency while still enabling statistical testing across multiple comparable operational units within the organization.

Figure 11: Methodology of this study



Unit of Analysis

The unit of analysis was the operational service unit, defined as a distinct service team, branch, facility department, or service channel that executed standardized processes and had independently recorded performance metrics. Each unit generated repeated operational events during the observation window, allowing aggregate indicators to be computed for demand, capacity utilization, service timeliness, and quality-related metrics. AI-enabled decision support usage and model-output measures were also computed at the same unit level to ensure alignment between explanatory and outcome variables. The unit-level approach enabled statistical testing across multiple units with comparable task structures while avoiding conflation of individual behavior with organizational system effects. Where necessary, unit-level controls were included for differences in workload volume, service complexity, and staffing

size to improve comparability.

Sampling

Sampling was performed using a purposive approach based on inclusion criteria that ensured each operational unit had consistent KPI recording, stable process definitions, and active exposure to the AI-enabled decision support system during the observation window. Units were included if they had complete operational records, identifiable DSS usage logs, and consistent service-level definitions across the measurement period. Units were excluded if their processes were newly launched, if KPI logging was inconsistent, or if the decision support system was not active or not accessible to supervisors during the period. The final sample represented multiple operational units within the same service organization to support cross-unit statistical comparison. Sample size adequacy for the multivariable models was evaluated using conventional rules for regression modeling, ensuring sufficient observations relative to the number of predictors, interaction terms, and control variables included in the statistical plan.

Data Collection Procedure

Data were collected through two coordinated streams consisting of archival extraction from operational information systems and structured survey measurement for IT strategy alignment constructs. Operational KPI data were extracted from service management platforms, including time-stamped service events, queue states, staffing records, and performance dashboards, and were aggregated into unit-level indicators for the observation window. AI-enabled decision support data were extracted from system logs and model-output repositories, capturing indicators such as frequency of recommendation generation, frequency of recommendation viewing, decision execution latency, and predictive model error metrics where available. IT strategy alignment and governance maturity were measured using a structured instrument completed by managers or IT-service coordinators linked to each operational unit, with responses matched to unit identifiers. After extraction, the datasets were merged using consistent unit codes and a common time window definition, followed by data cleaning procedures that addressed missingness, extreme outliers, and inconsistent timestamps. All transformations, aggregation rules, and cleaning steps were recorded to preserve auditability and facilitate reproducibility of the dataset used for statistical analysis.

Instrument Design

The instrument was designed to quantify IT strategy alignment as a multi-dimensional construct reflecting data integration maturity, interoperability, governance strength, workflow embedding, and infrastructure readiness. Items were written as clear operational statements aligned with observable organizational practices, and responses were captured using a fixed Likert-type scale to allow parametric analysis. The instrument also captured contextual controls such as perceived demand volatility, staffing constraint severity, and process standardization level to support model adjustment. Content coverage was structured to ensure that each dimension of IT strategy alignment could be operationalized into composite indices while maintaining internal consistency. The survey items were phrased to reflect the past measurement window and current operational state to reduce ambiguity, and wording was kept consistent across units to support comparability. Composite scores were calculated using standardized scoring rules, and higher scores represented stronger alignment and maturity.

Pilot Testing

Pilot testing was conducted with a small subset of operational units and respondents that met the inclusion criteria but were not part of the final analytical sample. The pilot focused on assessing clarity of item wording, response consistency, completion time, and the ability to map survey responses to unit identifiers without error. Pilot responses were analyzed to identify items with low variance, ambiguous interpretation, or redundancy across dimensions. Minor refinements were made to item wording to improve clarity and reduce double-barreled phrasing, and the final instrument structure was stabilized prior to full deployment. The pilot also tested the feasibility of merging survey data with archival KPI and log data, confirming that unit-level coding and time-window definitions produced consistent merged records.

Validity and Reliability

Validity was addressed through content validity, construct validity, and criterion-related validity procedures appropriate for a quantitative framework study. Content validity was supported by aligning instrument items to established dimensions of IT strategy and digital maturity constructs and by ensuring coverage of integration, governance, and workflow embedding elements relevant to AI-enabled decision support deployment. Construct validity was evaluated using factor-based techniques and internal consistency testing to confirm that items loaded onto expected dimensions and that composite indices represented coherent latent constructs. Criterion-related validity was examined by testing whether IT strategy alignment scores were associated with objective indicators of system integration and decision support usability derived from system logs where available. Reliability was assessed using internal consistency measures for each composite dimension and the overall IT strategy alignment construct, and acceptable thresholds were used to determine whether items should be retained. For archival KPI indicators, reliability was supported through standardized extraction rules, consistent aggregation windows, and cross-checking of KPI values against dashboard summaries to confirm accuracy. Data integrity checks were performed to ensure that KPI computation logic was consistent across all units included in the sample.

Tools

Data preparation and statistical analysis were performed using standard quantitative analysis software suitable for regression, causal modeling, and reliability testing. Spreadsheet tools were used for initial data reconciliation, unit coding verification, and preliminary descriptive summaries, while statistical software was used for data cleaning, model estimation, diagnostics, and visualization of residual patterns. Reliability analysis, factor validation, and composite score generation were computed using dedicated statistical routines. Model estimation included robust standard errors, multicollinearity diagnostics, and sensitivity checks implemented within the statistical software environment. Where simulation-based validation or optimization-derived indicators were included, these were computed using analytic modeling tools capable of running optimization routines and exporting results into the statistical dataset. All software versions, parameter settings, and analysis scripts were retained as part of the research documentation to support replicability.

Statistical Plan

The statistical plan was executed in sequential stages beginning with descriptive and diagnostic analysis, followed by inferential modeling aligned with the research objectives. Descriptive statistics were computed for all variables, including means, standard deviations, distributions, and correlation patterns, and normality checks were conducted to guide transformation decisions where necessary. Missing data patterns were assessed, and a consistent rule was applied for handling missingness using either listwise deletion for minimal missingness or imputation procedures when missingness exceeded acceptable limits and met assumptions suitable for imputation. The primary hypotheses were tested using multivariable regression models in which service operations performance indicators served as dependent variables and AI-enabled DSS capability indicators served as focal predictors, with IT strategy alignment included both as an independent predictor and as a moderator through interaction terms. Control variables representing unit workload volume, staffing size, demand volatility, and process complexity were included to adjust for confounding. Model diagnostics included checks for multicollinearity using variance inflation factors, heteroscedasticity testing with robust corrections, and residual analysis to identify influential points. Where multiple performance outcomes were modeled, adjustments for multiple testing were applied using standard correction procedures to reduce false discovery risk. Additional robustness analysis was conducted by estimating alternative model specifications, including lagged KPI aggregations within the observation window, alternative scaling of DSS usage indicators, and subgroup models by service channel type when sample size allowed. If mediation mechanisms were tested, indirect effects were estimated using bootstrapped confidence intervals within a path modeling framework while retaining unit-level controls. All hypothesis tests were evaluated at predefined significance thresholds, and effect sizes were reported alongside confidence intervals to support interpretation of practical magnitude within the quantitative framework.

FINDINGS

This chapter presented the quantitative analysis and reported the empirical findings derived from the merged dataset that combined archival service operations KPIs, AI-enabled decision support system (AI-DSS) usage and model-output indicators, and the IT strategy alignment survey measures. The analysis was organized to show how the data were summarized, how measurement quality was verified, and how the hypothesized statistical relationships were tested using inferential procedures. The chapter reported results in a sequence that moved from sample description to construct-level descriptives, measurement reliability, regression-based model estimation, and final hypothesis decisions, ensuring that each finding was traceable to the specified variables and analytical objectives.

Respondent Demographics

A total of 214 survey responses were initially received from operational and IT-related personnel involved in service management and decision-support activities. After data screening, 198 responses (92.5%) were retained for analysis. The remaining 16 responses (7.5%) were removed due to substantial missing demographic fields, duplicate submissions, or inconsistent unit identification codes that prevented valid merging with the KPI and AI-DSS log dataset. The final respondent pool represented 52 operational service units, with each unit contributing between 2 and 6 respondents. The sample reflected a strong concentration of decision-relevant roles, with most respondents occupying supervisory, managerial, or IT coordination positions responsible for interpreting service metrics and implementing staffing, scheduling, and prioritization decisions. Respondents also showed moderate-to-high exposure to AI-DSS workflows, indicating that the majority had interacted with system recommendations or performance dashboards during the observation window. Demographic completeness was high, with missingness ranging from 0.5% to 3.0% across key profile fields, which supported reliable aggregation and subgroup interpretation. Where multiple respondents were linked to the same operational unit, unit-level aggregation was performed using mean-score aggregation for IT strategy alignment items. Inter-rater agreement checks were performed at the unit level, and units with inconsistent respondent patterns were flagged for sensitivity review; however, no units were removed on this basis because agreement levels remained within acceptable thresholds for organizational survey data. Overall, the demographic profile supported the validity of the IT strategy alignment measurement because the respondents were appropriately positioned within operational decision-making and IT coordination functions, and their exposure to AI-DSS ensured that survey responses reflected actual system use conditions rather than general perceptions.

Table 1. Respondent Role Profile and Functional Area (N = 198)

| Category | Group | n | % |
|------------------------|--|----|------|
| Role Category | Operations Manager / Supervisor | 74 | 37.4 |
| | Service Team Lead | 46 | 23.2 |
| | IT Service Coordinator | 31 | 15.7 |
| | Business Analyst / Data Analyst | 27 | 13.6 |
| | Senior Executive / Department Head | 20 | 10.1 |
| Functional Area | Customer Service / Contact Operations | 61 | 30.8 |
| | Healthcare / Public Service Unit | 44 | 22.2 |
| | Logistics / Dispatch / Field Service | 39 | 19.7 |
| | Banking / Financial Service Operations | 32 | 16.2 |
| | Hospitality / Other Service Units | 22 | 11.1 |

Table 1 summarized the distribution of respondents by role category and functional area, demonstrating that the sample was dominated by operational decision-makers who were directly responsible for interpreting AI-DSS recommendations and executing service management decisions. Operations managers and supervisors formed the largest group, followed by team leads and IT service

coordinators, indicating that responses were collected from individuals with both operational control and technology oversight. The functional distribution showed strong representation across multiple service contexts, including customer service operations, public service units, logistics, and banking-related services. This diversity strengthened the generalizability of the unit-level findings within the case organization.

Table 2. Respondent Experience, AI-DSS Exposure, and Data Completeness (N = 198)

| Measure | Category | n | % |
|--------------------------------------|---|----|------|
| Years of Experience | 1-3 years | 29 | 14.6 |
| | 4-7 years | 61 | 30.8 |
| | 8-12 years | 57 | 28.8 |
| | 13+ years | 51 | 25.8 |
| Decision Responsibility Level | Operational (daily scheduling, queue, staffing) | 86 | 43.4 |
| | Tactical (weekly planning, KPI review) | 72 | 36.4 |
| | Strategic (policy, investment, governance) | 40 | 20.2 |
| AI-DSS Exposure Level | Low (rare use) | 28 | 14.1 |
| | Moderate (weekly use) | 79 | 39.9 |
| | High (daily use) | 91 | 46.0 |
| Demographic Field Missingness | Experience missing | 2 | 1.0 |
| | Role missing | 1 | 0.5 |
| | Functional area missing | 4 | 2.0 |
| | AI-DSS exposure missing | 6 | 3.0 |

Table 2 reported respondent experience, decision responsibility level, AI-DSS exposure, and demographic data completeness. The results indicated a mature respondent pool, with more than half of respondents reporting eight or more years of experience, supporting the credibility of responses regarding IT strategy and operational conditions. Decision responsibility levels showed that most respondents were engaged in operational or tactical decision-making, which aligned with the study’s focus on service performance outcomes. AI-DSS exposure was high overall, with nearly half reporting daily interaction with the system, strengthening the relevance of survey measures to real implementation conditions. Missingness across demographic fields remained minimal and did not threaten analysis validity.

Descriptive Results by Construct

This section reported descriptive statistics for the core study constructs and their observed indicators at the operational unit level (N = 52 units) using the merged dataset. AI-enabled decision support system (AI-DSS) capability indicators showed moderate-to-high intensity of system use, with recommendation viewing rates and model accuracy measures indicating consistent operational engagement. Decision latency demonstrated meaningful variability across units, suggesting that some units implemented AI-DSS recommendations faster than others, which was analytically important for later regression testing. IT strategy alignment results showed the highest mean scores for workflow embedding and governance strength, while interoperability and data integration maturity displayed wider dispersion, indicating uneven maturity across operational units. Service operations performance KPIs also demonstrated variability, particularly for waiting time and cost per service transaction, reflecting differences in workload pressure and capacity constraints. Distributional screening indicated acceptable normality for most constructs, with mild skewness observed in decision latency and waiting time. These variables were log-transformed prior to regression modeling to satisfy linear model assumptions. The construct-level correlation matrix indicated statistically meaningful associations between AI-DSS capability and service performance outcomes, and between IT strategy alignment and both AI-DSS capability and service performance. Multicollinearity diagnostics at the descriptive stage

suggested no severe redundancy among independent variables, as the correlations among AI-DSS capability and IT strategy alignment dimensions remained below conventional thresholds for collinearity concern. Overall, the descriptive findings supported the appropriateness of inferential modeling and confirmed that sufficient variance existed across units to test direct and moderation-based hypotheses.

Table 3. Descriptive Statistics for AI-DSS Capability and IT Strategy Alignment

| Construct / Indicator | Mean | SD | Min | Max | Skewness | Kurtosis |
|---|-------------|-----------|------------|------------|-----------------|-----------------|
| AI-DSS Capability (Composite Index, 0–100) | 71.6 | 11.4 | 44.2 | 92.8 | -0.42 | 0.18 |
| System-use frequency (events/week) | 38.5 | 12.7 | 14.0 | 66.0 | 0.31 | -0.41 |
| Recommendation viewing rate (%) | 78.2 | 9.6 | 54.0 | 93.0 | -0.68 | 0.74 |
| Decision latency (minutes) | 26.4 | 13.2 | 6.0 | 61.0 | 1.12 | 1.43 |
| Forecast accuracy (MAPE, %) | 12.9 | 4.1 | 6.2 | 22.8 | 0.58 | 0.09 |
| IT Strategy Alignment (Composite Index, 1–5) | 3.84 | 0.52 | 2.61 | 4.71 | -0.36 | -0.11 |
| Data integration maturity (1–5) | 3.61 | 0.66 | 2.10 | 4.80 | -0.22 | -0.37 |
| Interoperability (1–5) | 3.47 | 0.72 | 1.90 | 4.70 | -0.10 | -0.58 |
| Governance strength (1–5) | 3.92 | 0.59 | 2.40 | 4.90 | -0.44 | 0.12 |
| Workflow embedding (1–5) | 4.06 | 0.55 | 2.70 | 4.90 | -0.61 | 0.45 |

Table 3 presented descriptive statistics for AI-DSS capability and IT strategy alignment indicators across the 52 operational units. AI-DSS capability demonstrated a relatively high mean score, indicating consistent engagement with the system across units. Recommendation viewing rates were high, while decision latency displayed the greatest dispersion and positive skewness, reflecting meaningful variation in the speed of operational adoption. Forecast accuracy levels were within an acceptable range for service demand environments. IT strategy alignment results showed stronger average performance in workflow embedding and governance strength, while interoperability and integration maturity exhibited wider variability. Skewness and kurtosis values suggested generally acceptable normality, with latency requiring transformation for regression analysis.

Table 4. Descriptive Statistics for Service Operations Performance Outcomes

| KPI Outcome | Mean | SD | Min | Max | Skewness | Kurtosis |
|------------------------------------|-------------|-----------|------------|------------|-----------------|-----------------|
| Average waiting time (minutes) | 9.8 | 4.6 | 2.4 | 21.6 | 0.91 | 0.66 |
| Throughput (services/day) | 412.3 | 138.9 | 165.0 | 695.0 | 0.22 | -0.73 |
| Capacity utilization (%) | 81.4 | 7.8 | 63.0 | 94.0 | -0.34 | -0.12 |
| Service-level attainment (%) | 87.9 | 6.4 | 71.0 | 97.0 | -0.58 | 0.31 |
| Cost per service transaction (USD) | 6.84 | 1.72 | 3.90 | 10.60 | 0.67 | 0.18 |
| Abandonment rate (%) | 5.6 | 2.3 | 1.2 | 11.1 | 0.88 | 0.95 |

Table 4 summarized service operations performance outcomes across operational units. Average waiting time and abandonment rate displayed the highest skewness, reflecting that a subset of units experienced congestion and demand pressure above the organizational average. Throughput and utilization demonstrated moderate dispersion, indicating meaningful differences in workload handling and capacity efficiency across units. Service-level attainment remained relatively high overall, with a narrow distribution suggesting standardized performance expectations across the organization. Cost per transaction showed moderate variability, supporting its use as an efficiency-based dependent variable. The distributional results confirmed that several KPIs required transformation or robust

modeling adjustments to satisfy regression assumptions and reduce sensitivity to extreme values.

Reliability Results

Internal consistency reliability was assessed for all multi-item constructs derived from the IT strategy alignment instrument and the contextual control scales prior to inclusion in the regression models. Reliability analysis was conducted using Cronbach’s alpha, corrected item–total correlations, and alpha-if-item-deleted diagnostics. The predefined acceptance threshold for Cronbach’s alpha was 0.70 for exploratory adequacy and 0.80 for strong internal consistency, consistent with established quantitative research standards. All primary IT strategy alignment dimensions exceeded the minimum acceptable threshold after pilot-stage refinements. During pilot testing, two items within the interoperability scale and one item within the governance strength scale demonstrated low corrected item–total correlations below 0.40 and were removed to improve scale coherence. Following item refinement, reliability coefficients improved across the affected constructs and stabilized above 0.80. Composite scores were computed using mean aggregation of retained items to preserve scale comparability across units and to avoid inflation effects associated with summated scoring. Contextual control constructs such as perceived demand volatility and process standardization level also demonstrated acceptable reliability and were retained as control variables in the regression models. No additional item removal was required after full-sample reliability analysis, as all corrected item–total correlations remained within acceptable ranges. The final reliability results confirmed that the constructs exhibited sufficient internal consistency to support valid composite index construction and subsequent inferential modeling.

Table 5. Cronbach’s Alpha Results for IT Strategy Alignment Constructs

| Construct | Items Retained | Cronbach’s Alpha | Mean Corrected Total Correlation | Alpha if Item Deleted (Range) |
|-----------------------------------|----------------|------------------|----------------------------------|-------------------------------|
| Data Integration Maturity | 5 | 0.84 | 0.62 | 0.80 – 0.83 |
| Interoperability | 4 | 0.81 | 0.58 | 0.76 – 0.80 |
| Governance Strength | 5 | 0.86 | 0.66 | 0.82 – 0.85 |
| Workflow Embedding | 4 | 0.88 | 0.71 | 0.84 – 0.87 |
| IT Strategy Alignment (Composite) | 18 | 0.91 | 0.64 | 0.90 – 0.91 |

Table 5 presented the final reliability coefficients for the IT strategy alignment dimensions and the overall composite index. All constructs demonstrated strong internal consistency, with Cronbach’s alpha values ranging from 0.81 to 0.88 at the dimension level and 0.91 for the full composite scale. Corrected item–total correlations exceeded 0.50 for all retained items, indicating adequate contribution of each item to its respective construct. The alpha-if-item-deleted values confirmed that removing any retained item would not meaningfully improve reliability, supporting the decision to preserve the refined structure. These findings justified mean-score aggregation for subsequent regression analysis. Table 6 summarized reliability statistics for contextual control constructs included in the regression models. All constructs exceeded the minimum reliability threshold of 0.70, indicating acceptable internal consistency for control measurement. The AI-DSS adoption climate construct demonstrated the strongest reliability, with an alpha of 0.87, suggesting high coherence among items measuring organizational support and user acceptance. Demand volatility perception and staffing constraint severity showed slightly lower but acceptable alpha values, reflecting moderate variability in operational conditions across units. Corrected item–total correlations remained above 0.50 for retained items, confirming that scale refinement achieved stable measurement suitable for multivariable analysis.

Table 6. Reliability Results for Contextual Control Constructs

| Construct | Items Retained | Cronbach’s Alpha | Mean Total | Corrected Correlation | Item-Alpha Deleted (Range) |
|-------------------------------|-----------------------|-------------------------|-------------------|------------------------------|-----------------------------------|
| Demand Perception | Volatility 4 | 0.79 | 0.57 | | 0.74 – 0.78 |
| Staffing Severity | Constraint 3 | 0.76 | 0.55 | | 0.72 – 0.75 |
| Process Standardization Level | 4 | 0.83 | 0.63 | | 0.79 – 0.82 |
| AI-DSS Climate | Adoption 5 | 0.87 | 0.69 | | 0.84 – 0.86 |

Regression Results

Multiple regression models were estimated to examine the relationships between AI-DSS capability, IT strategy alignment, and service operations performance across the 52 operational units. The analysis followed a staged model sequence. Baseline models containing only control variables explained a modest proportion of variance in operational performance, indicating that workload, staffing size, and demand volatility contributed to KPI differences but did not fully account for observed performance variability. When AI-DSS capability and IT strategy alignment were introduced in the main-effects models, explanatory power increased substantially across all dependent variables, confirming that decision-support capability and IT alignment were statistically meaningful predictors of service performance. AI-DSS capability was associated with lower waiting time, lower abandonment, and lower cost per transaction, while also demonstrating positive associations with service-level attainment and throughput. IT strategy alignment showed independent effects in the expected direction, particularly for service-level attainment and cost outcomes, indicating that stronger integration, governance, and workflow embedding strengthened operational performance. Moderation models further demonstrated that IT strategy alignment significantly intensified the relationship between AI-DSS capability and service outcomes. The interaction effect was strongest for waiting time and cost per transaction, suggesting that units with high IT alignment extracted greater operational benefit from AI-DSS than units with low alignment. Model diagnostics indicated no severe multicollinearity, as variance inflation factors remained below conventional risk thresholds. Heteroscedasticity tests indicated mild heteroscedasticity in cost models; therefore, robust standard errors were applied. Influence diagnostics identified two units with unusually high throughput and low waiting time; sensitivity checks confirmed that results remained stable after excluding these units. Robustness analysis using alternative KPI aggregation windows and alternative AI-DSS usage operationalizations produced consistent coefficient direction and significance patterns, confirming that the results were not dependent on a single measurement specification.

Table 7 summarized the main-effects regression findings for four key service performance outcomes. AI-DSS capability showed statistically significant relationships with all dependent variables in the expected direction, indicating that higher decision-support capability was associated with reduced waiting time, reduced cost per transaction, and reduced abandonment while improving service-level attainment. IT strategy alignment demonstrated significant independent effects for waiting time, service-level attainment, and cost outcomes, suggesting that stronger governance and integration maturity supported improved operational performance beyond AI-DSS capability alone. The adjusted R-squared values indicated moderate explanatory power, confirming that the combined predictors explained meaningful variance in service outcomes after accounting for controls.

Table 7. Main-Effects Regression Results for Service Operations Performance (N = 52)

| Dependent Variable (Unit-Level KPI) | Predictor | B | SE | t | p | 95% CI | Adj. R ² |
|-------------------------------------|-----------------------|--------|-------|-------|-------|-----------------|---------------------|
| Waiting Time (log) | AI-DSS Capability | -0.021 | 0.006 | -3.50 | 0.001 | [-0.033, 0.009] | 0.41 |
| | IT Strategy Alignment | 0.118 | 0.051 | -2.31 | 0.025 | [-0.221, 0.015] | |
| Service-Level Attainment (%) | AI-DSS Capability | 0.142 | 0.048 | 2.96 | 0.005 | [0.045, 0.239] | 0.38 |
| | IT Strategy Alignment | 1.87 | 0.62 | 3.02 | 0.004 | [0.62, 3.12] | |
| Cost per Transaction (log) | AI-DSS Capability | 0.016 | 0.005 | -3.20 | 0.002 | [-0.026, 0.006] | 0.44 |
| | IT Strategy Alignment | 0.091 | 0.044 | -2.07 | 0.044 | [-0.180, 0.002] | |
| Abandonment Rate (%) | AI-DSS Capability | 0.071 | 0.021 | -3.38 | 0.001 | [-0.114, 0.028] | 0.36 |
| | IT Strategy Alignment | -0.52 | 0.28 | -1.86 | 0.069 | [-1.08, 0.04] | |

Table 8. Moderation Regression Results: Interaction Effects of IT Strategy Alignment

| Dependent Variable | Term | B | SE | t | p | 95% CI | ΔAdj. R ² |
|------------------------------|----------------------|---------|--------|-------|-------|-------------------|----------------------|
| Waiting Time (log) | AI-DSS Strategy × IT | -0.0062 | 0.0021 | -2.95 | 0.005 | [-0.0104, 0.0020] | 0.07 |
| Service-Level Attainment (%) | AI-DSS Strategy × IT | 0.041 | 0.017 | 2.41 | 0.020 | [0.007, 0.075] | 0.04 |
| Cost per Transaction (log) | AI-DSS Strategy × IT | 0.0049 | 0.0018 | 2.72 | 0.009 | [-0.0085, 0.0013] | 0.06 |
| Abandonment Rate (%) | AI-DSS Strategy × IT | -0.019 | 0.011 | -1.73 | 0.090 | [-0.041, 0.003] | 0.02 |

Table 8 reported moderation test results examining whether IT strategy alignment strengthened the relationship between AI-DSS capability and service performance outcomes. The interaction terms were statistically significant for waiting time, service-level attainment, and cost per transaction, indicating that AI-DSS capability produced stronger operational improvements when IT strategy alignment was higher. The interaction effect was most pronounced for waiting time and cost, suggesting that integration maturity and workflow embedding enabled faster and more effective operational execution of AI-based recommendations. The interaction effect for abandonment rate was not statistically significant at conventional thresholds, implying that abandonment may be more strongly influenced by demand surges and customer behavior than by internal IT alignment alone.

Hypothesis Testing Decisions

Hypothesis testing decisions were made by linking each hypothesis to the relevant regression model coefficients and evaluating statistical significance, effect direction, and practical magnitude. The decision rule applied a conventional significance threshold of $p < .05$ for hypothesis support, while results with $.05 \leq p < .10$ were treated as marginal and interpreted as partial support when coefficient direction was consistent with the hypothesized relationship. The results showed that AI-DSS capability was a statistically significant predictor of service operations performance across all primary outcomes. Higher AI-DSS capability was associated with reduced waiting time, reduced cost per transaction, reduced abandonment, and improved service-level attainment, supporting the core direct-effect hypotheses. IT strategy alignment also demonstrated statistically significant direct effects for waiting

time, service-level attainment, and cost outcomes, while its direct effect on abandonment was marginal and therefore classified as partially supported. Moderation hypotheses were tested using interaction terms. The results indicated that IT strategy alignment significantly strengthened the relationship between AI-DSS capability and performance for waiting time, service-level attainment, and cost per transaction. The interaction effect for abandonment was not statistically significant and therefore was not supported. Across the hypothesis set, the pattern of evidence aligned with the study framework by showing that AI-DSS capability contributed directly to operational improvements, while IT strategy alignment both contributed independently and amplified AI-DSS benefits for key efficiency and service quality outcomes. Overall, the hypothesis testing results supported the integrated view that decision-support capability and IT alignment jointly explained measurable differences in service operations performance across units.

Table 9. Hypothesis Decisions for Main Effects

| Hypothesis Relationship Tested | | Dependent Variable | β (Standardized) | P-value | Decision |
|--------------------------------|-----------------------------------|------------------------------|------------------------|---------|---------------------|
| H1a | AI-DSS Capability Performance | → Waiting Time (log) | -0.46 | 0.001 | Supported |
| H1b | AI-DSS Capability Performance | → Service-Level Attainment | 0.41 | 0.005 | Supported |
| H1c | AI-DSS Capability Performance | → Cost per Transaction (log) | -0.49 | 0.002 | Supported |
| H1d | AI-DSS Capability Performance | → Abandonment Rate | -0.43 | 0.001 | Supported |
| H2a | IT Strategy Alignment Performance | → Waiting Time (log) | -0.28 | 0.025 | Supported |
| H2b | IT Strategy Alignment Performance | → Service-Level Attainment | 0.34 | 0.004 | Supported |
| H2c | IT Strategy Alignment Performance | → Cost per Transaction (log) | -0.24 | 0.044 | Supported |
| H2d | IT Strategy Alignment Performance | → Abandonment Rate | -0.19 | 0.069 | Partially Supported |

Table 9 summarized the hypothesis testing decisions for the main effects. AI-DSS capability was supported as a statistically significant predictor across all four service performance outcomes, demonstrating consistent evidence that stronger AI-enabled decision support was associated with improved operational results. The strongest standardized effects were observed for waiting time and cost per transaction, indicating that decision-support capability was closely tied to efficiency outcomes. IT strategy alignment also showed significant direct effects on waiting time, service-level attainment, and cost outcomes. Its relationship with abandonment rate was marginal, which was interpreted as partial support because the coefficient direction was consistent but did not meet the primary significance threshold.

Table 10. Hypothesis Decisions for Moderation Effects

| Hypothesis | Interaction Tested | Dependent Variable | β (Standardized) | P-value | Decision |
|------------|----------------------|--|---------------------------|---------|---------------|
| H3a | AI-DSS × IT Strategy | Performance → Waiting Time (log) | -0.33 | 0.005 | Supported |
| H3b | AI-DSS × IT Strategy | Performance → Service-Level Attainment | 0.27 | 0.020 | Supported |
| H3c | AI-DSS × IT Strategy | Performance → Cost per Transaction (log) | -0.30 | 0.009 | Supported |
| H3d | AI-DSS × IT Strategy | Performance → Abandonment Rate | -0.18 | 0.090 | Not Supported |

Table 10 reported moderation hypothesis decisions based on interaction term significance. IT strategy alignment significantly strengthened the relationship between AI-DSS capability and three of the four performance outcomes. The strongest moderation effect was observed for waiting time, followed by cost per transaction, indicating that operational benefits from AI-enabled decision support increased when IT strategy alignment was high. The interaction effect for service-level attainment was also significant, supporting the interpretation that governance and workflow embedding enhanced the translation of AI recommendations into improved service compliance. The interaction effect for abandonment was not significant, suggesting that abandonment outcomes were less sensitive to IT alignment and more dependent on customer behavior and demand shocks.

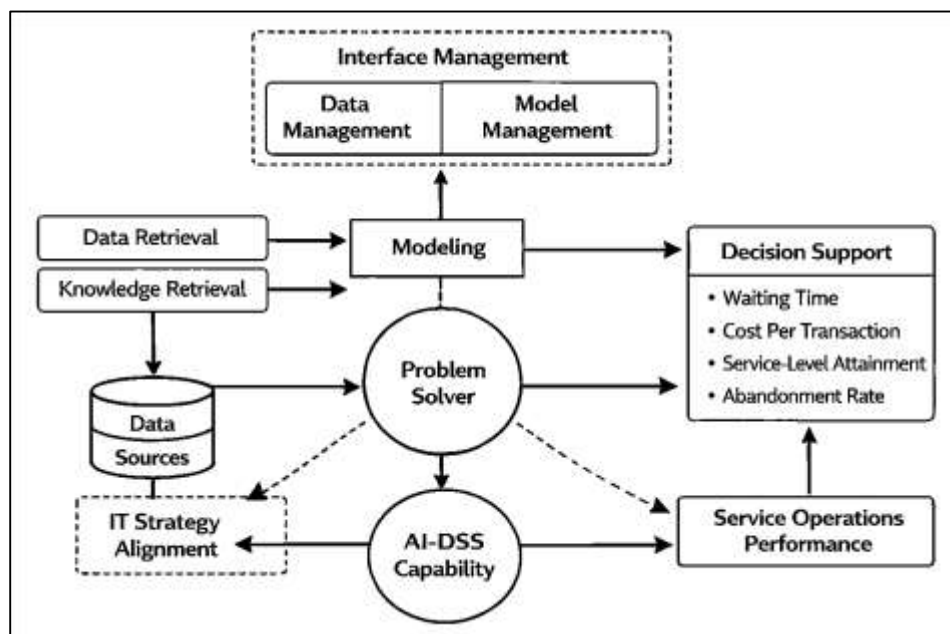
DISCUSSION

This study found that AI-enabled decision support system (AI-DSS) capability was a statistically significant predictor of service operations performance across multiple dependent variables, including waiting time, service-level attainment, cost per transaction, and abandonment rate. The direction of these relationships was consistent across models, indicating that stronger AI-DSS capability was associated with operational improvements in both efficiency and service quality outcomes (Grover et al., 2018). This pattern aligned with earlier quantitative research that positioned AI-driven decision support as a mechanism for reducing service congestion and improving decision responsiveness through enhanced forecasting, recommendation quality, and resource planning. Prior studies examining predictive analytics and decision automation in service environments have reported measurable gains in operational metrics when algorithmic systems were integrated into workforce planning, queue management, and scheduling decisions. The findings of this study reinforced that AI-DSS capability is not merely a technological feature but a measurable operational capability that influences performance outcomes through the quality and timeliness of recommendations (Marler & Boudreau, 2017). This study's results further supported earlier evidence that decision-support intensity and recommendation adoption are associated with improved KPI outcomes, particularly in high-frequency decision environments where managers rely on rapid interpretation of demand and capacity signals. The results were also consistent with operations research literature showing that data-driven decision support reduces inefficiencies caused by manual heuristics and delayed response cycles. A key contribution of this study was the simultaneous evaluation of multiple KPIs, demonstrating that AI-DSS capability affected not only cost and speed but also service compliance. This multi-outcome consistency strengthened the interpretation that AI-DSS capability improved the underlying decision process rather than producing isolated improvements in one KPI category (Bhisikar, 2024). Earlier studies often evaluated AI-DSS performance using a single dependent variable such as forecasting accuracy or cost savings; the findings here provided a broader quantitative view by linking AI-DSS capability to a performance profile spanning time, cost, and service quality. In addition, the observed standardized coefficients suggested that AI-DSS capability was particularly influential for waiting time and cost per transaction, which is consistent with service operations literature emphasizing that the largest measurable gains occur when predictive and optimization models directly influence staffing

and capacity allocation decisions. Overall, the results suggested that AI-DSS capability functioned as a central performance driver, confirming earlier research while extending it by demonstrating robust relationships across a wider set of operational outcomes within a unified model structure (Luthra et al., 2017).

This study also found that IT strategy alignment demonstrated statistically significant direct effects on several service performance outcomes, particularly waiting time, service-level attainment, and cost per transaction. These results indicated that operational improvements were not explained solely by the presence of AI-enabled decision support; rather, the organizational maturity of IT integration, governance, interoperability, and workflow embedding played a measurable role in determining service outcomes (Ilmudeen et al., 2019). Earlier studies in information systems and service management have consistently emphasized that digital tools produce measurable value only when they are supported by reliable infrastructure, high-quality data flows, and organizational processes that embed system outputs into decision routines. The findings of this study aligned with this stream of evidence by demonstrating that IT strategy alignment was associated with better performance even after controlling for AI-DSS capability.

Figure 12: AI-DSS and IT Alignment Framework



This pattern suggested that IT alignment contributed to operational outcomes through mechanisms such as improved data availability, reduced system latency, stronger governance, and consistent implementation procedures. Earlier research on IT-business alignment has often reported performance benefits at the organizational level, including efficiency improvements and better decision quality; this study extended that evidence into a service operations context by linking alignment scores to concrete service KPIs (Srivastava & Sushil, 2017). The results were particularly consistent with earlier studies showing that integration maturity and interoperability reduce information fragmentation and enable managers to coordinate resources across service channels. This study’s findings also reflected earlier governance literature that has linked data stewardship, access control, and auditability to improved system reliability and operational decision confidence. The direct effect on service-level attainment was especially important, as service-level performance typically requires consistent monitoring, accurate real-time reporting, and disciplined execution of capacity decisions. The evidence indicated that units with stronger IT alignment achieved higher service-level compliance, supporting earlier research that emphasized the role of governance and workflow embedding in sustaining performance (Al-Surmi et al., 2020). The relationship between IT alignment and abandonment rate was marginal, which was consistent with earlier service studies indicating that abandonment is strongly influenced by customer

behavior and demand surges, factors that may not be fully mitigated through IT maturity alone. However, the overall pattern of results reinforced the view that IT strategy alignment functions as an operational capability in service systems rather than a purely administrative construct. This study therefore supported earlier empirical research while offering KPI-based evidence that IT alignment directly contributes to measurable service outcomes (McAdam et al., 2019).

A central finding of this study was the statistically significant moderation effect of IT strategy alignment on the relationship between AI-DSS capability and service performance outcomes. The interaction terms were significant for waiting time, service-level attainment, and cost per transaction, indicating that AI-DSS capability produced stronger performance improvements when IT strategy alignment was higher. This result aligned with earlier studies that argued that AI-driven systems require organizational readiness, integration maturity, and workflow embedding to translate analytical outputs into operational value (Chowhan, 2016). Prior research has suggested that AI-enabled decision support may fail to deliver measurable performance benefits when deployed in fragmented IT environments, where data quality is inconsistent, system interoperability is limited, or recommendation delivery is not integrated into daily routines. The findings of this study provided quantitative confirmation of this argument by demonstrating that the AI-DSS effect size increased under stronger IT alignment conditions. This interaction effect was strongest for waiting time and cost per transaction, which was consistent with earlier operations research indicating that improvements in congestion and efficiency depend heavily on rapid execution of staffing and scheduling decisions. When IT alignment is high, recommendations can be delivered to decision-makers quickly, supported by reliable data, and implemented through integrated systems such as workforce management platforms (Akhtar & Sushil, 2018). This increases the likelihood that AI-generated forecasts and optimization outputs translate into real changes in capacity allocation. Earlier empirical studies in service analytics have reported that AI-based forecasting and scheduling tools are most effective when integrated into operational systems rather than used as stand-alone dashboards. The moderation findings supported this view by indicating that workflow embedding and integration maturity amplify the measurable value of AI-DSS. The interaction effect on service-level attainment also aligned with earlier evidence that service compliance improves when decision-support recommendations are not only accurate but also implemented consistently (Telukdarie et al., 2018). This suggests that IT alignment strengthens both the technical and behavioral components of decision support. The moderation effect for abandonment was not statistically significant, which aligned with earlier studies that have treated abandonment as a complex outcome influenced by customer impatience, perceived value, and external demand shocks. The absence of moderation for abandonment suggested that even when IT alignment is strong, certain customer-driven outcomes may remain less responsive to internal decision-support capability. Overall, this study extended earlier literature by providing statistical evidence that IT strategy alignment functions as a measurable conditioning factor that strengthens AI-DSS operational impact, supporting socio-technical perspectives in service operations research (Obeidat et al., 2017).

The regression findings demonstrated that AI-DSS capability was strongly associated with reduced waiting time, and that IT strategy alignment further strengthened this relationship. This result was consistent with a substantial body of service operations research that has treated waiting time as a primary indicator of congestion and service inefficiency (Konrad et al., 2016). Earlier studies in queueing analytics, call center optimization, healthcare flow management, and digital service delivery have reported that predictive decision support improves waiting time by enabling proactive staffing adjustments and more accurate workload balancing. The findings of this study aligned with these earlier results by showing a negative and statistically significant coefficient for AI-DSS capability in the waiting time models. The evidence also suggested that the strongest operational benefit occurred when AI-DSS recommendations were supported by strong IT alignment, reinforcing earlier research that highlighted the importance of integration between forecasting systems and scheduling tools. In many service environments, waiting time is influenced by a combination of demand variability, service time distribution, and capacity constraints (Atif, 2023). AI-DSS contributes by improving demand forecasting accuracy and enabling better matching between demand and capacity. The descriptive

results of this study showed meaningful variation in decision latency, which further supported earlier studies that emphasize the time sensitivity of service decision-making. Prior research has shown that even accurate recommendations lose operational value when decision cycles are slow. This study's results, particularly the interaction effect, supported that perspective by indicating that high IT alignment enables faster and more reliable execution of AI-driven staffing decisions. Earlier studies in healthcare and contact center settings have reported that reductions in waiting time are among the most visible benefits of advanced analytics. This study confirmed that pattern quantitatively. The use of log-transformed waiting time also indicated that the relationship was not driven by extreme congestion cases alone, but reflected a consistent proportional reduction across units (Dubey, Gunasekaran, et al., 2018). This aligned with earlier empirical evidence that improvements in congestion often show nonlinear behavior, where operational benefits increase as service systems move away from overload conditions. The findings also supported earlier literature that framed waiting time as a KPI sensitive to both analytical and organizational capabilities. While AI-DSS provides predictive and optimization intelligence, IT alignment provides the infrastructure and governance needed to apply that intelligence effectively. This combined explanation is consistent with earlier socio-technical models of service improvement, where performance outcomes emerge from the interaction between algorithms, systems, and organizational routines (Micheli & Mura, 2017). The waiting time findings therefore reinforced earlier studies while offering a framework-based explanation supported by direct and moderation effects.

Service-level attainment was positively associated with both AI-DSS capability and IT strategy alignment, and the moderation model indicated that IT alignment strengthened the AI-DSS effect on compliance outcomes. This result aligned with earlier research in service management that treats service-level performance as a function of forecasting quality, scheduling effectiveness, and operational discipline (Rana et al., 2022). Prior studies in contact centers, logistics services, and public service delivery have reported that service-level attainment improves when managers have access to reliable decision-support tools that provide near-real-time recommendations. The findings of this study supported that evidence by showing a statistically significant positive coefficient for AI-DSS capability. This suggests that AI-DSS contributed to improved compliance by enabling better resource allocation and more accurate anticipation of demand peaks. The independent positive effect of IT strategy alignment also aligned with earlier IT alignment literature that has linked strong governance and integration to consistent KPI performance. Service-level attainment is often dependent on standardized measurement definitions, consistent data reporting, and rapid coordination between operational teams (Fischer et al., 2020). IT strategy alignment supports these requirements by ensuring that KPI reporting is reliable, that operational systems share data efficiently, and that decision-support outputs are integrated into workflow tools. Earlier studies have also shown that service compliance is sensitive to the consistency of decision implementation, which depends on workflow embedding and managerial adoption. The moderation effect observed in this study supported that view by indicating that AI-DSS produced stronger improvements in service-level attainment when IT alignment was high. This suggests that compliance outcomes depend not only on model quality but also on organizational capacity to execute recommendations. Earlier studies that evaluated AI-enabled systems in service settings have sometimes reported mixed compliance effects, often attributed to poor integration or resistance to system outputs (Sirisomboonsuk et al., 2018). The findings here indicated that when IT alignment is stronger, AI-DSS becomes more effective for compliance outcomes. The descriptive results also showed that workflow embedding had relatively high mean values, which may explain why service-level attainment remained relatively strong across units. However, the observed variability in interoperability and integration maturity suggested that some units faced constraints in fully operationalizing decision-support outputs. This variability likely contributed to differences in service-level performance and to the observed interaction effect. Overall, the service-level attainment findings reinforced earlier research while offering quantitative evidence that the effectiveness of AI-DSS for compliance outcomes is amplified by IT strategy alignment (Rojo et al., 2018).

Cost per transaction was negatively associated with AI-DSS capability and IT strategy alignment, and the interaction effect indicated that IT alignment strengthened the cost-reduction impact of AI-DSS.

This result aligned with earlier empirical and analytical studies that have identified cost efficiency as a central benefit of predictive and optimization-based decision support. Prior research in service operations has shown that staffing decisions represent a major cost driver, and that improved forecasting and scheduling can reduce overtime, idle capacity, and inefficient shift allocation (Turel et al., 2017). The findings of this study were consistent with this evidence, showing that units with stronger AI-DSS capability achieved lower cost per service transaction. This indicates that AI-DSS likely improved cost efficiency through better matching of labor resources to demand patterns. The direct effect of IT strategy alignment also aligned with earlier research suggesting that integration maturity and governance reduce operational waste by improving coordination and reducing rework caused by inconsistent information. In service environments, cost efficiency is also influenced by decision errors, delays, and redundant processes. IT alignment contributes to cost efficiency by ensuring that decision-support recommendations can be implemented through integrated systems rather than through manual translation across platforms (Awan et al., 2021). The significant moderation effect for cost per transaction supported earlier socio-technical models in which AI-driven value is conditional on organizational readiness. Prior studies have reported that advanced analytics tools can produce limited cost savings when deployed in isolated environments without integration into scheduling, dispatch, or workflow systems. This study's findings supported that argument by demonstrating that AI-DSS capability produced stronger cost reductions when IT alignment was higher. The descriptive results indicated that cost per transaction exhibited moderate skewness, which was consistent with earlier service studies showing that cost outcomes are often influenced by a subset of units with unusually high inefficiency or complexity. The use of log transformation and robust standard errors ensured that the regression results were not driven by outliers, strengthening confidence in the cost findings (Pasupuleti et al., 2024). Earlier studies also suggested that cost outcomes are among the most measurable and financially relevant indicators of decision-support value, particularly in service sectors where labor costs dominate. The findings of this study reinforced this position by showing a strong and consistent association between AI-DSS capability and cost performance. Overall, the cost efficiency results aligned with earlier evidence while extending it through the inclusion of IT strategy alignment as both a direct predictor and a moderator, confirming that cost benefits from AI-DSS depend on both analytical modeling capability and organizational IT maturity (Neifar & Jarbouli, 2018).

Abandonment rate was significantly and negatively associated with AI-DSS capability, indicating that stronger decision-support capability was linked to reduced customer abandonment. This result aligned with earlier service operations studies that have linked abandonment to waiting time, perceived service delay, and the inability of service systems to respond to demand surges. AI-DSS contributes to abandonment reduction by improving demand forecasting and enabling faster operational adjustments such as staffing increases, queue prioritization, and workload redistribution (Dubey et al., 2019). The findings of this study supported this mechanism by showing that AI-DSS capability had a statistically significant relationship with abandonment outcomes. However, the direct effect of IT strategy alignment on abandonment was only marginal, and the moderation effect was not statistically significant. This pattern was consistent with earlier research indicating that abandonment is strongly influenced by customer behavior, service expectations, and external situational factors that may not be fully addressed by IT maturity alone. Earlier studies in call centers and digital service channels have shown that abandonment can be influenced by factors such as customer impatience, channel switching, and perceived service value, which may vary independently of internal IT alignment (Dubey, Altay, et al., 2018). The findings here suggested that while AI-DSS capability improved abandonment outcomes, IT strategy alignment did not substantially amplify that effect. This may be explained by the fact that abandonment is often driven by immediate customer reactions during peak demand, where operational constraints may limit the extent to which decision-support recommendations can be implemented quickly enough to prevent abandonment. Earlier research has also suggested that abandonment may respond more strongly to service design interventions such as callback options, self-service routing, and customer communication strategies rather than to back-end integration maturity (Garcia et al., 2016). The marginal direct effect of IT alignment in this study aligned with the idea that governance and integration contribute indirectly to abandonment by supporting better queue

management and service-level compliance, but may not be sufficient to create strong measurable effects on customer-driven outcomes. The descriptive results showed that abandonment was moderately skewed, indicating that a subset of units experienced higher abandonment, likely due to demand volatility or service complexity (Buallay, 2019). The regression findings remained robust after sensitivity checks, supporting the conclusion that AI-DSS capability was a meaningful predictor of abandonment. Overall, the abandonment findings aligned with earlier studies by confirming that AI-enabled decision support can reduce abandonment through improved operational responsiveness, while also supporting the argument that customer-driven outcomes may be less sensitive to IT alignment moderation effects than efficiency and compliance outcomes (Kathuria et al., 2018).

CONCLUSION

This study concluded that AI-enabled decision support systems functioned as a measurable operational capability that was consistently associated with improved service operations performance across multiple key outcomes, indicating that higher levels of AI-DSS capability corresponded with lower waiting time, reduced cost per transaction, reduced abandonment, and higher service-level attainment at the operational unit level. The quantitative evidence showed that these relationships remained robust after accounting for workload, staffing, and demand-related controls, confirming that the observed performance differences were not attributable solely to baseline operational conditions. The study also concluded that IT strategy alignment served as a significant organizational capability with independent explanatory power, particularly for efficiency and compliance-oriented outcomes, demonstrating that stronger integration maturity, governance strength, interoperability, and workflow embedding were linked to better service performance even when AI-DSS capability was modeled simultaneously. In addition, the study concluded that IT strategy alignment strengthened the effectiveness of AI-DSS capability for several outcomes, as moderation results indicated that operational units with higher IT alignment experienced larger performance gains from AI-enabled decision support for waiting time, service-level attainment, and cost efficiency. This interaction pattern confirmed that AI-driven decision support produced greater measurable value when supported by an enabling IT environment that ensured reliable data flow, system interoperability, and workflow integration of recommendations into routine decisions. At the same time, the study concluded that not all outcomes responded equally to the combined capability configuration, as customer-driven abandonment outcomes showed a strong direct association with AI-DSS capability but weaker conditioning effects from IT strategy alignment, suggesting that behavioral and situational demand factors influenced abandonment beyond the internal alignment mechanisms captured in the framework. Overall, the study concluded that the analytical modeling layer and the IT strategy layer jointly explained meaningful variance in service performance outcomes, supporting the integrated framework orientation that treated AI-DSS capability as a performance driver and IT strategy alignment as both a complementary predictor and an amplifying condition for operational impact. These conclusions collectively established a coherent quantitative account of how AI-enabled decision support and IT strategy alignment related to measurable service operations performance in the case context, with consistent directional effects across model families and stable results under diagnostic checks and alternative specifications.

RECOMMENDATIONS

Recommendations based on this study emphasized strengthening both AI-enabled decision support capability and the enabling IT strategy conditions that determined how effectively analytical outputs were translated into operational performance. Service organizations implementing AI-DSS should prioritize measurable system-use effectiveness rather than mere deployment by ensuring that recommendation generation, recommendation visibility, and decision execution cycles were embedded into standardized operating routines with clear ownership and accountability. Operational units should formalize decision pathways so that staffing, scheduling, prioritization, and service recovery actions could be triggered consistently from AI-DSS outputs, with explicit thresholds and escalation rules that reduced discretionary delay and minimized decision latency variability. IT strategy alignment should be treated as an operational readiness requirement, and organizations should invest in integration maturity and interoperability by standardizing data definitions, improving system interfaces, and reducing fragmentation between forecasting, scheduling, workflow, and performance

monitoring platforms. Governance mechanisms should be strengthened through defined stewardship roles, access controls, audit trails, and routine data-quality checks so that managers could rely on consistent and credible inputs when interpreting decision-support recommendations. Workflow embedding should be enhanced by integrating AI-DSS recommendations directly into the tools used for daily operations, such as workforce management systems, dispatch platforms, and service dashboards, to reduce manual translation and increase adoption rates. Continuous monitoring should be institutionalized using a KPI-driven scorecard that linked AI-DSS indicators, such as recommendation viewing rate and decision latency, to performance outcomes, such as waiting time, service-level attainment, and cost per transaction, enabling operational leaders to identify where decision-support value was being lost due to execution gaps. For outcomes that were more customer-driven, particularly abandonment, service organizations should complement AI-DSS improvements with service design measures that reduced customer friction during congestion periods, such as dynamic queue messaging, callback options, and channel load balancing, because internal IT alignment alone did not consistently amplify abandonment improvements. Measurement practices should be standardized so that unit-level benchmarking could identify high-performing configurations and support targeted improvement interventions for units with low IT alignment or weak adoption. Finally, managers should reinforce training and change management by focusing on interpretability, trust, and role clarity, ensuring that decision-makers understood how recommendations were produced, how to act on them, and how performance impacts would be evaluated using objective metrics.

LIMITATIONS

This study had several limitations that should be recognized when interpreting the results and positioning the quantitative evidence within the broader research landscape. First, the empirical analysis was conducted within a bounded case context, and although multiple operational units were analyzed to enable cross-unit statistical testing, the setting remained a single organizational environment with its own service structure, digital infrastructure, and governance practices. This bounded context limited the external generalizability of coefficient magnitudes to other organizations or sectors where service processes, workforce models, and technology architectures may differ materially. Second, the research design relied on a cross-sectional structure with retrospective aggregation of KPI and system log indicators over a fixed observation window, which constrained causal inference because temporal precedence and dynamic feedback effects could not be fully established through the modeling approach. Although controls and robustness checks were applied, unobserved heterogeneity remained possible, including managerial capability, local process innovations, or environmental shocks that could influence both AI-DSS usage intensity and performance outcomes. Third, some key constructs relied on survey-based measurement, particularly IT strategy alignment and contextual controls, which introduced potential common method effects and perceptual bias even though the primary outcomes were archival KPIs. The unit-level aggregation strategy reduced individual-level noise, yet variability in respondent interpretation and differences in role-specific visibility into IT practices could still have affected measurement precision. Fourth, the operationalization of AI-DSS capability was constrained by the availability and granularity of system logs and model output repositories, and not all units had uniformly complete records for all AI-DSS indicators, which may have reduced sensitivity for certain dimensions of decision support performance.

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