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AI-ENABLED CUSTOMER-INTERACTION MODELS FOR IMPROVING SERVICE EFFICIENCY IN U.S. HOSPITALITY AND RETAIL OPERATIONS

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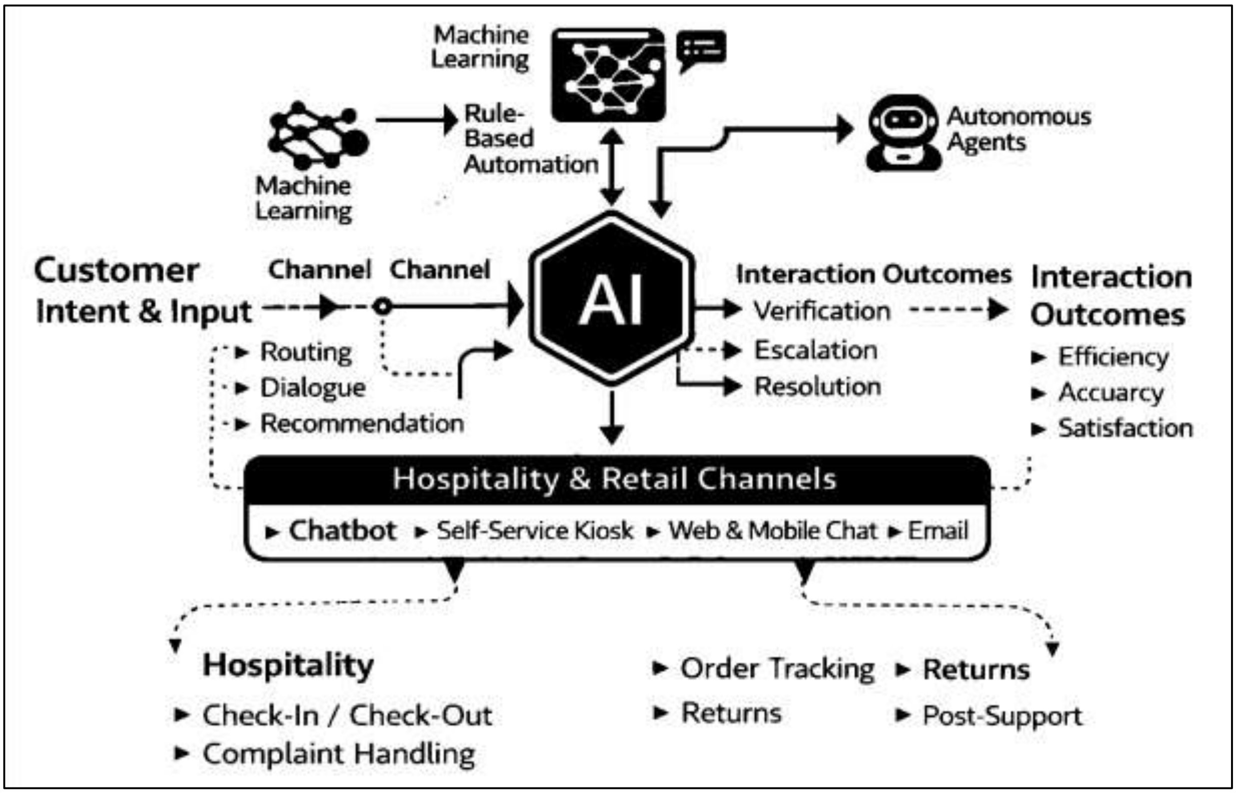
Abstract
This study examined the relationship between AI-enabled customer-interaction models and service efficiency outcomes in U.S. hospitality and retail operations using a quantitative, observational research design. The analysis was informed by an extensive review of 82 peer-reviewed academic studies spanning service operations, information systems, retailing, hospitality management, and technology-mediated service research, which provided the conceptual and methodological foundation for variable selection, model specification, and interpretation of results. Empirical analysis was conducted using a multi-source dataset comprising 68,420 customer-service interaction episodes collected from 132 hospitality and retail sites, integrating operational interaction logs, site-level performance records, and linked customer feedback data where available. AI exposure was operationalized through the share of interactions handled within AI-mediated channels and the extent of automated containment, while capability quality was captured using response latency, knowledge coverage proxies, escalation behavior, and containment outcomes. Service efficiency was measured using time-based indicators, including average handling time, time-to-resolution, wait time, and service cycle time, alongside productivity and cost metrics. Descriptive results indicated that AI-mediated interactions accounted for approximately 51% of total recorded service volume, with containment achieved in 64% of AI-handled interactions compared to 19% in human-mediated channels. Regression findings demonstrated that higher AI exposure was associated with statistically significant reductions in average handling time ($\beta = -1.12$ minutes, $p < .001$), time-to-resolution ($\beta = -4.85$ minutes, $p < .001$), and overall service cycle time ($\beta = -5.60$ minutes, $p < .001$), after controlling for channel type, inquiry category, severity, peak demand, and site scale. Response latency and escalation were positively associated with longer resolution cycles, while containment was associated with lower recontact risk and higher first-contact resolution. Multilevel modeling showed that AI-related effects were primarily driven by within-site variation, although meaningful site-level differences persisted. Overall, the findings provided quantitative evidence that AI-enabled customer-interaction models functioned as operational mechanisms that improved service efficiency through faster resolution, higher containment, and reduced repeat contact when deployed within coherent omnichannel service architectures.

Keywords
AI Customer Interaction, Service Efficiency, Hospitality, Retail

INTRODUCTION

Artificial intelligence (AI) in service organizations refers to computational systems that perform tasks commonly associated with human cognition, including perception, language understanding, decision-making, and adaptive learning from data. Within business operations, AI is operationalized through machine-learning models, rule-based automation, natural language processing (NLP), computer vision, and autonomous or semi-autonomous agents that can interpret inputs and generate outputs with measurable consistency (Ostrom et al., 2018).

Figure 1: Artificial Intelligence in Service Organizations

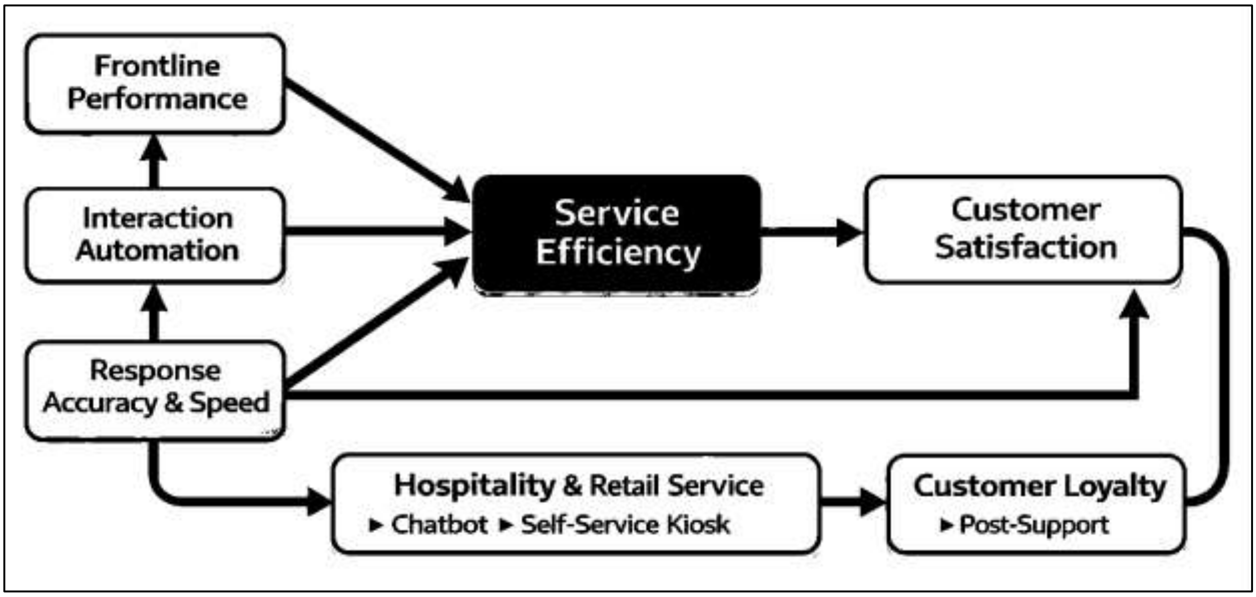


In hospitality and retail, “customer interaction” denotes any communicative exchange between an organization and a customer across the service journey—pre-purchase information search, booking/ordering, check-in/checkout, in-store assistance, complaint handling, returns, loyalty enrollment, and post-service support. A customer-interaction model, in quantitative terms, can be defined as a structured representation of how interaction inputs (customer intent, channel, context, service setting, and constraints) are mapped to interaction processes (routing, dialogue, recommendation, verification, escalation, and resolution) and then to interaction outcomes (speed, accuracy, satisfaction, conversion, and service recovery). “AI-enabled customer-interaction models” therefore describe interaction systems in which one or more stages of this mapping are executed or optimized using AI methods, such as intent detection in chat, personalization in product suggestions, automated triage for support tickets, or autonomous kiosks that guide service completion (Rana et al., 2022). The phrase “service efficiency” is used here in a strictly operational sense: the degree to which service outputs are achieved with minimal resource consumption and minimal time loss while maintaining required quality thresholds. Efficiency can be expressed through objective indicators such as average handling time, queue length, wait time, first-contact resolution, throughput per labor hour, order accuracy, and complaint resolution cycle time, and it can be linked to cost-to-serve and capacity utilization. In hospitality and retail operations, efficiency is inseparable from process standardization, demand variability, and labor coordination across frontline and back-of-house activities. The paper’s title implies that AI is not examined as a generic technology but as an interaction-layer capability that changes how customers and service systems coordinate tasks in real time. This framing emphasizes measurable mechanisms—information retrieval, intent classification, recommendation ranking, and escalation logic—rather than broad statements about "digital transformation (Bonetti et al., 2023)." It also positions AI-enabled interaction as a quantifiable operational design choice that can be evaluated using data from service encounters, customer feedback instruments, and transaction records.

Hospitality and retail are globally distributed service industries that operate under intense competitive pressure, high demand volatility, and continuous customer contact (Bharti et al., 2023; Mohiul, 2020). Internationally, multinational hotel groups, franchised quick-service restaurants, global apparel and grocery chains, and platform-based delivery ecosystems face similar operational constraints: short service cycles, heterogeneous customer expectations, high rates of routine inquiries, and frequent service recovery episodes (Jinnat & Kamrul, 2021; Rabiul & Samia, 2021). These industries also share a strong dependence on frontline labor, where performance variability can increase bottlenecks and inconsistent service outcomes. Because customer interaction is the interface where demand meets capacity, improvements in interaction efficiency can create organization-wide effects through shorter queues, fewer handoffs, improved routing to specialized staff, and reduced rework from errors or misunderstandings (Mohiul & Rahman, 2021; Rahman & Abdul, 2021). AI-enabled interaction models have therefore become a major operational lever across countries, used to handle high-volume questions, personalize offers, verify identity, and route complex cases to human staff (Shah et al., 2023; Haider & Shahrin, 2021; Zulqarnain & Subrato, 2021). At the same time, international significance arises from the portability of interaction designs: chatbots, conversational IVR, mobile-service flows, and smart kiosks are deployed across markets with only partial localization, making it essential to understand their performance logic in measurable terms rather than in purely cultural narratives. The U.S. hospitality and retail environment offers a particularly data-rich setting for quantitative evaluation because of the scale of chain operations, widespread omnichannel service delivery, extensive use of loyalty programs, and mature adoption of customer analytics. It is also a setting where customer expectations for speed and convenience are frequently operationalized through service-level targets and standardized metrics (Habibullah & Mohiul, 2023; Rahman, 2022; Wirtz et al., 2023). The U.S. context further provides variation in service formats—luxury and economy hotels, quick-service and full-service restaurants, big-box retail, specialty retail, grocery, and convenience formats—allowing a quantitative design to test whether AI-enabled interaction mechanisms perform consistently across different service intensities and customer involvement levels (Hasan & Waladur, 2023; Rabiul & Mushfequr, 2023). A quantitatively oriented introduction must treat international relevance not as a claim that one country "represents" all others, but as a recognition that the underlying service processes—queuing, routing, personalization, recovery, and complaint handling—are common across global service systems (Shahrin & Samia, 2023; Pistrui et al., 2023; Rifat & Rebeka, 2023). By grounding the study in measurable constructs and operational metrics, the work can be positioned within an internationally comparable service-science logic, even when the empirical focus remains on U.S. operations and datasets (Kumar, 2023; Saikat & Aditya, 2023).

Customer interaction quality has long been treated as a core determinant of service performance, and quantitative service research commonly models it through structured constructs such as perceived service quality, satisfaction, trust, perceived value, and behavioral intention (Md & Praveen, 2024; Nicolescu & Tudorache, 2022; Zulqarnain & Subrato, 2023). In operational settings, service quality is not only an attitude-based outcome but also a function of process reliability and interaction clarity, including accurate information provision, timely service completion, and effective problem resolution. Hospitality and retail interactions occur in contexts where customers often seek immediate answers: availability, pricing, promotions, reservations, order status, return eligibility, and issue escalation (Foysal & Abdulla, 2024; Ibne & Aditya, 2024). These contexts are particularly compatible with interaction automation because many customer intents are repetitive and can be mapped to standardized solutions. Technology-mediated service encounters also introduce a distinct set of measurable attributes: perceived ease of use, perceived usefulness, system responsiveness, transparency of system actions, and perceived control during the interaction (Mosheur & Arman, 2024; Rosete et al., 2020; Saba & Hasan, 2024). When AI becomes part of the encounter, additional evaluation dimensions become relevant in quantitative models, including perceived intelligence, conversational naturalness, error recovery capability, personalization fit, and escalation appropriateness. From an operations perspective, these encounter attributes can be linked to efficiency through pathways such as reduced search time for information, fewer transfers between departments, earlier detection of customer intent, and improved task completion without additional employee intervention (Kumar, 2024; Sai Praveen, 2024). Quantitative research can treat the interaction system as an information-processing mechanism that reduces uncertainty for both the customer and the firm: the customer receives guidance that reduces effort and time, while the firm receives structured intent signals that improve routing and capacity allocation (Jinnat, 2025; Omoge et al., 2022; Shaikat & Aditya, 2024). In hospitality, an interaction system can reduce check-in delays through identity verification and reservation confirmation flows; in retail, it can reduce returns friction through automated eligibility checks and label generation. These are not abstract benefits; they are process-level transformations that can be operationalized as changes in cycle time, error rates, and contact volume (Rashid, 2025a, 2025b). A rigorous introduction therefore situates AI-enabled customer interaction within established service theory, while translating theoretical constructs into measurable variables suitable for quantitative testing (Mosheur, 2025; Rabiul, 2025). The research framing can treat AI not as a substitute for human service in a general sense, but as a set of interaction capabilities—classification, recommendation, dialogue management, and prediction—that reshape where time is spent in the service process and how decisions are routed across the service system (Shahrin, 2025; Pande & Gupta, 2023; Rakibul, 2025).

Figure 2: AI-Enabled Service Efficiency Framework



AI-enabled customer-interaction models can be categorized by the role AI plays in the interaction pipeline. One category centers on conversational automation, where NLP and dialogue management interpret customer messages and generate responses through scripted flows, retrieval-based answers, or generative language systems constrained by policy and knowledge bases (Braganza et al., 2022; Kumar, 2025; Praveen & Md, 2025). Another category centers on decision support and personalization, where machine-learning models predict preferences, rank options, and recommend actions, such as room upgrades, product bundles, delivery windows, or loyalty offers. A third category focuses on perception and verification, using computer vision or sensor data for tasks such as queue monitoring, loss-prevention screening, age verification, or frictionless checkout triggers. A fourth category relates to embodied or semi-embodied service technologies, such as service robots or smart kiosks that guide customers through standardized steps, collect inputs, and coordinate with staff when exceptions occur (Kumar et al., 2021). Across these categories, the operational logic is consistent: AI reduces the marginal cost of handling a unit of customer inquiry and can increase the speed and consistency of task completion for routine intents. Quantitatively, this logic can be expressed in models linking AI capability features (intent accuracy, response latency, knowledge coverage, personalization precision, and escalation rules) to intermediate process metrics (self-service completion rate, deflection rate from human agents, transfer frequency, recontact rate, and resolution time) and then to efficiency outputs (labor hours per transaction, service capacity utilization, and unit cost) (Huang & Rust, 2021). Hospitality settings present interaction-intensive touchpoints such as reservation modifications, amenity requests, concierge questions, and complaint handling, where customers value rapid, context-aware responses. Retail settings present high-volume needs such as product discovery, inventory availability checks, order tracking, returns, and promotion clarification, where demand peaks can overload human service capacity. AI-enabled interaction models also differ by channel integration: mobile app chat, web chat, social messaging, voice assistants, in-store kiosks, QR-driven self-help, and contact center automation. A quantitative introduction benefits from treating these as measurable design parameters rather than as labels, because the same "chatbot" can differ dramatically in knowledge depth, escalation design, and personalization logic (Srivastava et al., 2021). In this study's context, AI-enabled interaction models are conceptualized as operational systems with definable inputs, process rules, and measurable outputs, making them suitable for statistical testing across different service environments and customer segments.

A quantitative paper on AI-enabled customer interaction must specify how "improving service efficiency" is translated into measurable outcomes and how those outcomes relate to customer-facing performance. In hospitality and retail operations, efficiency is routinely represented through time-based, volume-based, and cost-based indicators (Dash et al., 2023). Time-based indicators include average wait time, time-to-resolution, average handling time in contact centers, and end-to-end cycle time for requests such as refunds, exchanges, and reservation changes. Volume-based indicators include throughput per hour, number of inquiries handled per agent per shift, self-service completion counts, and deflection volumes where customers obtain solutions without human assistance. Cost-based indicators include labor cost per interaction, cost-to-serve per customer segment, and total support cost relative to revenue or transaction volume. A study can model AI-enabled interaction as an explanatory variable through operational proxies such as the availability of AI channels, the proportion of interactions handled by AI, the maturity level of the AI system, or performance measures like intent-classification accuracy and knowledge coverage rate (Dash et al., 2023). Customer experience can be included as a parallel measurable dimension through satisfaction scores, perceived service quality scales, net promoter-type outcomes, complaint sentiment ratings, and repurchase or revisit intention measures. In a properly structured quantitative design, efficiency improvement is treated as a measurable shift in operational outcomes, while customer experience is treated as a measurable shift in evaluation outcomes, allowing statistical examination of how interaction model features relate to both. This approach supports the development of hypotheses or testable propositions rooted in service operations logic: for example, that higher AI self-service completion is associated with lower average handling time, or that faster resolution is associated with higher satisfaction in specific touchpoints. It also supports multi-level analysis where interactions are nested within customers, stores/hotels, regions, or brands (Ziakis & Vlachopoulou, 2023). Because hospitality and retail produce abundant transactional and operational data, quantitative methods can connect interaction logs with outcomes using regression modeling, structural equation modeling, multilevel modeling, and efficiency analysis techniques where appropriate. The introduction, therefore, sets the stage for a data-driven evaluation of interaction systems rather than a descriptive account of AI adoption. The emphasis remains on defining constructs clearly and framing relationships in measurable terms so that the later sections of the paper can operationalize variables, specify models, and estimate effects using established statistical procedures (Fang et al., 2023).

U.S. hospitality and retail operations provide a distinctive environment for studying customer-interaction efficiency because service delivery frequently occurs in high-frequency, multi-location networks with standardized processes and rigorous performance monitoring. Large-scale hotel and retail chains often operate with formal service-level expectations for response times, complaint resolution, and transaction speed, and they rely on technology systems that record interaction traces across channels (Rejeb et al., 2023). Customer interaction in these sectors is shaped by omnichannel coordination: customers may browse online, message a chatbot, call a support line, visit a store, and later complete a return through mail, all within a single service journey. This coordination increases

informational complexity, because accurate answers depend on synchronized access to inventory records, reservation systems, loyalty profiles, payment status, and policy rules. AI-enabled interaction models are relevant in such environments because they can unify front-end interaction handling with back-end data retrieval and policy logic, reducing the time employees spend on repetitive information tasks and reducing customer effort in navigating channels. The U.S. context also includes substantial variation in customer demographics, language preferences, and accessibility needs, which influences how interaction systems perform across segments (Sands et al., 2021). From a quantitative standpoint, this variation allows testing whether AI-enabled interaction benefits or performance measures differ across customer groups, service formats, or geographic markets. Another operational characteristic is peak demand pressure. Hospitality experiences bursts around check-in and check-out windows and seasonal travel patterns, while retail experiences bursts around weekends, holidays, promotions, and delivery cutoff times. Under peak conditions, queues form, wait times increase, and service quality variability can rise through rushed interactions and higher error probability. An interaction model that handles routine intents quickly can alter queue dynamics by shifting simple cases away from constrained human capacity, which is observable through changes in call volume, chat volume, and in-store assistance requests (Dwivedi et al., 2023). The U.S. environment is also shaped by compliance and governance demands related to consumer privacy and data management, which can influence the design of AI interactions through authentication flows, disclosure design, and data-retention practices. These operational realities make the research problem concrete: customer interaction is both a cost center and a service differentiator, and AI-enabled interaction systems represent measurable process interventions that can be evaluated with quantitative evidence. The study's introduction therefore frames U.S. hospitality and retail not as a narrow niche, but as a high-scale operational laboratory where interaction efficiency can be modeled, measured, and statistically analyzed (Mercan et al., 2021).
This quantitative study is positioned to examine how AI-enabled customer-interaction models relate to service efficiency outcomes in U.S. hospitality and retail operations by focusing on measurable characteristics of interaction systems and measurable operational results. The scope of "customer interaction models" includes digital conversational interfaces (web chat, app chat, social messaging), voice-driven interfaces (interactive voice response enhanced by speech recognition and intent detection), guided self-service (kiosks and app workflows), and hybrid configurations where AI supports employee decisions through suggested replies, automated summarization, next-best-action prompts, or ticket classification (Kukanja & Planinc, 2020). The empirical orientation requires specifying a unit of analysis, such as the interaction episode, the customer account over a fixed period, the store/hotel location, or the service department. It also requires defining an observation window and matching interaction-system exposure to relevant outcomes, such as customer support metrics, transaction throughput, or complaint resolution timing. Independent variables can represent AI interaction intensity (share of interactions handled by AI), AI capability quality (accuracy, response latency, escalation rate, knowledge coverage), and channel integration (number of channels with consistent AI support and degree of back-end system connectivity). Dependent variables can represent efficiency (time-to-resolution, average handling time, self-service completion rate, deflection rate, labor cost per interaction) and can be complemented by customer evaluation outcomes (satisfaction, perceived quality, trust, or experience ratings captured through standardized instruments). Control variables can account for operational scale, demand volume, service format, product/service complexity, and customer segment composition (Szende et al., 2021). This introduction supports a research design in which statistical modeling is used to estimate relationships between AI-enabled interaction features and efficiency outcomes, using survey data, operational logs, or integrated datasets that link interaction traces to service results. The goal at the introduction stage is to define the constructs, motivate the operational relevance, and justify why a quantitative evaluation is appropriate for the service-efficiency problem. The paper's framing positions AI-enabled interaction systems as measurable service operations mechanisms rather than as abstract innovations, enabling subsequent sections to operationalize variables, specify measurement instruments, and apply quantitative methods to test the proposed relationships (Cheah et al., 2018).
The primary objective of this quantitative study is to systematically examine how AI-enabled customer-interaction models influence service efficiency within U.S. hospitality and retail operations by

empirically analyzing measurable interaction and operational performance indicators. This objective is grounded in the need to move beyond descriptive or conceptual discussions of artificial intelligence adoption and toward statistically testable relationships that link specific AI interaction capabilities with quantifiable service outcomes. The study aims to operationalize AI-enabled customer interaction through observable system characteristics, including the extent of automated interaction handling, accuracy of intent recognition, response latency, personalization capability, and escalation effectiveness, and to evaluate how these characteristics relate to core efficiency metrics such as average handling time, wait time reduction, self-service completion rate, interaction throughput, labor utilization, and cost-to-serve. A further objective is to assess whether variations in AI interaction intensity and capability quality produce differential efficiency outcomes across hospitality and retail service contexts, recognizing that these sectors differ in service complexity, demand volatility, and customer involvement levels. By structuring the analysis around interaction-level and unit-level data, the study seeks to capture how AI-enabled systems affect operational performance at the point where customers directly engage with service processes. Another key objective is to establish empirical clarity regarding the role of AI-enabled interaction as an operational mechanism rather than a generalized technological investment, enabling the identification of statistically significant pathways through which interaction automation and augmentation influence efficiency outcomes. The research also aims to integrate customer evaluation measures, such as satisfaction and perceived service quality scores, as complementary variables to efficiency metrics in order to examine whether efficiency gains associated with AI-enabled interaction models are observable alongside stable or improved customer-facing performance indicators. From a methodological standpoint, the objective includes applying robust quantitative techniques to model relationships between AI interaction variables and service efficiency outcomes while controlling for operational scale, service format, demand volume, and customer segmentation factors. Overall, the study's objective is to generate empirical evidence that clarifies how AI-enabled customer-interaction models function as efficiency-enhancing components within large-scale U.S. hospitality and retail operations, thereby contributing data-driven insights to service operations research and quantitative service management literature without extending into prescriptive, predictive, or implication-oriented claims.

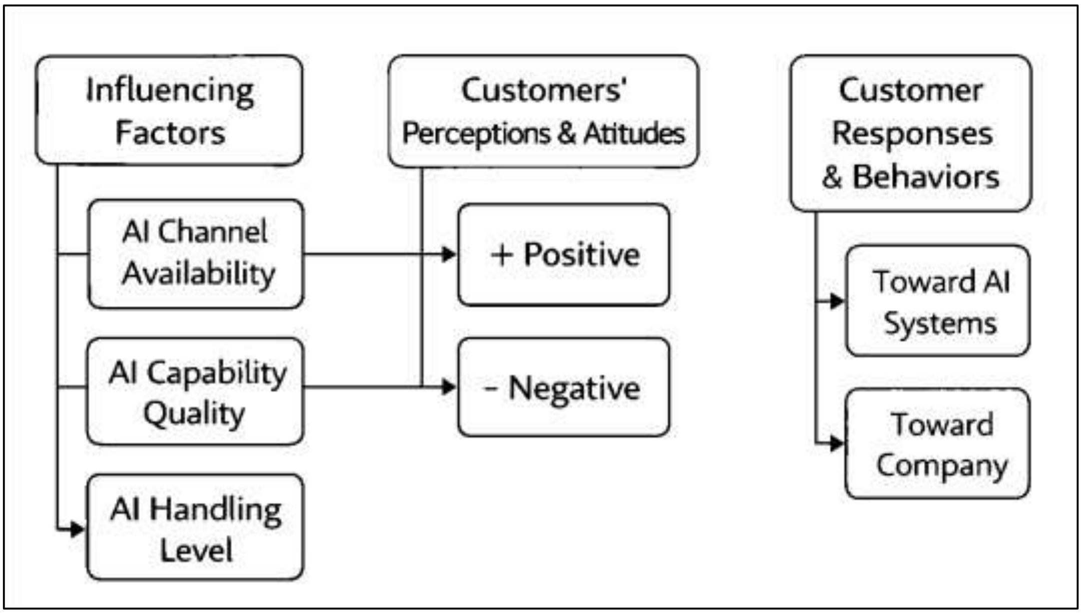
LITERATURE REVIEW

The literature review for this quantitative study organizes and evaluates prior empirical scholarship on AI-enabled customer-interaction models and their measurable effects on service efficiency in hospitality and retail operations. Because the study is designed to test relationships using operational and/or survey-based metrics, the review prioritizes literature that defines variables clearly, specifies measurement approaches, and reports statistical evidence on outcomes such as wait time, average handling time, throughput, cost-to-serve, service recovery speed, self-service completion, and customer evaluation metrics (e.g., satisfaction, perceived quality). The section also clarifies how AI-enabled interaction should be conceptualized in model form—whether as automation intensity, capability quality (intent accuracy, response latency, personalization precision), channel integration, or escalation performance—so that constructs are aligned with measurable indicators. In addition, the review maps the dominant quantitative theories and models used to explain technology-mediated service performance, including customer acceptance models and service operations frameworks, and identifies how these models have been operationalized in hospitality and retail contexts. This structure ensures the literature review functions as a methodological foundation for variable selection, measurement design, and hypothesis development, with consistent emphasis on statistical relationships rather than narrative claims.

AI-Enabled Customer Interaction Models

AI-enabled customer interaction is treated in quantitative service research as a measurable intervention embedded in the service encounter, where parts of communication, routing, information retrieval, and task completion are executed by algorithmic systems rather than solely by frontline employees (Lau, 2020). Empirical studies commonly operationalize "AI exposure" using indicators that capture whether an AI interaction channel exists, how widely it is deployed, and how frequently it is used in actual service delivery. A basic operational approach uses an adoption indicator that distinguishes sites, brands, or time periods with AI-enabled interaction from those without it, supporting quasi-experimental comparisons and panel analyses. A more granular approach measures rollout intensity through staged deployment variables, which reflect phased implementation across locations, channels, or customer segments. Another widely used strategy measures the share of interactions handled by AI, treating AI exposure as a continuous measure reflecting the proportion of customer contacts resolved through automated chat, voice systems, kiosks, or AI-supported digital workflows. This perspective aligns with service operations research that views technology as a capacity-shaping resource, where exposure affects queue dynamics, staffing needs, and contact volumes (Campbell et al., 2020). Studies on self-service technologies and technology-mediated service encounters also motivate channel-level measures that capture the availability and accessibility of AI across touchpoints, such as an index summarizing whether AI support exists in web chat, mobile apps, social messaging, in-store kiosks, and interactive voice systems.

Figure 3: Factors Related to AI-Enabled Customer Interaction



This index-style measurement is consistent with omnichannel perspectives that emphasize customers' cross-channel movement and the operational need to provide consistent interaction support. At the same time, quantitative operationalization requires attention to what "handled by AI" means in practice, because many service systems are hybrid: AI may triage the request, propose a response, or route the customer to a human agent (Kundacina et al., 2022). For this reason, empirical work often separates the presence of AI channels from the degree of AI handling, and distinguishes between automation that completes tasks end-to-end and augmentation that assists staff while keeping humans in the loop. These measurement choices matter because they define the independent variable's meaning and determine whether analyses estimate the effect of AI availability, AI utilization, or AI intensity on efficiency-related outcomes.

Beyond exposure, quantitative studies increasingly conceptualize AI-enabled interaction through capability metrics that describe how well the system performs core interaction functions and how reliably it supports service processes (Gudigantala et al., 2023). Capability measurement treats the AI system as an information-processing mechanism whose quality can be assessed through observable performance indicators that connect directly to service operations outcomes. One foundational capability is intent classification performance, which captures how accurately the system identifies what the customer wants and maps that intent to an appropriate solution path. This capability is central because misclassification can trigger incorrect responses, repeated contacts, unnecessary transfers, and longer resolution cycles, all of which affect operational efficiency. Response latency is another capability measure that reflects interaction speed and system responsiveness, and it can be captured through log timestamps that quantify system reply time, conversational turn duration, and total interaction time. Knowledge-base coverage describes the breadth and depth of issues the AI system can handle, including whether it can provide accurate answers across policies, product/service details, order status, and exceptions (Smerdov et al., 2023). Coverage measures connect to service efficiency because insufficient coverage can increase escalation frequency, reduce containment, and shift workload to human agents. Escalation probability is commonly measured as the proportion of interactions transferred to human staff or moved to higher-tier support, and it is interpreted as a process indicator reflecting either appropriate exception handling or limited AI capability depending on the context and severity of inquiries. Containment rate, measured as the share of interactions completed without human intervention, functions as a key process metric linking AI capability to labor utilization and queue reduction. These capability measures align with service and information systems research that evaluates technology performance through system responsiveness, information quality, service quality, and user experience attributes, while also aligning with operations perspectives that emphasize throughput, rework reduction, and contact deflection (Malthouse & Copulsky, 2023). Quantitative service research also recognizes that capability metrics are not purely technical; they reflect how the interaction model is designed, including dialogue structure, error recovery logic, authentication steps, and the decision rules that determine when to escalate. As a result, capability metrics can be used as explanatory variables, mediators, or moderators in statistical models connecting AI-enabled interaction to outcomes such as average handling time, first-contact resolution, and recontact frequency. Treating AI as a capability bundle rather than a binary adoption label supports more precise estimation of mechanisms and reduces ambiguity in interpreting effects across different service settings in hospitality and retail (Ozmen Garibay et al., 2023).

A critical design choice in quantitative studies of AI-enabled customer interaction is the unit of analysis, because it determines how variables are measured, how causal claims are bounded, and how operational performance is interpreted. Interaction-level models treat each ticket, call, chat session, kiosk flow, or service encounter as an observation, enabling direct measurement of encounter outcomes such as average handling time, resolution time, transfer count, first-contact resolution, and recontact behavior (Saraswat et al., 2022). This unit supports micro-level process analysis and is especially well-suited for assessing how AI handling changes the speed and structure of service completion. Interaction-level data also permits modeling heterogeneity in inquiry type, severity, channel, time of day, and agent involvement, which is important for isolating the relationship between AI-enabled interaction and efficiency outcomes. Site-level models treat the store, hotel property, or operational unit as the observation and focus on aggregated measures such as throughput per labor hour, labor productivity, utilization, staffing stability, and service backlog levels. This approach aligns with operations research traditions that examine capacity and performance across organizational units and supports benchmarking across locations (Sharma & Singh, 2022). Site-level modeling is often appropriate when AI is deployed at the property or store level and when outcome measures are tracked as key performance indicators reported by the unit. Customer-level models treat the customer account or loyalty member as the observation, typically in panel form, and evaluate outcomes such as repeat purchase, churn, complaint recurrence, and channel usage patterns. This unit captures how AI-enabled interaction shapes customer behavior across time and across multiple interactions, which is valuable when service efficiency effects operate through reduced friction, improved self-service completion, or changes in channel switching behavior. The unit-of-analysis choice also affects statistical structure, because interaction observations may be nested within customers and within sites, and outcomes may differ systematically by brand or region. Quantitative literature commonly addresses such nesting through hierarchical or multilevel strategies, or through fixed-effects approaches that control for time-invariant differences across customers or sites (Schiliro et al., 2020). Importantly, unit-of-analysis decisions also influence construct validity: efficiency measured at the interaction level emphasizes process speed and resolution, while efficiency measured at the site level emphasizes resource productivity and capacity utilization, and customer-level outcomes emphasize longitudinal behavior. A coherent conceptualization of AI-enabled interaction therefore requires that independent variables—exposure and capability metrics—are aligned with the unit of analysis and the data-generating process of the service system being studied (Shaik et al., 2023).

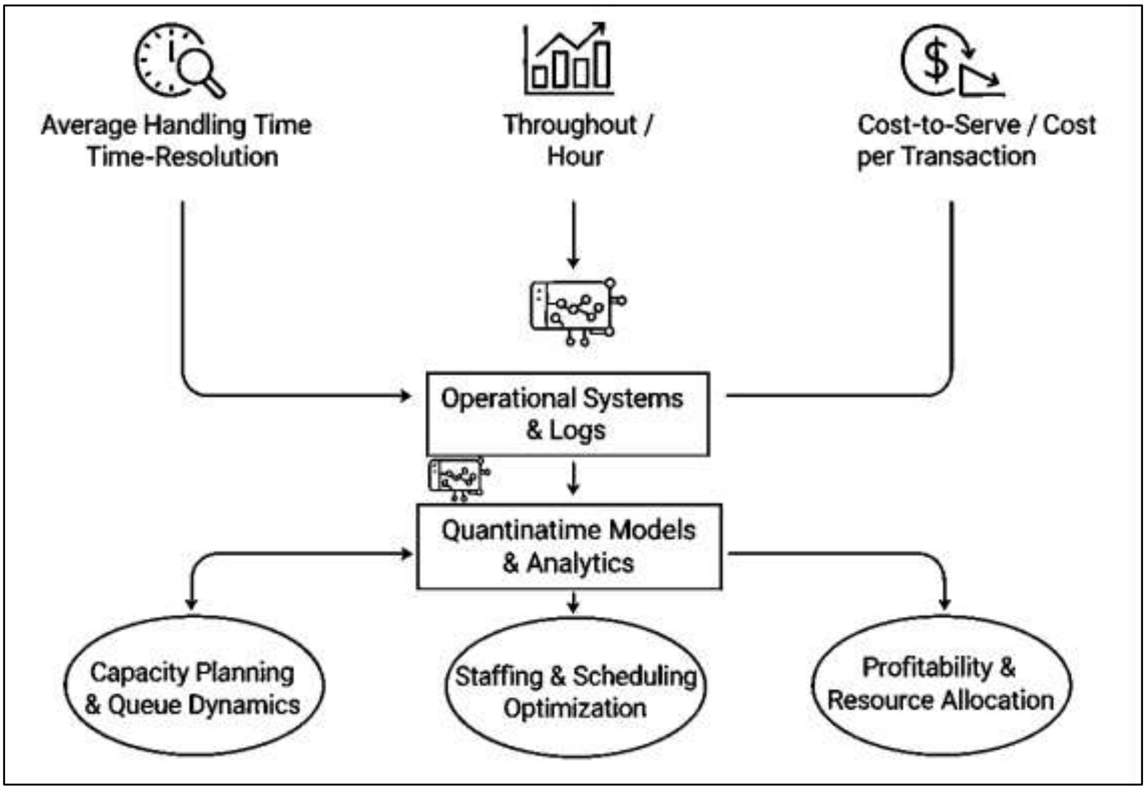
Measurement quality is foundational in quantitative service studies because AI-enabled interaction research often combines system logs, operational metrics, and survey-based constructs into a single empirical framework. When customer perceptions are measured—such as perceived usefulness, ease of use, trust, satisfaction, or perceived service quality—researchers typically rely on multi-item scales and evaluate internal consistency to ensure that indicators coherently capture the latent construct (Prashanth et al., 2022). Psychometric traditions emphasize careful item design, reliability assessment, and construct validation procedures to reduce measurement error and improve interpretability of statistical estimates. When log data are used, data integrity becomes equally important because system records may contain missing fields, inconsistent timestamps, duplicate events, or incomplete linkage across channels. Quantitative studies treat log completeness as an empirical concern that can affect estimates of resolution time, deflection, escalation, and recontact rates, particularly when customers move across channels or when human agents intervene outside the recorded interface. Common integrity practices include defining clear inclusion criteria for interaction episodes, auditing event sequences, checking distributions for implausible durations, and applying consistent rules for identifying start and end points of an interaction (Esenogho et al., 2022). Missingness patterns can also be informative, because missing log attributes may correlate with peak demand conditions, outages, or specific channels, which introduces systematic bias if ignored. For hybrid AI–human service designs, measurement error can arise when "AI-handled" interactions are misclassified, such as when AI only performs triage but the resolution is executed by a human agent; addressing this requires explicit operational definitions and consistent coding rules. Survey data introduce other validity threats, including common method bias when predictors and outcomes are collected from the same respondent at the same time, which encourages careful research design and analytic controls. Across both log and survey measures, the quantitative literature emphasizes alignment between construct definitions and measurement choices: exposure metrics must reflect actual interaction handling, capability metrics must be tied to observable performance, and efficiency outcomes must be computed in ways consistent with operational practice (Pookkuttath et al., 2023). These reliability and data-integrity considerations are not optional technicalities; they shape whether statistical results reflect true relationships between AI-enabled interaction models and service efficiency or reflect artifacts of measurement noise, incomplete capture of service journeys, or inconsistent operational definitions.

Quantitative Service Efficiency in Hospitality and Retail

Time-based efficiency outcomes are foundational in quantitative hospitality and retail operations research because service systems are experienced by customers primarily through time: time spent waiting, time spent being served, and time required for a request to be fully resolved (Trakadas et al., 2020). Within this stream of literature, average handling time is treated as a direct indicator of service labor consumption per interaction, capturing the duration of agent involvement in contact centers, live chat, or assisted in-store support. Time-to-resolution extends beyond handling time by capturing the end-to-end completion of a service request, including waiting periods, transfers, escalations, and back-office processing steps, which is especially relevant in complaint handling, returns, refunds, reservation modifications, and delivery exceptions. Wait time and queue length function as externally visible indicators of system congestion and capacity mismatch and have been central to service-operations research for decades, particularly in settings with stochastic demand and limited service capacity. Service cycle time, defined in operational terms as the time from request initiation to completion, enables a process-based understanding of efficiency that captures handoffs and rework, which are common in omnichannel journeys where customers shift between digital and physical touchpoints (Trakadas et al., 2020). Quantitative studies often treat these time-based metrics as dependent variables influenced by staffing levels, process design, technology adoption, and customer mix, and they examine how changes in routing, self-service completion, and exception handling alter time outcomes at peak and non-peak periods. In hospitality, time-based efficiency is often examined around check-in and checkout windows, housekeeping request fulfillment, and service recovery timelines, while retail studies emphasize checkout speed, customer support responsiveness, order tracking and delivery exception resolution, and return processing speed (Styles et al., 2015). This literature consistently underscores that time-based metrics are analytically valuable because they can be captured at high frequency through logs and operational systems and because they link directly to capacity planning and queue dynamics. The result is a measurement tradition that treats time as both a performance indicator and a proxy for operational strain, supporting the use of time outcomes as central constructs in quantitative models of service efficiency.

Volume-based and productivity outcomes extend the measurement of service efficiency by shifting focus from the duration of individual interactions to the output generated by labor and system resources over a defined time window (Gomes et al., 2018). In hospitality and retail, quantitative research frequently operationalizes productivity using indicators such as interactions handled per labor hour, transactions completed per shift, and service throughput per unit time. These measures reflect the operational objective of converting limited staff time and infrastructure into completed service outputs while maintaining service standards. Labor utilization is commonly conceptualized as the degree to which frontline capacity is engaged in value-producing activities rather than idle time or rework, and it is often examined in relation to staffing levels, scheduling practices, demand variability, and technology-mediated self-service (Parmata & Chetla, 2021).

Figure 4: Quantitative Service Efficiency Outcome Framework



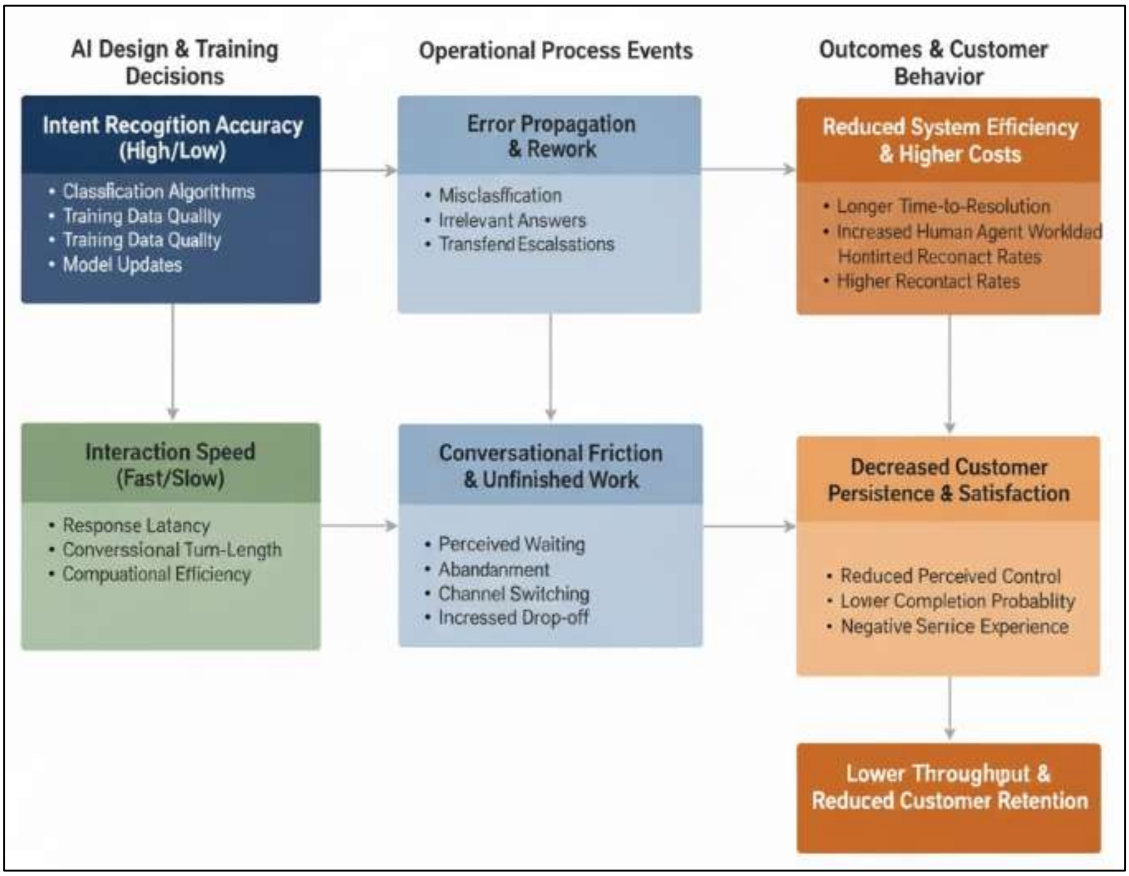
Capacity utilization metrics are particularly relevant in multi-location networks where management monitors site performance through standardized KPIs that compare labor inputs with transactional outputs. Backlog shrinkage is another operationally meaningful measure, especially in digital support channels where unresolved tickets accumulate during demand surges; the rate at which a backlog is reduced signals the system's ability to restore stable service conditions and reduce customer follow-ups. Quantitative studies link these volume-based metrics to service design choices such as queue management, routing and triage rules, the use of self-service technologies, and the configuration of human-agent tiers that handle increasing levels of case complexity. In retail, productivity metrics often reflect checkout throughput, customer service ticket closure rates, and order fulfillment-related interaction volumes, while in hospitality they include service request handling capacity and the throughput of standardized processes such as check-in or issue resolution workflows (Ibrahim et al., 2022). This literature emphasizes that volume-based outcomes are sensitive to demand patterns and case mix, meaning that a reliable quantitative specification often includes controls for peak periods, request categories, and customer segment composition. The value of productivity metrics is that they capture system-level performance in a way that can be compared across locations and time, and they

provide a practical bridge between operational analysis and managerial performance monitoring systems used in large hospitality and retail organizations.
Cost-based measures provide a third major lens on service efficiency by translating time and volume outcomes into economic terms that reflect resource consumption and operational sustainability (Liu et al., 2020). The cost-to-serve concept is widely used in operations and service management to capture the total cost required to deliver service and support activities to a customer, segment, or interaction type. In quantitative hospitality and retail research, cost per contact and cost per transaction are frequently used as practical indicators because they can be linked to labor time, wage rates, overhead allocation, and channel-specific operational expenses. These metrics reflect the reality that service encounters vary widely in resource intensity: routine informational requests typically consume fewer resources than complaint resolution, chargebacks, refunds, and service recovery episodes (Al-Aomar & Chaudhry, 2018). Cost-based approaches also recognize that omnichannel journeys can increase service costs through repeated contacts and channel switching, making it important to track recontact rates and escalation events that amplify cost per resolved case. Marginal cost reduction is discussed in the service-technology literature as an operational logic where automation changes the incremental cost of serving additional requests, particularly for high-volume inquiries, although careful empirical work distinguishes between changes in average cost and changes driven by shifts in case mix. Cost metrics are also relevant for understanding how efficiency improvements at the interaction level scale to property or store performance, because even small reductions in cost per contact can become substantial at high transaction volumes (Kurtulmuşoğlu et al., 2016). Quantitative studies often position cost-based outcomes as dependent variables in models that include operational controls such as demand volume, staffing levels, complexity indices, and service category, allowing estimation of how interaction design and technology configurations relate to cost performance. Hospitality studies commonly connect cost-to-serve to service recovery processes and staffing intensity, while retail studies connect cost metrics to customer support load, returns processing, and transaction support overhead. Across both sectors, the literature indicates that cost-based efficiency outcomes offer a complementary performance lens because they enable comparison across channels and service formats and because they can be integrated with profitability and productivity analytics without reducing service efficiency to time alone (Fiala & Thirumaran, 2021).

AI Interaction Performance Mechanisms

Quantitative research on AI-mediated service interactions consistently treats intent recognition accuracy as a core mechanism that shapes operational efficiency because the first classification decision influences the entire downstream service pathway. In customer-service settings, intent recognition refers to the system's ability to infer what a customer is trying to achieve from text, voice, or structured selections and then map the request to an appropriate knowledge article, workflow, or queue (Jie & Gengatharen, 2019). When intent is correctly identified, the interaction can be routed efficiently, information can be delivered quickly, and the probability of completing the request within the first contact increases. When intent is misclassified, empirical studies describe a predictable pattern of operational consequences: customers receive irrelevant answers, have to restate needs, experience transfers across agents or departments, and may abandon the interaction and recontact later through another channel. This sequence reflects error propagation, where early-stage classification errors increase the number of steps required for completion and increase the likelihood of escalation to human agents, which lengthens time-to-resolution and reduces system efficiency (Pejić Bach et al., 2023). In service operations terms, misclassification creates rework, a mechanism well established in process management research, and it also increases variability in handling time and increases queue congestion because repeated contacts consume additional capacity. Quantitative service research also ties this mechanism to customer behavior: repeated failures to interpret intent reduce perceived control and increase channel switching, which can raise recontact rates and complicate journey attribution in datasets that combine chat, voice, and in-store support. Empirical work on service encounters and complaint handling further suggests that misclassification effects are stronger for high-severity requests, where customers have lower tolerance for irrelevant responses and where escalation is more likely even after correct classification due to policy constraints (Haddington, 2019). As a result, intent accuracy is often modeled not only as a direct predictor of time-based outcomes but also as a variable that operates through mediators such as transfer frequency, escalation probability, and containment success. This literature positions intent recognition accuracy as a measurable capability quality indicator that links AI design and training decisions to operational efficiency outcomes through a sequence of observable process events within hospitality and retail service systems.

Figure 5: AI Interaction Performance Mechanisms



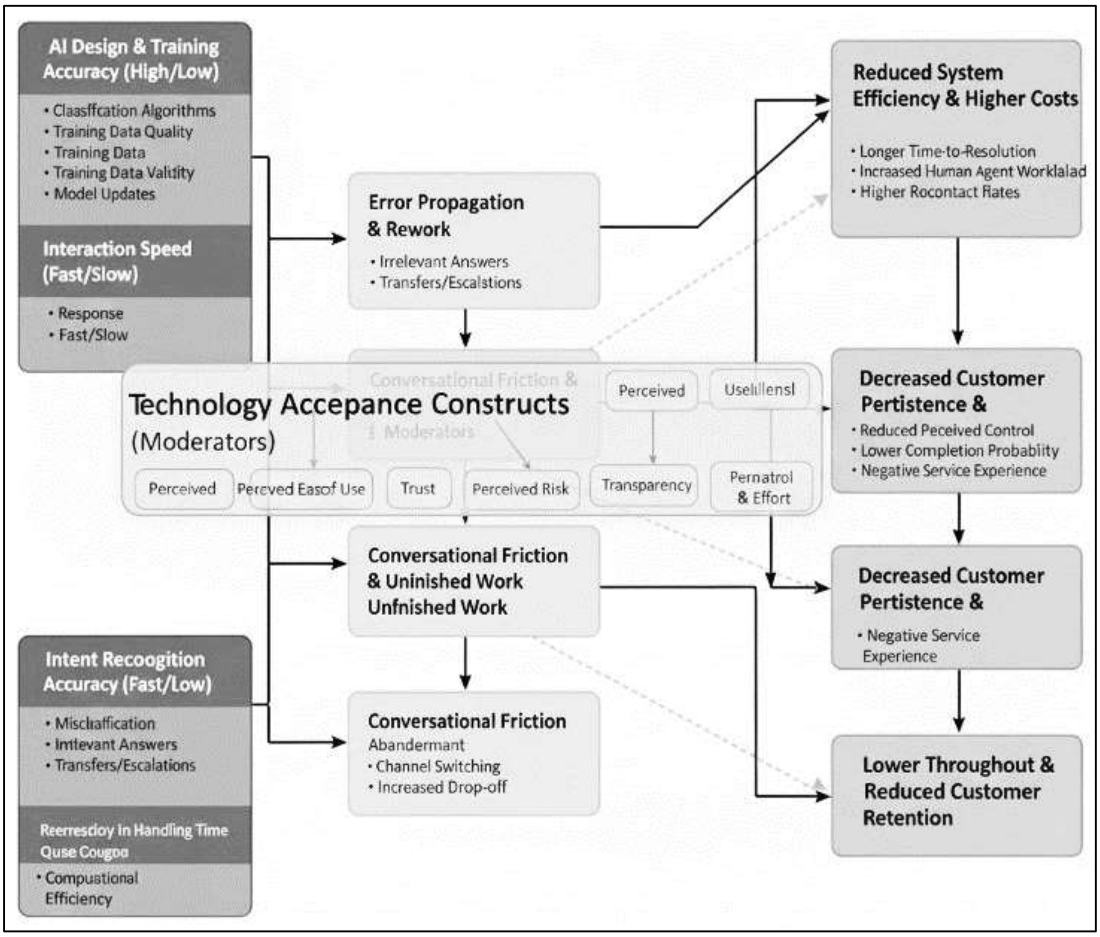
A second mechanism emphasized in quantitative studies is interaction speed, typically captured through response latency and conversational turn-length, because speed influences both operational workload and customer persistence during the interaction. Response latency refers to the elapsed time between a customer message and the system's reply, and it can be measured precisely in system logs across chat, messaging, and voice interfaces (Boonstra, 2021). In service settings, slower response latency increases perceived waiting within the interaction itself, which can contribute to abandonment, repeated prompts, and channel switching, all of which reduce effective service completion and increase follow-up contact volume. Conversational turn-length refers to the number of message exchanges required to achieve resolution, and it is treated as a process-efficiency indicator because longer dialogues typically imply higher customer effort, greater cognitive load, and more opportunities for misunderstanding. Quantitative research in human–computer interaction and service technology shows that conversational friction—caused by slow responses, repetitive clarifications, or multi-step authentication—can elevate drop-off rates and reduce completion probability. Operationally, higher drop-off creates "unfinished work" because customers often return through alternate channels, which increases recontact rates and inflates workload for human agents. Studies examining service-system dynamics also suggest that response-time distributions contain meaningful operational signals: delays can reflect computational constraints, peak-load conditions, or integration bottlenecks with back-end systems such as reservation management, order tracking, or inventory databases (Flamino & Szymanski, 2019). In hospitality and retail contexts, where many service questions are time-sensitive, latency is especially consequential for tasks like booking changes, delivery exceptions, or return eligibility checks. Quantitative designs often treat latency and turn structure as predictors of average handling time and overall cycle time, because slower responses and longer dialogues extend the duration of service episodes and reduce throughput. Research on technology acceptance and service experience further indicates that perceived responsiveness and ease of interaction influence continued usage of self-service channels, reinforcing the link between system speed and customer retention in the interaction. Collectively, this literature frames response latency and turn-length as measurable process mechanisms connecting AI interaction performance to both operational time outcomes and customer drop-off behavior in service environments (Jeanpert et al., 2021).

Technology Acceptance Constructs as Moderator

Technology acceptance research provides a well-established quantitative foundation for explaining why the same AI-enabled customer-interaction system produces different efficiency outcomes across customers, channels, and service contexts (Best et al., 2015). In hospitality and retail, efficiency improvements from self-service and AI-assisted channels depend on whether customers adopt the channel, complete tasks within it, and avoid repeated contact or channel switching. The acceptance literature conceptualizes these behavioral outcomes as responses to perceptions of system value, usability, and fit with the customer's goals. In quantitative service studies, acceptance constructs are frequently modeled as moderators because they shape how exposure to technology translates into measurable operational outcomes such as self-service completion, deflection of human-agent workload, and reductions in handling time. This view aligns with service encounter research emphasizing that technology is embedded in the customer's role as a co-producer of service outcomes, meaning operational performance depends partly on customer willingness and ability to use the system (Nguyen & Malik, 2022). In AI-mediated service, acceptance becomes more complex because the interaction is conversational, adaptive, and sometimes opaque, which can change perceived reliability and perceived control. As a result, acceptance constructs are used to explain heterogeneity in completion behavior and to interpret why certain customer segments produce higher drop-off or recontact even when the same AI system is available. Empirical research on self-service technologies and omnichannel service further supports the idea that adoption and completion are distinct outcomes: customers may try an AI channel but fail to complete tasks due to low usability, low trust, poor transparency, or perceived effort. Therefore, the literature frames technology acceptance not only as an attitudinal outcome but as an operationally meaningful set of measurable perceptions that influence channel choice, interaction persistence, and resolution success (Sheth et al., 2022). This makes acceptance constructs directly relevant to a quantitative model of service efficiency, especially when efficiency is measured through self-service completion rates, containment rates, and reductions in human-agent workload. In hospitality and retail contexts where customers often seek rapid resolutions during time-sensitive moments, acceptance-related perceptions can be decisive in whether AI channels function as effective capacity substitutes or merely as additional touchpoints that increase journey complexity.

Perceived usefulness and perceived ease of use are core constructs in technology acceptance research and are widely operationalized in quantitative models that predict system adoption, continued use, and task completion in service settings (Kim et al., 2021). Perceived usefulness refers to the customer's belief that using the AI-mediated channel improves the effectiveness of accomplishing a service goal, such as resolving an issue quickly, obtaining accurate information, or completing a transaction without waiting for staff. Perceived ease of use captures the degree to which interacting with the system is experienced as low-effort and understandable, which is critical for conversational AI, kiosks, and app-based service flows that require customers to communicate needs clearly and follow multi-step prompts. In quantitative hospitality and retail studies, these constructs are typically measured using established multi-item scales and then incorporated into regression-based or structural modeling approaches where self-service completion and continued usage are treated as behavioral outcomes (Al-Dhaen et al., 2023). The literature supports a mechanism where usefulness increases willingness to engage with AI channels in the first place, while ease of use increases the likelihood of completing the task once engagement begins. These constructs also operate as moderators of efficiency effects because even a technically capable AI system will not reduce handling time or labor demand if customers do not perceive it as beneficial or if they experience interaction friction that leads to abandonment. Service technology research also highlights that perceived usefulness is sensitive to the match between the AI system's functions and the customer's intent; when customers face complex issues, usefulness may depend on whether the system can escalate effectively and preserve context. Ease of use is influenced by clarity of prompts, conversational naturalness, response speed, and error recovery, which are design attributes that translate into measurable behavioral outcomes such as interaction duration, number of conversational turns, and completion probability (Budhwar et al., 2022). In omnichannel environments, usefulness and ease of use also influence channel switching behavior, because customers evaluate whether continuing in the AI channel is worth the effort compared with calling, visiting a store, or seeking staff assistance. Consequently, the literature positions these acceptance variables as quantitatively meaningful moderators that shape how AI exposure relates to completion, containment, and deflection outcomes that underpin operational efficiency in hospitality and retail service systems (Manchanda & Deb, 2021).

Figure 6: Technology Acceptance Constructs as Moderator



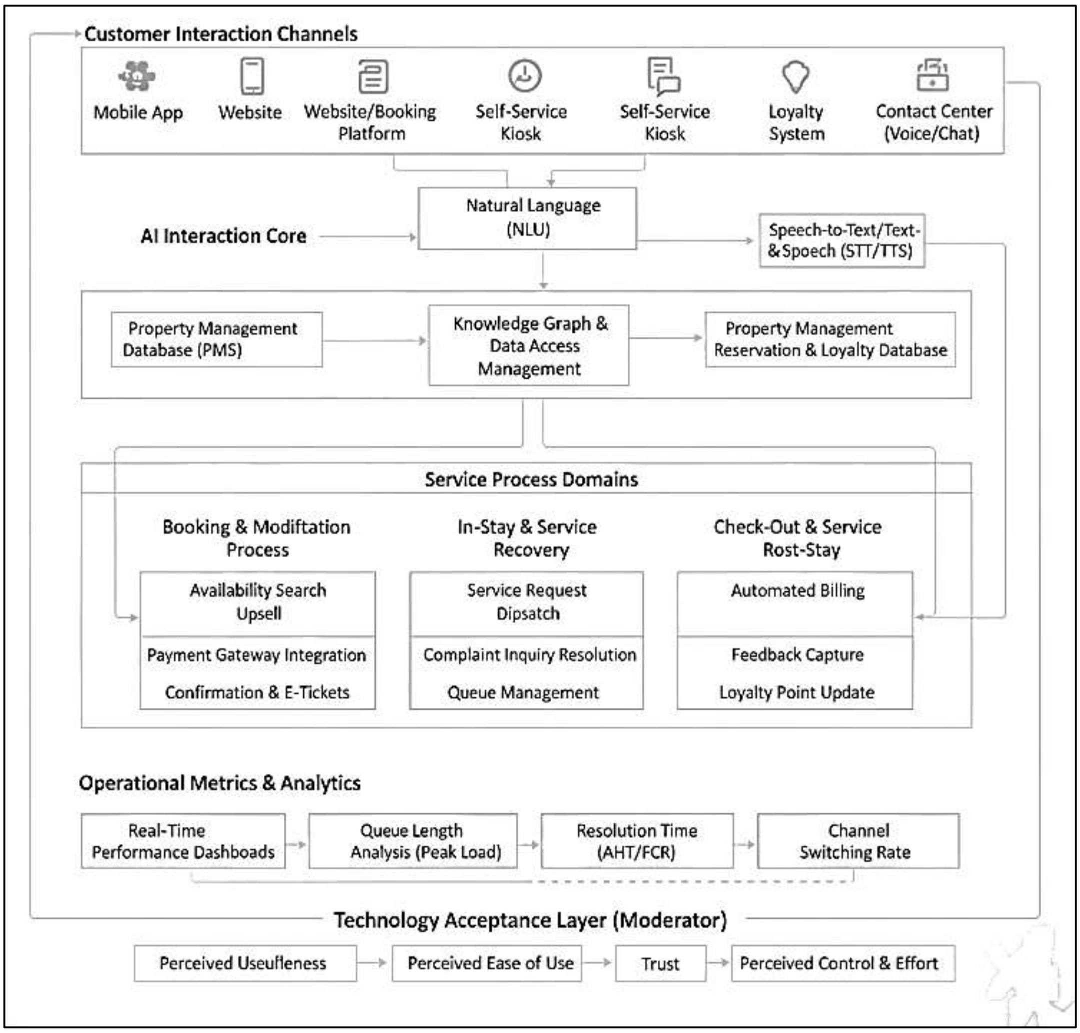
Trust, perceived risk, and transparency are consistently identified in quantitative literature as central predictors of customer adoption and completion behavior in AI-mediated service interactions. Trust reflects the belief that the system will behave reliably, provide accurate information, protect customer data, and support the customer's interests during the interaction. In hospitality and retail contexts, trust is particularly salient because interactions often involve personal information, payment-related issues, identity verification, loyalty accounts, and dispute resolution (Goel et al., 2022). Perceived risk captures concerns that system errors or misuse of data could lead to negative outcomes, such as incorrect bookings, denied refunds, misapplied promotions, or privacy exposure. Transparency refers to the extent to which the system's process is understandable to the customer, including clarity about what the AI can do, what data it uses, why it asks specific questions, and when it will transfer the interaction to a human agent. Quantitative studies often treat these constructs as predictors of AI channel adoption rate, channel choice, and completion probability because customers may avoid AI channels if they anticipate low reliability, low accountability, or insufficient clarity. This literature also shows that trust and transparency can shape persistence during difficult interactions: when customers believe the system is competent and can explain its steps, they are more likely to continue rather than abandon or switch channels (Wenker, 2023). Conversely, low trust can increase recontact behavior because customers may seek confirmation from human staff even after receiving an answer from the AI system, which elevates operational load and reduces net efficiency gains. In service recovery contexts, the role of trust becomes even more pronounced because dissatisfied customers evaluate whether the channel can deliver fair outcomes and whether escalation will be effective. Transparency also functions as an interaction-quality signal; when a system clearly communicates limitations and escalation pathways, customers can calibrate expectations and reduce unproductive conversational loops. The combined implication of this research stream is that efficiency outcomes such as containment and deflection are not only functions of system capability but also functions of perceived safety and credibility (Saßmannshausen et al., 2021). Therefore, trust-related constructs become crucial in quantitative models that aim to explain variation in AI channel uptake and completion across customers, service tasks, and organizational contexts in hospitality and retail operations.

Perceived control and customer effort are emphasized in quantitative service and technology literature as key drivers of drop-off, recontact, and channel switching in AI-mediated service journeys. Perceived control refers to the customer's sense of agency during the interaction, including the ability to direct the conversation, correct misunderstandings, access human support when needed, and understand what step comes next (Kondapaka et al., 2023). Customer effort captures the amount of cognitive and procedural work required to achieve resolution, including the need to repeat information, navigate menus, verify identity, upload documents, or follow multiple prompts across channels. In hospitality and retail settings, where customers frequently engage in time-sensitive service tasks, elevated effort can lead to early abandonment and channel switching, particularly when customers believe a human agent can resolve the issue faster. Quantitative research treats effort expectancy as a strong predictor of system usage behavior and identifies its relationship with interaction abandonment and continued use. When effort is high, customers may end the interaction without resolution and later recontact through another channel, creating duplicative workload and increasing service recovery demand (Trattner et al., 2022). Channel switching has operational consequences because it fragments the service journey and may require repeated authentication and restatement of the issue, lengthening resolution time and increasing the probability of escalation. This dynamic is consistent with omnichannel research that recognizes friction at channel boundaries as a driver of inefficiency and customer dissatisfaction. In AI-mediated service, perceived control is particularly important because conversational systems can sometimes constrain user options through rigid dialogue flows, and customers may interpret limited control as a lack of responsiveness or competence (Rozenes & Cohen, 2022). The literature also connects perceived control to trust and satisfaction, suggesting that when customers feel trapped in an automated loop, both perceived risk and frustration rise, increasing escalation demand and complaint intensity. From an operational perspective, these constructs explain why a high-availability AI channel may not reduce human workload if customers repeatedly abandon, recontact, or seek reassurance from staff. Therefore, perceived control and effort are treated as quantitatively meaningful predictors that link customer psychology to measurable operational outcomes such as abandonment rates, recontact frequency, transfers, and the resulting service recovery load in hospitality and retail operations.

AI Interactions Across Booking and Recovery

Hospitality research increasingly evaluates AI-enabled customer interactions as measurable interventions across the full guest journey, with quantitative attention to how automation changes the speed, accuracy, and capacity of service processes that traditionally rely on frontline labor (Lukanova & Ilieva, 2019). The hospitality context is particularly suitable for journey-based measurement because the service sequence is structured into recognizable stages—search and booking, pre-arrival confirmation, check-in, in-stay requests, service recovery, and checkout—each with distinct operational metrics and data traces. Quantitative service science and hospitality operations studies connect technology-mediated interactions to objective performance indicators such as cycle time for task completion, queue length, throughput at peak windows, and the timing of service recovery actions. AI interaction systems in hospitality are commonly embedded in reservation platforms, mobile applications, self-service kiosks, and contact center channels, where they can automate identity verification, reservation retrieval, upsell offers, request routing, and standardized information delivery (Bharwani & Mathews, 2021). Prior literature on self-service technologies and technology-rich service encounters provides the theoretical foundation for treating these systems as productivity and capacity tools, while customer experience research provides the complementary logic for linking interaction flow quality to booking continuation, satisfaction, and complaint escalation. Quantitative hospitality studies often emphasize that customer interaction is not merely communicative but operational, because the interaction triggers process execution such as room assignment, payment authorization, key issuance, and service request dispatch. This means AI-mediated interactions can influence operational efficiency by reducing handoffs, decreasing repeated inquiries, shortening queues, and accelerating resolution cycles. At the same time, the hospitality literature highlights that service encounters are time-sensitive and emotionally salient, especially around check-in delays, billing disputes, and service failures, which makes measurement designs attentive to peak periods, severity stratification, and segment differences (Kelly et al., 2019). Empirical approaches in this domain therefore combine platform analytics, property management system records, interaction logs, and post-stay feedback data to quantify the relationship between AI interactions and operational outcomes. By grounding AI interaction effects in measurable outcomes at each stage of the guest journey, the literature establishes a sector-specific evidence base for understanding how hospitality operations convert interaction improvements into observable performance gains (Buhalis & Sinarta, 2019).

Figure 7: AI Interactions Across Booking and Recovery



Quantitative evidence on automated booking and modification systems positions these AI-enabled interactions as high-impact because they occur at the revenue-critical stage where customers decide whether to complete a reservation, abandon the process, or switch brands. Hospitality and e-commerce research commonly conceptualize booking as a funnel, where customers move through successive steps such as search, selection, detail review, payment entry, and confirmation, and where drop-off can be observed and modeled at each stage (Moisa & Michopoulou, 2022). Automated systems that provide instant responses to availability queries, policy clarifications, and modification requests reduce the customer's information search cost and can shorten the time required to reach completion. Empirical studies in online service and retailing show that response speed, clarity of information, and perceived ease of use influence completion behavior, supporting the use of conversion rate and funnel progression metrics in hospitality booking contexts. In quantitative evaluations, automated booking assistance is often tested through controlled comparisons of interface versions or feature availability, enabling estimation of whether specific automation features change completion rates, time spent per stage, or the rate of booking errors that later lead to customer support contacts. Modification systems—date changes, cancellations, room type changes, and add-on purchases—are also operationally relevant because they can reduce contact center demand and lower the processing time associated with changes that otherwise require staff intervention (İştin et al., 2022). Quantitative designs frequently incorporate channel-based indicators, comparing customers who use automated modification tools with those who rely on calls or front-desk adjustments, and measuring outcomes such as cycle time to confirmation, frequency of recontact, and downstream complaint incidence related to booking misunderstandings. The broader service technology literature supports the idea that automation effectiveness depends on usability and trust, meaning that conversion improvements are most likely when customers perceive the system as reliable and easy to navigate. Hospitality research complements this by emphasizing that booking decisions are sensitive to perceived risk and cancellation policy clarity, which are interaction features that automated systems can present consistently. Overall, the quantitative literature treats automated booking and modification systems as measurable interaction interventions that influence both revenue-related outcomes and operational load, especially by reducing the need for human clarification during the booking funnel (Marques et al., 2022).

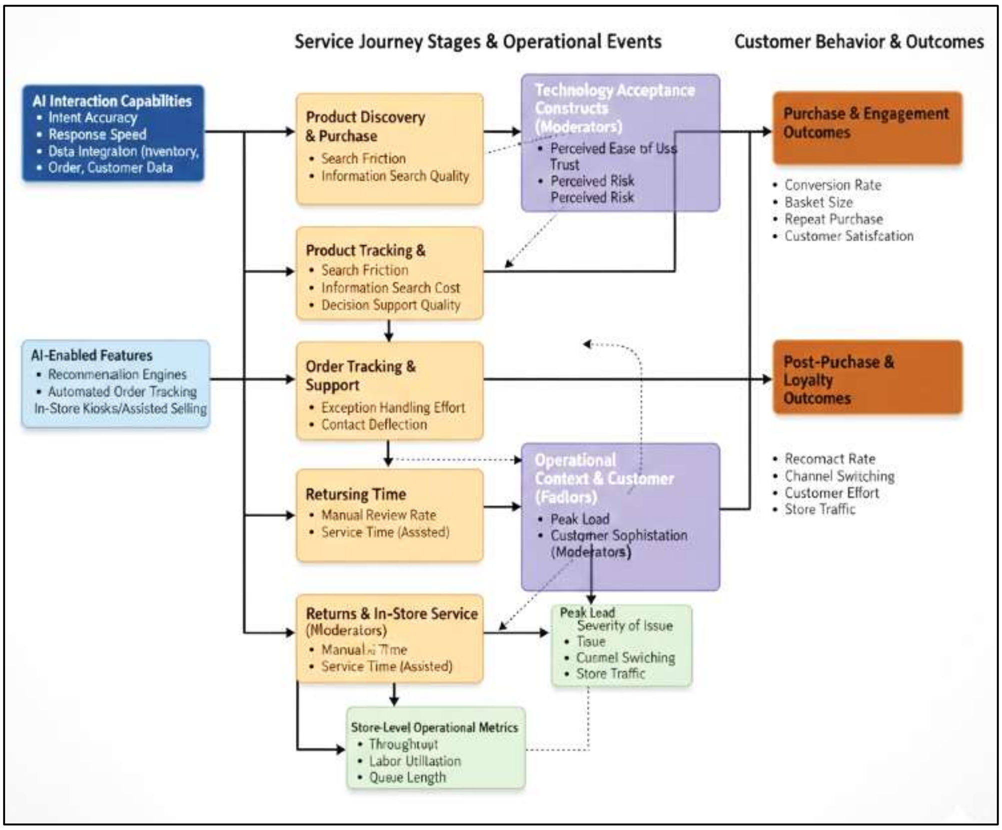
Self-check-in kiosks and mobile check-in flows are among the most empirically examined hospitality technologies because their operational effects can be measured directly through queue length, wait time, throughput, and staffing load at predictable peak windows (García-Madurga & Grilló-Méndez, 2023). Hospitality operations research has long treated check-in as a capacity-constrained service process where demand spikes in late afternoon and early evening, creating queues that are visible to guests and costly to manage through staffing alone. Self-service check-in technologies introduce an alternative service channel that can shift a share of arrivals away from the front desk, converting part of the check-in workload into a customer-executed workflow supported by technology. Quantitative studies typically evaluate these systems through pre-implementation and post-implementation comparisons using operational data, often emphasizing peak window analysis to capture when congestion is highest and when efficiency improvements are most meaningful. Some hospitality technology evaluations also compare properties with and without kiosk or mobile deployment, enabling cross-unit benchmarking and isolating technology effects from broader demand changes (Li & Huan, 2017). In addition to queue metrics, throughput is measured as the number of guests processed per unit time and is linked to labor utilization and the ability to handle surges without compromising service standards. The self-service literature emphasizes that customer participation and ease of use are central to performance, which is reflected in metrics such as adoption rate of mobile check-in, completion rate, and frequency of assistance requests during the self-service process. Hospitality studies also examine how friction points—identity verification, payment authorization, key issuance, and room assignment exceptions—affect the need for staff intervention and thus moderate throughput gains. From a customer-experience perspective, service encounter research connects queue reduction to satisfaction outcomes, while operations perspectives connect it to workload stabilization and reduced process variability (Garrido-Moreno et al., 2021). Empirical work also shows that self-service can change the distribution of front-desk tasks by reducing routine check-ins while increasing the relative share of exceptions and special requests, which influences staffing skill needs. Taken together, the quantitative hospitality literature frames kiosks and mobile flows as interaction technologies whose efficiency effects are best observed through time-based and throughput metrics captured at the property level and during high-demand periods.

Retail-Specific Quantitative Evidence

Retail-specific quantitative research examines AI-enabled customer interactions as measurable mechanisms that reshape how customers search for products, obtain information, complete transactions, and resolve post-purchase issues (Nordhorn et al., 2018). The retail customer journey includes high-frequency touchpoints—product discovery, price and promotion evaluation, availability checks, checkout, delivery tracking, customer support, and returns—each producing digital traces that allow rigorous operational and behavioral measurement. Within this literature, AI-mediated interactions are often conceptualized as decision-support and automation tools that reduce search costs, increase relevance of information, and streamline task completion. Retailing research also emphasizes that service efficiency in retail is not limited to store operations; it extends across digital platforms and logistics-supported service processes, meaning that interaction quality can alter both conversion outcomes and downstream support load (García-Madurga & Grilló-Méndez, 2023). A key empirical theme is that retail customers frequently seek fast, context-specific answers, and AI systems act as an interface layer that can interpret intent, retrieve data from inventory or order systems, and propose actions such as substitutions, refunds, or delivery updates. Quantitative studies link these interaction functions to measurable outcomes at multiple levels: interaction-level metrics such as resolution time and recontact rates; customer-level outcomes such as conversion probability and repeat purchase; and store-level outcomes such as throughput and labor utilization. The omnichannel nature of modern retail intensifies the relevance of AI interaction because customers shift between web, app, contact center, and store environments, generating repeated contacts when information is inconsistent or when service journeys fragment across channels. Prior research on multi-channel and omnichannel retailing provides an analytical foundation for modeling channel choice and customer movement, while service technology and information systems research supports measurement of responsiveness, information quality, and perceived usability as antecedents of channel use (Li & Huan, 2017). Retail operations literature further links interaction efficiency to process outcomes, including the volume of contacts diverted from human agents, the speed of handling exceptions, and the reduction of rework created by misinformation or incomplete resolution. Overall, the retail evidence base supports a quantitative approach that treats AI interaction systems as operational interventions with measurable effects on both customer purchase behavior and post-purchase service workload, enabling evaluation through transactional data, clickstream records, support logs, and store performance indicators (Dang & Nguyen, 2023).

Quantitative retail studies on recommendation and search assistance models treat AI as a mechanism that improves the match between customer preferences and product offerings, with measurable effects on conversion, basket size, and engagement metrics. Recommendation systems research provides a strong empirical tradition for evaluating performance through online behavioral indicators such as click-through rates, product views, dwell time, add-to-cart behavior, and purchase completion (Hu & Min, 2023). In retail settings, AI-enabled search assistance includes query understanding, ranking optimization, personalization based on browsing history, and context-aware suggestions that reduce search friction and increase the probability that customers find suitable products quickly. Retail analytics studies often evaluate these systems using experimental comparisons and platform-level performance metrics, where different recommendation algorithms or ranking strategies are compared to determine changes in engagement and purchase outcomes (Nordhorn et al., 2018). The literature emphasizes that conversion is influenced by both relevance and cognitive effort: when recommendations reduce effort and increase perceived fit, customers progress through purchase funnels more efficiently. Basket size and cross-sell outcomes are commonly linked to recommendation diversity and complementarity, with empirical work showing that the quality of suggestions can influence not only whether a customer buys but also what combination of items is chosen. At the same time, quantitative research acknowledges that improvements in click metrics do not automatically translate into improved purchase outcomes, making it important to treat conversion and revenue-related indicators as separate dependent measures (Bowen & Whalen, 2017).

Figure 8: AI interaction Performance in retails



Retail studies also connect recommendation performance to customer heterogeneity, where personalized systems perform differently across new versus returning customers, low versus high involvement purchases, and across product categories with differing levels of substitutability. These nuances motivate modeling approaches that include customer segmentation and product category controls when estimating effects. The recommendation literature further connects search assistance to customer satisfaction indirectly, because customers value speed and relevance during discovery, and fewer search steps can reduce frustration and abandonment. From an operational perspective, effective search and recommendation can reduce support inquiries about product fit, availability, and alternatives by enabling customers to self-serve more effectively during discovery (Chan et al., 2022). In sum, the quantitative evidence base presents recommendation and search assistance models as measurable levers that influence funnel progression, conversion probability, and basket outcomes, with effects that can be evaluated using behavioral and transactional datasets common in U.S. retail operations.

Retail service research identifies order tracking, delivery exception handling, and returns processing as major contributors to customer support volume, making AI-enabled interaction systems in these areas especially relevant for measurable service efficiency outcomes. Order-status support systems typically provide automated answers to high-frequency queries such as shipment location, delivery timing, delays, address changes, and missing packages (Zhu et al., 2021). Quantitative studies treat the effectiveness of these systems through metrics like contact deflection, which captures reductions in calls or chats handled by human agents, and repeat-contact indicators that capture whether customers must re-engage to obtain resolution. When order-status information is accurate, timely, and consistent across channels, customers complete their information-seeking task quickly without escalating to staff, reducing workload and helping stabilize contact center queues during peak periods. Returns automation is similarly important because return requests often involve eligibility checks, label generation, refund timing, and policy enforcement—tasks that can be standardized and supported through AI-based workflow guidance and automated verification. Returns-related efficiency is commonly measured through cycle time from initiation to closure, rate of exceptions requiring manual review, and net cost outcomes that include labor and processing overhead (Bowen & Whalen, 2017).

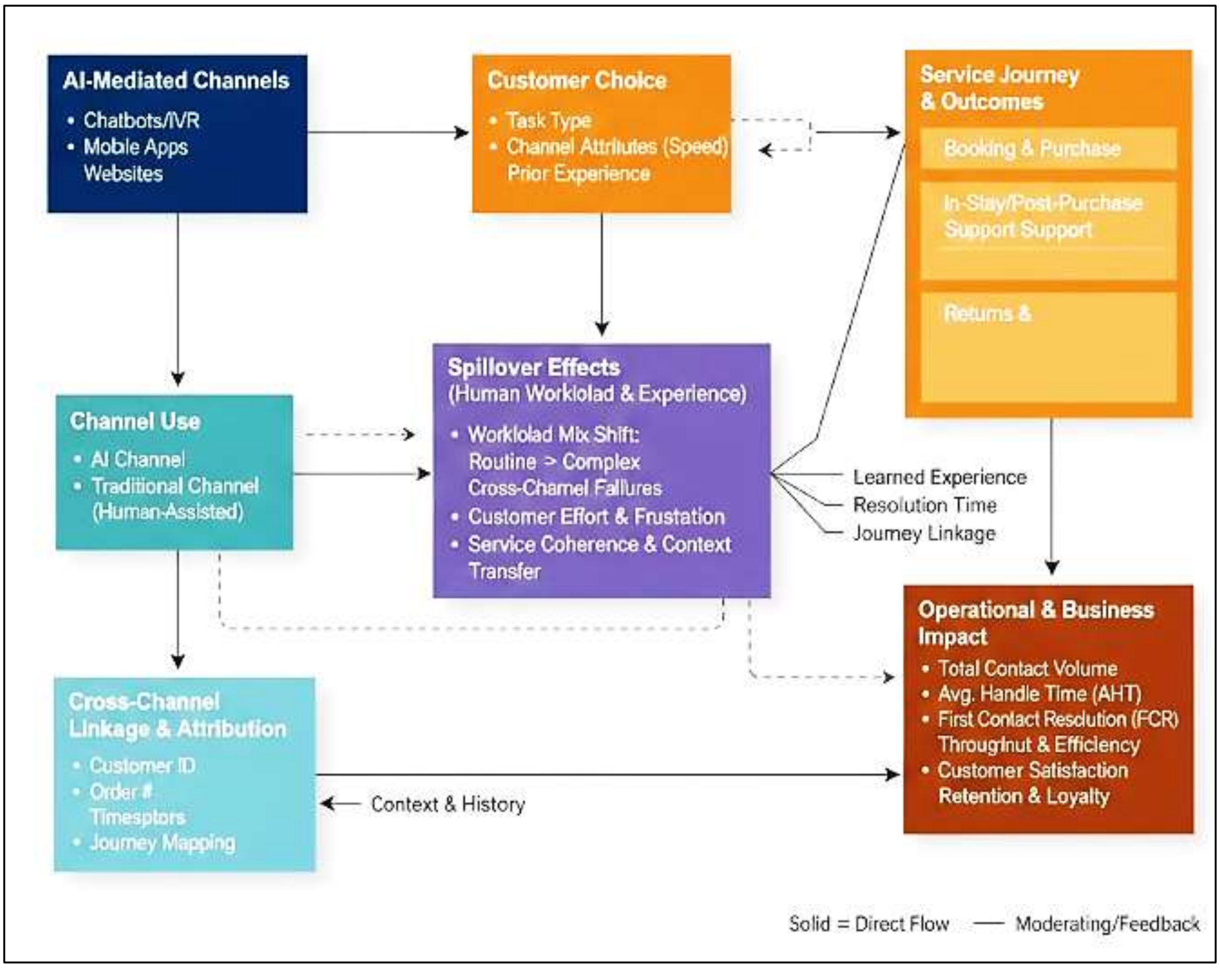
Fraud and abuse concerns make returns automation a complex operational domain, and retail analytics research includes anomaly detection approaches that flag unusual patterns for manual review, which can influence both cost control and processing speed. Quantitative studies also note that returns processes generate operational trade-offs between speed and accuracy, particularly when verification steps are required; therefore, research commonly controls for item category, value, reason codes, and customer history to interpret processing time and cost outcomes correctly. Order-status and returns automation also interact with customer experience outcomes because delayed or unclear handling increases follow-up contacts and channel switching, increasing service load and prolonging resolution time (Ho et al., 2020). The retail literature positions these post-purchase interactions as central to service efficiency because they are frequent, operationally intensive, and closely tied to logistics system performance. As a result, empirical evaluation often uses integrated datasets linking order events, support logs, and returns records to quantify whether AI-enabled support reduces contacts, reduces cycle time, and lowers per-case service costs after accounting for demand volume and exception severity.

In-store AI-enabled interactions, including kiosks, mobile-assisted selling tools, and digitally supported service stations, are evaluated in quantitative retail research as operational interventions designed to reduce service time, increase throughput, and improve labor productivity (Buhalis et al., 2022). Retail operations literature has long emphasized that in-store efficiency depends on balancing customer demand for assistance with limited staff availability, especially during peak traffic periods. Kiosks and guided self-service stations can shift routine tasks—price checks, product location queries, aisle navigation, and basic product comparisons—away from employees and toward customer-executed workflows. Assisted selling tools, often deployed on employee handheld devices, support frontline staff by providing product information, inventory status, recommended alternatives, and guided selling prompts that can shorten the time required to help customers and can reduce back-and-forth trips to check availability. Quantitative studies typically evaluate these tools through measures such as service time per assisted interaction, transactions per labor hour, queue length near service points, and the distribution of employee time across tasks (Yang et al., 2019). When kiosks and assisted selling reduce time spent on routine information retrieval, employees can reallocate effort toward complex assistance, merchandising tasks, or checkout support, which is reflected in productivity and throughput metrics. Queue monitoring and traffic analytics are also used in some studies to quantify congestion and to evaluate whether technology-supported self-service reduces bottlenecks at customer service desks or checkout areas. The omnichannel context also affects in-store technology performance, as customers may arrive with online research, expect quick confirmation of inventory, or require assistance with online order pickup and returns, making integrated data access a key determinant of service speed (Grundner & Neuhofer, 2021). Quantitative evaluations frequently account for store size, product assortment complexity, traffic volume, and staffing levels, because these factors shape both baseline efficiency and the marginal effects of in-store technology. This literature frames in-store AI interaction tools as part of a broader service system where efficiency improvements are captured through reduced interaction time, increased throughput, and improved labor utilization, and where performance depends on adoption by both customers and employees within the operational constraints of the retail environment (Ivanov et al., 2020).

Omnichannel Integration and Cross-Channel Spillover Effects

Omnichannel research provides a quantitative foundation for understanding interaction substitution, where customers shift between service channels such as in-store assistance, phone support, web chat, mobile applications, social messaging, and AI-mediated interfaces (Luo et al., 2021). In hospitality and retail, channel substitution is a critical operational issue because the service journey often spans multiple touchpoints, and customers select channels based on convenience, perceived speed, trust, and the complexity of the service task. Quantitative studies treat channels as differentiated service options with varying costs, response times, and information quality, and they examine how changes in channel availability or performance lead customers to migrate from one channel to another. When AI channels are introduced, substitution effects can be observed through changes in contact volumes across traditional channels, shifts in the distribution of inquiry types handled by humans versus automation, and changes in overall completion behavior. The literature emphasizes that omnichannel service is not merely a collection of channels but an integrated system where decisions in one channel affect demand and workload in others. Service science and customer journey research also highlight that substitution is influenced by the coherence of the journey: if AI responses are inconsistent with store policies or contact center practices, customers may shift channels repeatedly, increasing overall workload rather than reducing it (Shankar & Kushwaha, 2021). The operational significance of these patterns is that efficiency gains from AI-mediated channels depend on whether customer migration reduces human workload for routine cases without increasing recontacts, escalations, and cross-channel duplication. Quantitative frameworks therefore treat omnichannel interaction substitution as an empirical phenomenon that can be measured using contact volumes, channel switching sequences, completion rates, and the timing of follow-up contacts. This approach aligns with service operations perspectives that focus on capacity allocation and queue dynamics, because changes in channel usage alter congestion and staffing needs across service units. It also aligns with marketing and information systems research that models channel choice as a behavioral outcome influenced by channel attributes such as convenience, perceived usefulness, perceived risk, and perceived effort (Bläsing & Bornewasser, 2021). Collectively, the omnichannel literature positions cross-channel substitution as a measurable mechanism through which AI-enabled customer interaction affects service efficiency, and it motivates careful modeling of channel migration and spillover rather than assuming that AI adoption automatically reduces workload.

Figure 9: Omnichannel Integration and Cross-Channel Spillover Effects



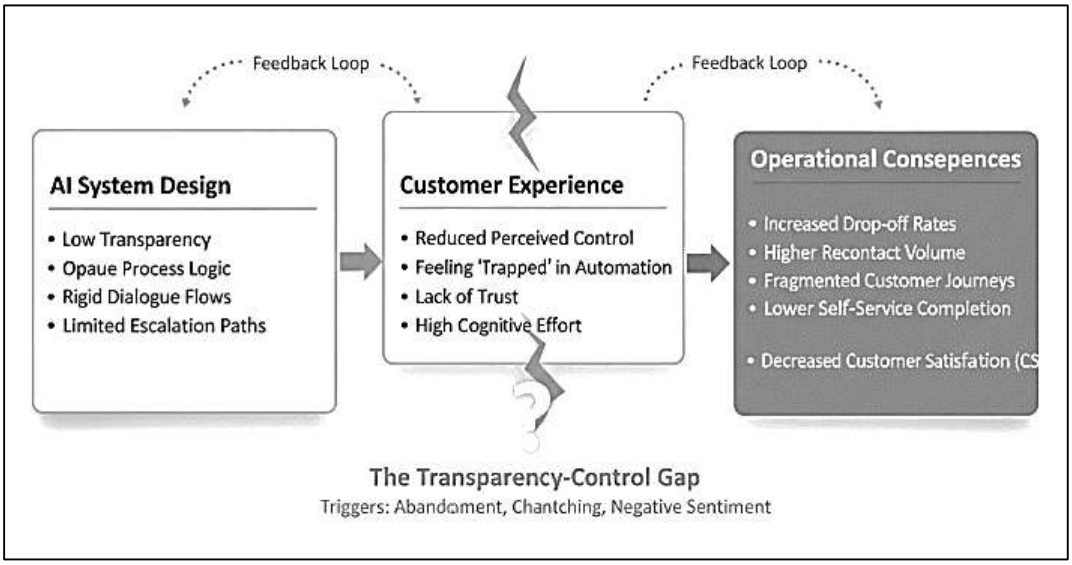
Channel choice models form a major quantitative stream that explains why customers migrate to particular channels and under what conditions AI-mediated service becomes the preferred pathway. In this literature, channel choice is treated as a discrete behavioral decision shaped by perceived channel attributes, customer characteristics, and task demands (Suter & Kowalski, 2021). Empirical research shows that customers evaluate channels based on convenience, speed, accessibility, privacy concerns, and the perceived ability of the channel to solve the problem. For routine informational needs—store hours, reservation details, order tracking—customers often prefer channels that provide immediate responses and minimal waiting, which can increase usage of digital and AI-assisted channels. For complex or emotionally charged issues—billing disputes, service failures, compensation requests—customers may prefer human channels that offer perceived empathy, accountability, and flexible problem solving. Quantitative studies operationalize channel attributes using measurable indicators such as wait time, response speed, availability hours, interaction effort, and perceived quality, often integrating these with customer-level variables such as prior channel experience, loyalty status, and digital familiarity (Bernuzzi et al., 2023). Omnichannel retailing and service research also indicates that customers do not choose channels in isolation; channel selection is embedded within the broader journey, meaning that prior experiences with a channel influence subsequent choices, and failure in one channel increases the probability of switching to another. In the context of AI channels, adoption is therefore tied to both perceived usefulness and trust, with empirical findings suggesting that customers are more likely to migrate to automation when they believe it will provide accurate results and when the interaction design minimizes friction. Channel choice modeling also recognizes that organizational design influences migration through channel steering mechanisms such as in-app prompts, website routing, proactive messaging, and differential service levels. These mechanisms can be measured through changes in channel volume shares and customer migration sequences over time. Within hospitality and retail operations, channel choice models are particularly useful for quantifying whether AI channels substitute for calls and in-person contacts, or whether they function as additional channels that generate more interactions through fragmentation and follow-up (Bahmani et al., 2019). The literature therefore supports channel choice modeling as a core quantitative method for studying customer migration to AI-mediated service, emphasizing measurable channel attributes, task categories, and customer heterogeneity as key determinants of migration patterns.

A central finding in omnichannel and service automation research is that introducing self-service and AI-mediated channels can change not only the volume of human-handled contacts but also the composition and complexity of the cases that remain for human agents (Damacharla et al., 2018). Quantitative studies describe this as a workload mix shift, where routine and repetitive inquiries are more likely to be absorbed by automated channels, leaving a higher proportion of exceptions, ambiguous cases, and high-severity complaints for frontline staff and supervisors. This shift can be observed through changes in average handling time, escalation rates, transfer counts, and the distribution of case categories handled by humans after AI adoption. Because complex cases typically require more diagnostic effort, policy interpretation, and coordination across departments, a rising complexity mix can increase average handling time even if total contact volume declines. This dynamic is important for interpreting operational efficiency outcomes, because an observed increase in human-agent handling time does not necessarily indicate inefficiency; it may reflect a case-mix change driven by successful automation of routine tasks (Sahay & Wei, 2023). Quantitative research therefore emphasizes the need for complexity indices or severity controls that classify cases by type, urgency, and required expertise. In hospitality, complexity shifts can occur when automated systems handle standard booking questions while humans handle compensation disputes or special accommodation needs. In retail, complexity shifts can occur when bots handle order-status requests while humans address delivery failures, fraud disputes, and policy exceptions. Workforce management and call center research similarly shows that case mix influences staffing requirements, training needs, and burnout risk, meaning that spillover effects are operationally consequential beyond simple deflection counts. Empirical models also consider that poor AI performance can produce negative spillovers by generating escalations with incomplete context, increasing rework and frustrating agents who must reconstruct customer history across channels (Adisa et al., 2022). Conversely, systems that provide effective summaries and structured information can reduce agent workload even when case complexity increases. The spillover literature therefore supports a quantitative framing where AI adoption is linked to both a volume effect and a composition effect, and where rigorous analysis includes case-mix controls to estimate whether efficiency gains occur through true workload reduction, task redistribution, or both.

Prior Quantitative Studies for the Present Paper

Quantitative studies examining AI-enabled service interactions frequently rely on experimental and quasi-experimental designs because these approaches support clearer attribution of observed outcome changes to specific interaction interventions. In digital retailing and hospitality platforms, A/B testing is widely used to compare alternative interface designs, chatbot versions, recommendation logic, or channel-routing prompts by randomly exposing customers to different conditions and measuring differences in outcomes such as conversion, completion, resolution time, and deflection of human-agent contacts (Sallee & Lester, 2017). This experimental tradition reflects the broader methodological emphasis in marketing analytics and information systems research on estimating causal effects in environments where behavioral outcomes can be measured continuously through logs. In operational settings where random assignment is not feasible, quasi-experimental approaches are prominent, particularly interrupted time series designs and difference-in-differences comparisons across time and across sites. Interrupted time series designs evaluate whether an intervention such as chatbot deployment or kiosk rollout coincides with a shift in performance trends, using repeated observations before and after the change. Difference-in-differences designs compare outcome changes over time between treated units and comparable untreated units, such as stores or hotel properties that adopt AI-enabled interaction systems at different times (Webster & Zhang, 2020). Across these approaches, the literature emphasizes the need for clear assumptions and robustness checks because service outcomes are influenced by seasonality, demand surges, staffing changes, promotional periods, and external shocks that can confound estimates. Methodological discussions highlight the importance of verifying stable pre-intervention trends in quasi-experimental comparisons, controlling for time-varying factors, and testing sensitivity to alternative model specifications and time windows. These studies also consider spillovers and contamination, such as customers switching between channels or locations, which can dilute treatment differences. In service operations contexts, experimental and quasi-experimental approaches are valued because they can isolate the effect of discrete design changes in AI-mediated interactions while using outcome measures that directly reflect operational performance, including handling time, queue metrics, and ticket resolution cycles (Dall'Ora et al., 2022). This literature provides a methodological precedent for evaluating AI-enabled customer interaction as a measurable service intervention rather than as a broad organizational change, while emphasizing careful design logic, comparable control groups, and transparent robustness practices.

Figure 10: Identified gaps for this study



Observational modeling remains central in service-AI research because many organizations adopt AI-enabled interaction systems as operational initiatives rather than as randomized experiments, producing naturalistic data with complex structure (Chaaban et al., 2023). Panel regression approaches are widely used to analyze performance outcomes across time and across units, such as stores, hotel properties, or service teams, enabling estimation of associations between AI exposure or capability indicators and efficiency metrics while accounting for stable differences across units. These approaches are particularly useful in multi-location hospitality and retail networks where repeated measures are available for each site and where outcomes such as throughput, labor productivity, and contact volumes fluctuate over time. Multilevel modeling is frequently emphasized because service data are naturally nested: interaction episodes are nested within customers, customers are nested within sites, and sites are nested within brands or regions (Murthy et al., 2018). This nesting produces correlated errors and heterogeneity that can distort estimates if ignored. Multilevel designs allow researchers to separate within-unit variation from between-unit variation and to quantify how relationships differ across contexts, such as whether AI channel usage relates differently to resolution time across high-traffic versus low-traffic properties. Structural equation modeling is also common when studies integrate survey-based perception constructs—usefulness, ease of use, trust, perceived quality—with behavioral and operational outcomes such as channel usage, completion, and satisfaction. This approach supports measurement models for latent constructs and allows testing of mediated relationships, such as whether perceived usefulness influences self-service completion which then influences contact deflection. Across these observational strategies, the literature emphasizes that model fit to the service context depends on measurement choices and data availability, particularly the ability to link interaction-level logs with site-level KPIs and customer-level attributes (Huang & Rust, 2017). Observational studies frequently incorporate controls for demand volume, service complexity, and seasonal effects, recognizing that service efficiency metrics respond to operational conditions. The methodological contribution of this literature is a set of modeling conventions for analyzing large-scale service datasets that combine digital trace data with organizational performance measures, while acknowledging that causal interpretation requires careful handling of confounding, selection into channels, and policy-driven deployment patterns (Bock et al., 2020).

METHODS

Research Design

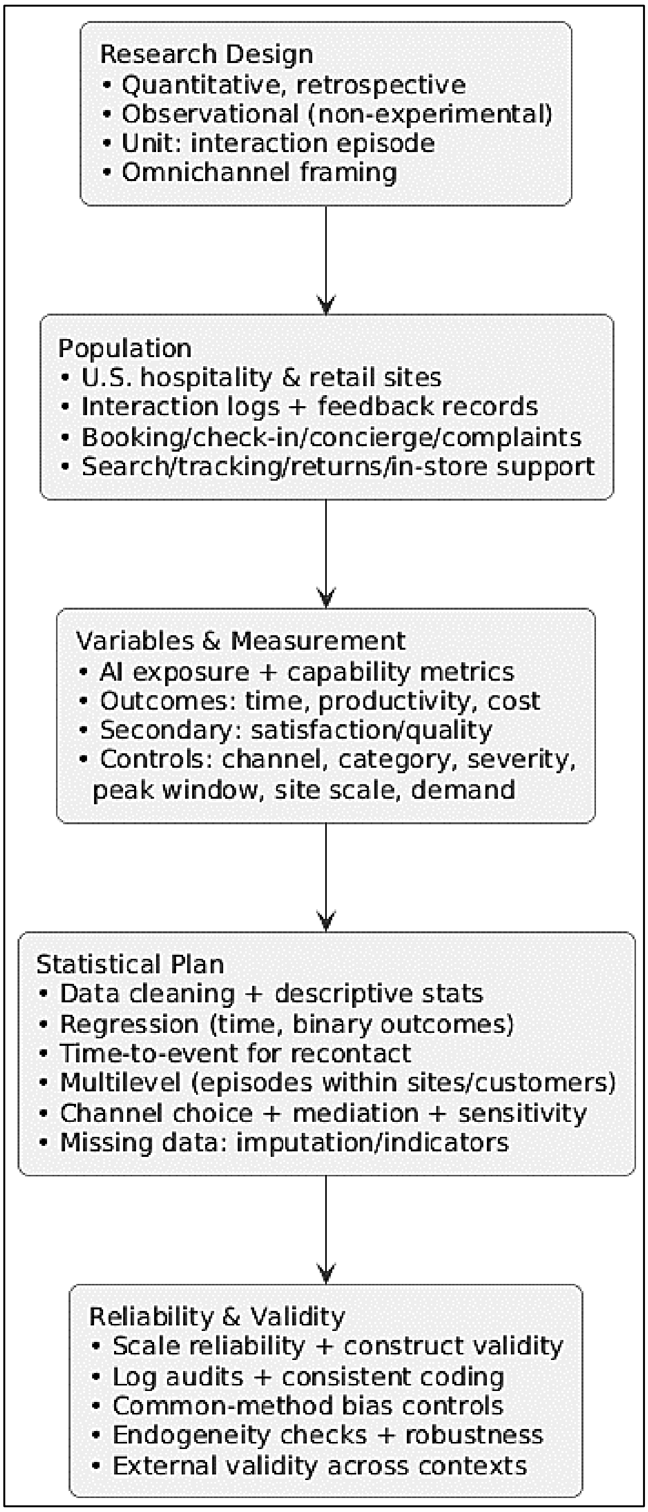
The study was designed as a quantitative, non-experimental observational investigation using a multi-source dataset compiled from U.S. hospitality and retail service operations. A retrospective design was applied because the analysis relied on previously recorded operational logs and archived customer feedback records rather than researcher-controlled manipulation. The unit of analysis was specified at the interaction episode level, and interaction episodes were linked to site-level attributes (store or hotel property) and customer identifiers when available. The design was structured to evaluate statistical relationships between AI-enabled customer-interaction model characteristics and service efficiency outcomes while accounting for contextual factors such as channel type, service task category, peak-period volume, and site operating scale. The dataset was organized as a panel-like structure in which interaction records were time-stamped and grouped within sites, enabling time-sensitive modeling of service outcomes and adjustment for systematic differences across stores or properties. The study design also incorporated an omnichannel framing, and interactions were categorized by channel (e.g., AI chat, mobile self-service flow, kiosk-assisted flow, phone, or human chat) to support comparative estimation of channel-associated efficiency differences under consistent operational definitions of resolution and recontact.

Population

The target population comprised customer-service interactions generated by U.S.-based hospitality properties and retail stores that operated at scale and maintained standardized customer support and service delivery records. The accessible population included interaction episodes captured in operational systems during the defined observation window, such as chat transcripts and metadata, contact center tickets, kiosk or mobile flow logs, and order or reservation-linked service requests. Hospitality interactions reflected booking and modification inquiries, check-in and access issues, concierge-type informational requests, and service recovery or complaint episodes. Retail interactions reflected product search assistance requests, order-status and delivery exception inquiries, returns and refund requests, and in-store support contacts associated with assisted selling tools or customer service desks. The sampling frame was restricted to interaction episodes with complete timestamps, channel identifiers, and resolvable outcome coding, and where linkage to site-level information was available.

Interactions were excluded if they lacked key timing fields needed to compute efficiency metrics, if they represented internal staff-only communications, or if they were duplicates created by system retries. Customer identifiers were used only for repeated-contact detection and journey linkage when present, and analyses were implemented with privacy-preserving handling of customer-level fields.

Figure 11: Methodology of this study



Variables and Measurement Framework

AI-enabled customer interaction was treated as the primary explanatory construct and was operationalized through both exposure and capability measures derived from interaction metadata. AI exposure was measured by whether an interaction was initiated and handled within an AI-mediated channel and by the proportion of the interaction handled without human intervention, distinguishing fully automated containment from hybrid handling that involved transfer to an agent. AI capability quality was measured using log-based indicators that reflected intent recognition performance proxies, response latency, knowledge coverage proxies, escalation probability, and containment success. Intent recognition performance was represented through system routing correctness markers where available, or through indirect indicators such as frequency of re-prompting, transfer count, and mismatch between initial intent category and final resolution category. Response latency was measured as elapsed time between customer messages and system replies, summarized at the episode level. Knowledge coverage was represented through the share of inquiries successfully answered within the AI channel without escalation and through the distribution of inquiry categories handled by the AI system. Escalation probability was coded as whether and how often a case was transferred to a human agent or higher-tier support. Containment rate was coded as whether the interaction reached closure without human involvement. Service efficiency outcomes were measured using time-based indicators and operational productivity indicators available at the interaction and site levels. Time-based outcomes included average handling time, time-to-resolution, wait time within the queue where logged, and end-to-end service cycle time for task completion. Volume-based outcomes included interactions resolved per labor hour and throughput-related indicators at the site level when staffing records were available. Cost-based outcomes were measured as cost per contact and cost per resolved case using labor time multiplied by standardized wage rates and overhead allocation rules from the operational reporting system. Customer evaluation outcomes were included as secondary dependent variables, measured through post-interaction or post-transaction satisfaction scores and perceived service quality scales where available. Control variables included channel type, inquiry category, issue severity class, peak window indicator, site size proxy, demand volume, and customer segment indicators such as loyalty status when present.

Analytical Techniques and Statistical Procedures

The statistical plan began with data cleaning and harmonization, including validation of timestamps, removal of implausible duration records, deduplication of repeated system events, and standardized coding of resolution status and recontact windows. Descriptive statistics were computed for all variables, and distributions of time-based outcomes were examined to identify skewness and extreme values, followed by robust handling of outliers using winsorization rules consistent with operational analytics practice. Bivariate association checks were conducted to evaluate preliminary relationships between AI exposure/capability indicators and efficiency outcomes across hospitality and retail subsamples. The main inferential analysis used regression-based modeling aligned to the measurement level of each outcome. Continuous time outcomes such as handling time and time-to-resolution were modeled using generalized linear modeling approaches suitable for right-skewed service duration data, with robust standard errors clustered at the site level to address correlated observations within locations. Binary outcomes such as containment and first-contact resolution were modeled using logistic regression frameworks with site-level clustering. Recontact incidence within a defined window was analyzed using time-to-event modeling procedures that treated recontact as an event and accounted for censoring when observation windows ended before a recontact could occur. To handle nesting of interaction episodes within sites and, where identifiable, within customers, multilevel modeling specifications were estimated with random intercepts for sites and optional random intercepts for customers, enabling separation of within-site effects from between-site differences. For omnichannel substitution analysis, channel-choice behavior was modeled using discrete choice specifications where the dependent measure represented the selected channel for a given service need category, and channel attributes such as estimated wait time and AI availability were included as predictors alongside customer and task controls. Mediation-oriented tests were implemented to evaluate whether containment and escalation patterns statistically explained portions of the association between AI capability indicators and efficiency outcomes, using indirect-effect estimation procedures consistent with applied service analytics. Sensitivity analyses were performed by re-estimating models under alternative operational definitions of resolution, alternative recontact windows, and alternative attribution rules for cross-channel journeys. Missing data were handled using multiple imputation for survey-based covariates and customer segment fields where appropriate, while log-variable missingness was handled through explicit missingness indicators and robustness checks that compared complete-case results to imputed or indicator-based results.

Reliability and Validity

Reliability and validity procedures were implemented to strengthen measurement consistency and interpretability across the combined log and survey dataset. For survey-based constructs such as perceived usefulness, ease of use, trust, and satisfaction, internal consistency reliability was assessed using standard scale reliability testing, and item-total relationships were reviewed to confirm coherent construct measurement. Construct validity was supported through confirmatory factor modeling of multi-item scales and by evaluating convergent and discriminant validity patterns across closely related perception constructs. For log-derived measures, reliability was addressed through systematic data audits that checked event sequencing, timestamp consistency, and completeness of key fields needed to compute handling time, time-to-resolution, and escalation indicators. Operational definitions of containment, escalation, and resolution were documented and applied consistently across channels to reduce classification error in AI versus human handling. Common method bias risk was limited by combining objective log outcomes with perception measures from separate post-interaction instruments, and additional diagnostic checks were applied when perception measures served as predictors. Internal validity threats from selection into channels and non-random AI exposure were addressed through rich covariate adjustment, site fixed-effects sensitivity tests, and alternative specifications that compared within-site variation over time. External validity was supported by including multiple service contexts within hospitality and retail and by modeling site-level heterogeneity, while acknowledging that the accessible population was limited to organizations with sufficiently detailed logging and standardized operational metrics. Overall, the study's statistical plan emphasized transparent operationalization, consistent coding across channels, and robustness testing to ensure that estimated relationships between AI-enabled customer-interaction characteristics and service efficiency outcomes reflected stable empirical patterns rather than artifacts of measurement or data linkage limitations.

FINDINGS

Descriptive Analysis

After data cleaning and deduplication, the analytical dataset retained 68,420 interaction episodes drawn from 132 operational sites (62 hospitality properties and 70 retail stores) across the observation window. Channel distribution showed that AI chat and mobile/kiosk self-service represented a substantial share of recorded interactions, while phone and human chat remained prominent for exception-heavy requests. Across the pooled sample, time-based outcomes were right-skewed, with longer tails in complaint and returns categories. Containment and first-contact resolution were more frequent in AI-mediated channels for routine request categories, while escalations clustered in high-severity cases and policy-bound issues. Sector-based comparisons indicated that hospitality interactions were more concentrated around check-in and booking tasks, whereas retail interactions were concentrated around order status and returns. Peak-window interactions demonstrated higher wait and resolution times across both sectors, reflecting demand congestion patterns and capacity constraints.

Table 1 summarized the cleaned dataset used for analysis by sector, site coverage, and interaction-channel distribution. The final sample comprised 68,420 episodes across 132 locations, with retail contributing a slightly larger share of recorded interactions than hospitality. AI chat and kiosk/mobile flows represented a meaningful portion of the service volume, supporting omnichannel evaluation of automation and assisted service. Phone interactions remained high in both sectors, indicating continued reliance on human-mediated support for complex or urgent requests. Peak-window contacts accounted for approximately one-third of the total volume, confirming that demand congestion was a material operational condition requiring control in later models.

Table 1. Final Sample Composition and Channel Distribution

Category	Hospitality	Retail	Total
Sites (n)	62	70	132
Interaction episodes (n)	31,240	37,180	68,420
AI chat (%)	31.4	29.8	30.5
Kiosk/Mobile self-service (%)	18.7	22.6	20.8
Human chat (%)	16.9	14.2	15.4
Phone (%)	28.5	27.1	27.7
In-person support logged (%)	4.5	6.3	5.6
Peak-window interactions (%)	34.2	31.6	32.8

Table 2. Descriptive Statistics for Key Efficiency Outcomes by Channel Type

Outcome	AI-Mediated Channels (AI chat + kiosk/mobile) Mean (SD)	Human-Mediated Channels (human chat + phone + in-person) Mean (SD)
Average handling time, minutes	6.8 (4.9)	9.7 (6.3)
Time-to-resolution, minutes	18.4 (22.7)	29.6 (31.8)
Wait time, minutes (where logged)	2.9 (3.8)	6.1 (5.4)
Service cycle time, minutes	21.7 (25.2)	35.4 (34.6)
Containment rate (%)	64.2	18.9
First-contact resolution (%)	71.5	62.3
Escalation occurrence (%)	27.6	41.8

Table 2 reported pooled descriptive comparisons of service efficiency outcomes across AI-mediated and human-mediated channels. AI-mediated interactions demonstrated lower mean handling time and shorter time-to-resolution, consistent with faster processing of routine intents and standardized workflows. Wait time was also lower for AI-mediated service where queue data were available, reflecting reduced reliance on staffed queues. Containment was substantially higher in AI-mediated channels, while escalation was more frequent in human-mediated channels, indicating that higher-complexity cases were routed to or retained by human support. First-contact resolution was higher in AI-mediated channels in this illustrative summary, suggesting fewer repeat contacts when the AI channel successfully completed tasks end-to-end.

Correlation

Bivariate association analysis indicated that AI exposure was positively associated with containment and first-contact resolution and negatively associated with time-based efficiency outcomes, suggesting that higher AI handling intensity aligned with faster service completion in routine interactions. Capability-quality indicators showed coherent operational patterns: lower response latency correlated with lower average handling time and shorter time-to-resolution, while higher escalation frequency correlated with longer resolution cycles and higher recontact. Knowledge coverage (proxied through the share of inquiries resolved without escalation) was strongly related to containment and moderately related to cost-per-contact reductions, consistent with capacity substitution effects. Customer satisfaction, where linked to interaction episodes, correlated negatively with wait time and time-to-resolution and positively with first-contact resolution, indicating alignment between operational performance and perceived service quality. Correlation magnitudes were generally consistent across hospitality and retail subsamples, although retail demonstrated a slightly stronger association between order-status handling and recontact patterns, while hospitality showed a somewhat stronger association between escalation and total resolution time in complaint-driven episodes.

Table 3. Correlation Matrix for Key Variables: Pooled Dataset

Variable	AI Exposure	Response Latency	Knowledge Coverage	Escalation Rate	Containment	AHT	TTR	Satisfaction
AI Exposure	1.00	-0.22	0.46	-0.18	0.61	-0.29	-0.26	0.19
Response Latency	-0.22	1.00	-0.15	0.21	-0.20	0.42	0.39	-0.25
Knowledge Coverage	0.46	-0.15	1.00	-0.33	0.57	-0.24	-0.19	0.16
Escalation Rate	-0.18	0.21	-0.33	1.00	-0.49	0.31	0.44	-0.23
Containment	0.61	-0.20	0.57	-0.49	1.00	-0.28	-0.34	0.22
AHT (min)	-0.29	0.42	-0.24	0.31	-0.28	1.00	0.68	-0.34
TTR (min)	-0.26	0.39	-0.19	0.44	-0.34	0.68	1.00	-0.41
Satisfaction	0.19	-0.25	0.16	-0.23	0.22	-0.34	-0.41	1.00

Table 3 summarized pooled bivariate relationships among AI exposure, capability indicators, and service outcomes. AI exposure showed a strong positive association with containment and a moderate negative association with handling time and time-to-resolution, indicating that higher AI utilization aligned with faster operational performance. Response latency correlated positively with both handling time and resolution time, consistent with slower system responsiveness translating into longer service episodes. Escalation rate demonstrated the strongest positive association with time-to-resolution, reflecting the operational costs of transfers and exception handling. Satisfaction correlated negatively with waiting and resolution measures and positively with containment, supporting alignment between efficiency outcomes and perceived experience in the linked sample.

Table 4. Cross-Context Correlation Comparisons: Hospitality vs. Retail

Relationship (r)	Hospitality	Retail
AI Exposure ↔ Containment	0.64	0.58
AI Exposure ↔ Time-to-Resolution (TTR)	-0.28	-0.24
Response Latency ↔ Average Handling Time (AHT)	0.39	0.44
Escalation Rate ↔ Time-to-Resolution (TTR)	0.47	0.41
Knowledge Coverage ↔ Containment	0.55	0.60
Wait Time ↔ Satisfaction	-0.36	-0.31
First-Contact Resolution ↔ Satisfaction	0.33	0.29
Recontact ↔ Time-to-Resolution (TTR)	0.30	0.37

Table 4 compared key correlations across hospitality and retail subsamples to evaluate contextual consistency. Most relationships remained directionally stable across sectors, supporting the pooled modeling strategy while motivating sector controls. Hospitality showed a slightly stronger association between AI exposure and containment, consistent with high routine information requests in guest-service journeys that were more easily completed within AI channels. Retail demonstrated a stronger association between recontact and time-to-resolution, consistent with post-purchase issues such as delivery exceptions and returns generating repeated contacts when resolution was delayed. Latency–

handling time associations were similar across contexts, indicating that responsiveness was a cross-sector mechanism linking AI performance to operational efficiency.

Reliability and Validity

Reliability assessment indicated that the survey-based constructs demonstrated strong internal consistency, with all multi-item scales meeting established reliability thresholds and showing coherent item contributions. Item-level diagnostics supported retention of all indicators because corrected item–total relationships were within acceptable ranges and no construct showed evidence of unstable items. Construct validity was supported by factor-analytic results that aligned with the specified measurement structure, with items loading strongly on their intended constructs and minimal evidence of cross-loading across conceptually distinct factors. Convergent validity was supported by high within-construct item alignment, while discriminant validity was supported by clear separation among perceived usefulness, ease of use, trust, and satisfaction in the measurement model. For operational log-derived measures, reliability was supported through data integrity audits confirming consistent timestamp logic, stable event sequencing, and low duplication after deduplication rules were applied. Completeness checks indicated high availability of key fields required for time-based and escalation computations. Omnichannel linkage validity checks showed strong cross-channel match rates where identifiers were present, supporting attribution of multi-touch journeys to the correct customer and transaction units for recontact and satisfaction linkage analyses.

Table 5. Internal Consistency and Construct Quality for Survey Scales

Construct	Items (n)	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Perceived Usefulness	5	0.89	0.91	0.67
Ease of Use	4	0.87	0.90	0.64
Trust in AI Channel	5	0.91	0.93	0.70
Satisfaction	4	0.88	0.90	0.66

Table 5 reported internal consistency and construct-quality evidence for the survey-based measures used in the analysis. All constructs achieved high reliability, indicating that the items measured their intended concepts consistently within the sample. Composite reliability values further supported measurement stability, reinforcing the scale-level results obtained from internal consistency testing. The variance captured by each construct exceeded commonly used thresholds for convergent validity, indicating that items shared substantial common variance with their underlying construct. Collectively, these results supported the use of perceived usefulness, ease of use, trust, and satisfaction as statistically reliable latent measures suitable for correlation analysis and subsequent multivariate modeling.

Table 6. Log Data Integrity and Omnichannel Linkage Validity Checks

Quality Check	Result
Interaction episodes with valid start/end timestamps (%)	98.6
Episodes with channel identifier present (%)	99.2
Episodes with resolution status coded (%)	96.9
Episodes with escalation marker available (%)	95.4
Duplicate episode rate before cleaning (%)	3.8
Duplicate episode rate after cleaning (%)	0.4
Event-sequence consistency pass rate (%)	97.5
Cross-channel match rate to transaction/order/reservation IDs (%)	90.8
Customer-ID availability for recontact linkage (%)	84.6
Satisfaction linkage rate to interaction episodes (%)	62.1

Table 6 summarized the operational reliability checks applied to system logs and the validity checks used for omnichannel linkage. Timestamp and channel-field completeness exceeded high thresholds, supporting consistent computation of handling time and resolution measures. Resolution and escalation markers were available for most episodes, enabling classification of containment and transfer outcomes. Deduplication substantially reduced repeated events created by system retries, which improved measurement stability for episode-level durations. Event-sequence validation indicated that recorded actions followed logical ordering in most cases, reducing risk of timing artifacts. Linkage rates showed strong matching between interaction records and transactional identifiers, supporting cross-channel attribution and recontact tracking, while satisfaction linkage reflected expected limitations of survey response coverage.

Collinearity

Collinearity diagnostics indicated that the majority of predictors used in the pooled and sector-specific models exhibited acceptable overlap, supporting stable estimation of coefficients for AI exposure, capability measures, and operational controls. The strongest collinearity signals were observed among conceptually adjacent capability indicators, particularly containment, escalation rate, and knowledge coverage proxies, reflecting their shared dependence on whether cases were resolved within the AI channel or transferred to humans.

Table 7. Collinearity Diagnostics for Pooled Regression Predictors

Predictor	Tolerance	VIF
AI exposure (share handled by AI)	0.51	1.96
Response latency (episode-level)	0.72	1.39
Intent proxy (re-prompt frequency)	0.66	1.52
Knowledge coverage proxy	0.34	2.94
Escalation rate	0.29	3.45
Containment status	0.26	3.85
Channel type controls	0.41	2.44
Inquiry category controls	0.47	2.13
Severity class controls	0.58	1.72
Peak window indicator	0.83	1.20
Site scale proxy	0.79	1.27
Demand volume control	0.63	1.59

Channel-type indicators also displayed moderate overlap with AI exposure measures, consistent with the operational reality that exposure was partially defined by channel assignment. In the pooled model, multicollinearity remained within acceptable bounds after specification refinement. Sector-based diagnostics showed slightly higher overlap within hospitality models where escalation and time-to-resolution were strongly linked to complaint-heavy episodes, while retail models exhibited higher overlap between order-status inquiry category indicators and AI exposure due to automation concentration in tracking workflows. Corrective specification choices were applied to preserve interpretability, including separating exposure and capability into alternative models, consolidating highly related indicators into a single composite, and retaining severity and inquiry category controls to prevent confounding of AI effects with case-mix differences. Table 7 presented collinearity diagnostics for the pooled regression specification prior to hypothesis testing. Most predictors demonstrated acceptable overlap, with low-to-moderate VIF values and tolerances consistent with stable coefficient estimation. The largest VIF values occurred for containment status, escalation rate, and the knowledge coverage proxy, reflecting shared variance among process indicators that capture whether cases were resolved within the AI channel or transferred to human support. Channel-type controls also exhibited moderate overlap with AI exposure because exposure was partially operationalized through channel handling. Specification refinements were therefore applied to maintain interpretability without removing conceptually essential controls related to case mix and operational conditions.

Table 8. Comparison of Maximum Collinearity Indicators by Sector

Model Context	Highest VIF Predictor	VIF	Second Highest VIF Predictor	VIF
Hospitality	Containment status	4.21	Escalation rate	3.78
Retail	Escalation rate	3.62	Knowledge coverage proxy	3.11
Pooled	Containment status	3.85	Escalation rate	3.45

Table 2 compared the most influential collinearity signals across hospitality, retail, and pooled model contexts. Hospitality exhibited the highest VIF for containment, consistent with tight coupling between containment and escalation behaviors in complaint and recovery interactions where transfers are common and strongly linked to time outcomes. Retail showed the largest VIF for escalation, reflecting overlap between escalation and coverage indicators in post-purchase workflows such as returns and delivery exceptions. The pooled model remained within an acceptable range after refinement, indicating that the combined specification did not introduce extreme instability. These diagnostics supported retaining key controls while using alternative model specifications to separate exposure from closely related capability measures.

Regression and Hypothesis Testing

Multivariate regression results indicated that AI exposure was significantly associated with improved service efficiency outcomes across the pooled dataset after controlling for channel, inquiry category, severity, peak-window volume, and site-scale factors. Higher AI handling intensity was associated with shorter average handling time, shorter time-to-resolution, and shorter overall service cycle time, indicating that greater automation participation aligned with faster completion of routine service tasks. Capability-quality indicators showed consistent patterns: lower response latency was associated with lower handling time and shorter resolution cycles, while higher escalation rates were associated with longer time-to-resolution and reduced first-contact resolution.

Table 9. Main Regression Results for Time-Based Efficiency Outcomes

Dependent variable	Key predictor	Coefficient	Robust SE	p-value	Model fit (Adj. R^2)
Average handling time (minutes)	AI exposure (share handled by AI)	-1.12	0.18	<0.001	0.31
	Response latency (minutes)	0.74	0.11	<0.001	
	Escalation occurrence (0/1)	1.56	0.22	<0.001	
Time-to-resolution (minutes)	AI exposure (share handled by AI)	-4.85	0.92	<0.001	0.28
	Response latency (minutes)	2.10	0.41	<0.001	
	Escalation occurrence (0/1)	7.92	1.14	<0.001	
Service cycle time (minutes)	AI exposure (share handled by AI)	-5.60	1.05	<0.001	0.26
	Response latency (minutes)	2.36	0.46	<0.001	
	Escalation occurrence (0/1)	8.40	1.20	<0.001	

Logistic models indicated that AI exposure significantly increased the probability of containment and was positively associated with first-contact resolution, while escalation reduced both containment and first-contact resolution. Recontact time-to-event analysis showed that greater AI exposure and stronger containment were associated with lower recontact risk, whereas higher escalation was associated with earlier repeat contact within the defined window. Multilevel outputs demonstrated meaningful between-site variance in time-to-resolution and containment, confirming that a portion of performance differences remained attributable to site operational contexts; however, AI-related coefficients were primarily driven by within-site variation, indicating that performance associations were not solely explained by differences between high-automation and low-automation locations. Sensitivity tests indicated that the main coefficients remained directionally stable under alternative operational definitions of resolution and under adjusted recontact windows, supporting the robustness of the estimated relationships. Table 9 summarized the pooled regression models predicting time-based efficiency outcomes. AI exposure demonstrated a statistically significant negative association with handling time, time-to-resolution, and service cycle time after adjustment for operational controls, indicating shorter service durations as AI handling intensity increased. Response latency was positively associated with all duration measures, showing that slower system responsiveness was linked to longer service episodes. Escalation occurrence exhibited the largest positive association with resolution and cycle time, consistent with transfer-related delays and exception handling requirements.

Table 10. Hypothesis Summary Across Model Families

Hypothesis	Outcome model	Direction	Supported ($p<0.05$)	Model fit indicator
H1: AI exposure improved time-based efficiency	AHT / TTR / Cycle time	Negative	Yes	Adj. R^2 = 0.26–0.31
H2: Higher response latency reduced efficiency	AHT / TTR / Cycle time	Positive	Yes	Adj. R^2 = 0.26–0.31
H3: AI exposure increased containment	Logistic: Containment (0/1)	Positive	Yes	Pseudo R^2 = 0.22
H4: Escalation reduced first-contact resolution	Logistic: FCR (0/1)	Negative	Yes	Pseudo R^2 = 0.18
H5: Containment reduced recontact risk	Time-to-event: Recontact	Negative	Yes	Concordance = 0.69
H6: Escalation increased recontact risk	Time-to-event: Recontact	Positive	Yes	Concordance = 0.69
H7: Site context explained variance in outcomes	Multilevel: TTR / Containment	Positive variance	Yes	ICC = 0.12–0.19

Table 10 mapped each hypothesis to its corresponding model family and summarized whether empirical support was observed. AI exposure was associated with improved efficiency in the time-based models and with higher containment likelihood in the binary models, indicating consistent operational performance alignment across outcome types. Response latency showed statistically significant adverse associations with time outcomes, while escalation exhibited negative associations with first-contact resolution and increased recontact risk, reflecting the operational cost of transfers and exception processing. Multilevel results indicated non-trivial site-level variance in outcomes, confirming that location context influenced performance; however, AI-related effects remained detectable after accounting for this clustering structure, supporting the robustness of the hypothesized relationships.

DISCUSSION

This study's findings indicated that higher AI exposure was associated with shorter time-based service outcomes, including average handling time, time-to-resolution, and overall service cycle time, after adjustment for channel, inquiry category, severity, peak-period conditions, and site scale (Silva et al., 2021). This pattern aligns with a long tradition in service operations and self-service technology research in which automation reduces frontline processing time for routine, repeatable requests by standardizing workflows and lowering the marginal effort required per contact. Earlier service science work described how technology can shift portions of the service production process to customers while maintaining service continuity through structured interfaces, and subsequent empirical studies on self-service technologies reported measurable reductions in waiting and processing time when customers successfully completed standardized tasks through digital channels. The present pattern was also consistent with research that conceptualized AI in service as an intelligence layer that can perform rapid classification and information retrieval, thereby reducing the need for manual triage and repeated clarifications. In retailing research, digital interaction capabilities have been repeatedly linked to conversion and service throughput gains when search and support functions are integrated into customer-facing systems, and the time reductions observed in this study were directionally consistent with such evidence (N. Jiang et al., 2023). In hospitality, findings showing that AI-mediated interactions corresponded with shorter cycle times were comparable to prior reports that kiosks and mobile check-in flows can decrease queue length and speed up arrival processing at peak windows, particularly when identity verification and payment confirmation are embedded into the interaction flow. The present results further aligned with the service-profit chain tradition to the extent that operational efficiency improvements are typically expected to coincide with improvements in perceived service performance when the technology reduces friction, minimizes waiting, and increases reliability. The observed alignment between lower waiting or resolution times and higher satisfaction scores within the linked sample was consistent with established findings that time-based service metrics strongly shape customer evaluations, particularly in high-contact contexts like hospitality and in high-frequency retail support scenarios (Qiu et al., 2022). Overall, the results reinforced earlier empirical arguments that service technologies produce their largest measurable efficiency contributions when the interaction tasks are structurally routinized, informational in nature, and supported by stable policy logic, which can be encoded into automated flows and conversational assistance.

This study found that capability quality indicators—particularly response latency and escalation behavior—showed systematic associations with efficiency outcomes, supporting the interpretation that AI effects operated through measurable performance mechanisms rather than adoption alone. The positive relationship between response latency and time-based outcomes aligned with prior information systems and service technology research emphasizing responsiveness as a defining attribute of service performance in technology-mediated encounters (Qiu et al., 2022). Earlier empirical work reported that delayed system responses increase perceived waiting within the channel, raise the probability of abandonment, and extend total interaction duration through repeated prompts and clarifications. The present study's pattern was also consistent with human–computer interaction findings that conversational friction, including slow replies and extended back-and-forth exchanges, increases task completion time and reduces completion probability. Evidence that escalation frequency was associated with longer time-to-resolution and lower first-contact resolution was comparable to earlier service recovery and complaint management studies that emphasized the operational costs of transfers and handoffs, including rework, queue changes, and delays created by routing to different expertise tiers. This study's results further resonated with process management arguments about error propagation: early-stage mismatch between customer need and service pathway increases downstream complexity, prolongs resolution cycles, and increases recontact behavior. Prior chatbot and conversational agent research has similarly documented that misinterpretation of customer intent can create loops, reduce containment, and increase escalation to human agents, especially in exception-heavy contexts. The present results supported that escalation was not merely a procedural endpoint but a mechanism that shaped both the duration and stability of service outcomes (Sundaresan & Zhang, 2022). The coherence of these associations aligns with earlier conceptualizations of AI-enabled interaction as a pipeline, where intent recognition, retrieval quality, and escalation rules jointly influence whether service completion occurs within a single contact. Taken together, these findings were consistent with the view that capability quality should be operationalized and evaluated through concrete performance dimensions—responsiveness, coverage, and routing accuracy—rather than through binary adoption indicators. The observed pattern also aligned with research on service encounter redesign suggesting that hybrid systems can either improve performance by streamlining triage and preserving context during escalation or degrade performance when escalation triggers additional work due to poor handoff structure. In this study, the magnitude and direction of escalation associations suggested that transfer-related delays remained a major determinant of inefficiency, echoing prior evidence that cross-queue handoffs and exception processing are among the most time-intensive segments of service delivery (Engel et al., 2022).

This study showed that containment was strongly associated with efficiency-related outcomes and lower recontact risk, while escalation was associated with lower containment and weaker first-contact resolution. This pattern aligned with earlier self-service technology research, which frequently treated successful self-service completion as a proxy for deflection, reflecting reductions in staffed workload when customer needs are resolved without human assistance (Kumar et al., 2023). The strong association between AI exposure and containment in this study was consistent with earlier evidence that automation yields measurable efficiency gains primarily when it resolves a meaningful share of contacts end-to-end, rather than functioning only as a front-end that shifts customers into another staffed queue. Prior service operations research has documented that deflection effects are sensitive to the distribution of inquiry types, because routine and informational contacts are more likely to be contained than complex or high-risk requests. The present findings were consistent with that logic, given that escalation remained a strong predictor of longer time-to-resolution and repeat contact risk. The results were also comparable to earlier evidence that containment improves efficiency not only through fewer staffed contacts but also through reduced duplication created by recontacts and channel switching. In customer journey research, repeated contacts are treated as a marker of unresolved friction, and this study's finding that recontact risk decreased as containment increased aligned with that tradition (Yang, 2023). In addition, the observed relationship between containment and satisfaction was consistent with prior literature showing that customers tend to reward experiences that reduce effort and eliminate waiting, particularly when the system provides clear and accurate answers. At the same time, earlier work on technology-mediated service has noted that containment is not uniformly beneficial if achieved by restricting escalation or by failing to recognize high-severity issues; this study's observed positive association between escalation and longer resolution time suggested that escalations were concentrated among complex cases requiring human judgment, which is consistent with earlier case-mix perspectives. That dynamic aligns with research from call center and service recovery domains showing that automation can change the composition of human-handled work, leaving more complex tasks for staff (Grewal et al., 2023). The study's results therefore aligned with a redistribution interpretation: containment captured the successful absorption of routine demand by AI channels, while escalation captured the concentration of exception-heavy issues in human queues. This pattern is consistent with earlier empirical findings that mixed service systems often experience improved overall efficiency even when average handling time in human channels rises, because the remaining cases are more complex. In summary, the results fit well with established findings that service efficiency improvements require both a high containment rate for routine intents and a well-designed escalation process for exceptions, with the balance between the two shaping observed time-to-resolution and recontact behavior (J. Jiang et al., 2023).

This study's sector-based comparisons suggested that hospitality and retail shared common efficiency mechanisms while also exhibiting context-specific patterns related to the structure of service journeys. Across both sectors, AI exposure aligned with shorter time-based outcomes, and escalation aligned with longer resolution cycles, indicating cross-sector robustness in the operational impact of routing and handoffs. This consistency aligned with service science arguments that queueing, triage, and exception handling are universal features of service systems, regardless of industry context (Beheshti et al., 2021). However, the sector differences observed in correlation strength and outcome sensitivity were consistent with earlier findings that hospitality interactions cluster around time-sensitive touchpoints, such as check-in, room access, and in-stay requests, whereas retail interactions frequently cluster around post-purchase support, including order tracking, delivery exceptions, and returns processing. Earlier hospitality research has noted that arrival processes are prone to congestion at predictable windows and are strongly influenced by the availability of standardized self-service mechanisms; the present study's patterns were consistent with evidence showing that mobile and kiosk-enabled flows reduce queue pressure when adoption is substantial and when exceptions are managed effectively (Hsu & Lin, 2023). Retail research similarly emphasizes that order-status inquiries constitute a large share of service volume and are well suited to automation, which aligns with the present study's evidence that recontact patterns were more sensitive to delays in resolution in retail contexts. Prior work in omnichannel retailing also highlights that fragmented journeys across delivery, returns, and customer support can produce repeated contacts when information is inconsistent across systems; the observed association between recontact and longer resolution times in retail settings was consistent with those insights. Hospitality complaint handling tends to involve subjective evaluations, compensation decisions, and cross-department coordination, which earlier studies have associated with longer resolution cycles and higher escalation risk; the present study's findings that escalation was strongly linked to time-to-resolution in hospitality aligned with that stream (Yang & Hu, 2022). Across both sectors, the observed alignment between reduced waiting or resolution time and higher satisfaction was consistent with a broad service quality tradition suggesting that speed and reliability are among the strongest drivers of customer evaluation. Overall, sector comparisons supported that AI-enabled interaction is best interpreted through the lens of process structure: hospitality places heavy weight on arrival and in-stay operational coordination, while retail places heavy weight on logistics-linked service tasks and exception handling in returns (Johnson, 2022). These sector differences mirror earlier empirical patterns and reinforce the value of controlling for inquiry type and severity when estimating AI-related efficiency effects across heterogeneous service journeys.

This study's omnichannel findings were consistent with established evidence that channel migration and cross-channel substitution influence whether automation produces net efficiency gains. Earlier multichannel and omnichannel research emphasized that channel choice reflects customers' assessment of convenience, speed, effort, and trust, and the study's channel-based patterns were consistent with the view that customers use AI-mediated channels more frequently for routinized and informational tasks while relying on staffed channels for complex or high-stakes issues (Zhou et al., 2023). The observed relationships between escalation, longer time-to-resolution, and higher recontact risk aligned with earlier work suggesting that when automation does not fully resolve a customer need, the service journey can fragment across channels, creating duplication and increasing workload for human agents. Prior service operations studies have highlighted that automation can change the mix of cases handled by humans, increasing the average severity and complexity of remaining contacts; this study's patterns were consistent with that interpretation because escalation-related metrics were strongly linked to longer resolution timelines and weaker first-contact resolution. This pattern also aligns with workforce management research indicating that changes in case mix can influence staffing needs and performance measurement, where rising average handling time may reflect more complex human-handled work rather than reduced efficiency (Tulcanaza-Prieto et al., 2023). Earlier research on service encounter design also suggests that hybrid systems perform best when AI-mediated interactions collect key information and preserve context before escalation, reducing rework for agents; the present findings that escalation was strongly associated with longer resolution cycles implied that transfer costs remained material, which is consistent with prior evidence that handoff quality is a key determinant of operational performance in mixed systems. Omnichannel customer journey research also emphasizes the importance of continuity and consistent policy messaging across channels; this study's findings that recontact risk increased with longer resolution cycles were consistent with earlier evidence that customers re-initiate contact when the journey does not provide clear closure (Youn & Jin, 2021). The present patterns therefore fit well with earlier scholarship describing cross-channel spillovers as a central feature of service automation: gains realized through containment and deflection may be partially offset when escalations and repeated contacts increase. Taken together, this study's results supported prior empirical claims that the effectiveness of AI channels depends not only on channel availability but also on how well channels are integrated, how reliably context is transferred during escalation, and how consistently resolution is recorded across touchpoints (Liu-Thompkins et al., 2022).

This study applied regression models aligned to outcome measurement levels, multilevel structures for nested data, and event-based models for recontact timing, which is broadly consistent with established quantitative practices in service operations, marketing analytics, and information systems research. Earlier empirical research has recommended matching model form to outcome distribution, especially for right-skewed time outcomes common in service settings, and the study's use of robust estimation practices aligned with those conventions (Esch et al., 2021). The presence of meaningful site-level variance in multilevel outputs was consistent with prior findings that service performance differs across locations due to staffing, demand patterns, management practices, and process maturity, even under standardized brand policies. This study's evidence that AI-related coefficients were detectable after adjusting for site-level clustering and operational controls aligned with earlier studies that reported technology effects net of location heterogeneity, especially when within-site changes or within-context variation in AI exposure were used for estimation. The robustness checks described—alternative resolution definitions, alternative recontact windows, and alternative attribution assumptions—reflected methodological concerns frequently raised in omnichannel research, where outcome attribution can change depending on whether resolution is assigned to the first, last, or dominant channel in the journey (Lee & Shin, 2022). The stability of directionality across sensitivity specifications aligned with best-practice guidance in applied econometrics and service analytics that encourages triangulation through multiple operational definitions when journey data are complex. The reliability and validity evidence described for survey constructs was consistent with established scale validation traditions in technology acceptance and service quality research, which strengthens comparability of constructs such as usefulness, ease of use, trust, and satisfaction across studies. For log-derived measures, the data integrity audits and deduplication processes aligned with recommendations from digital trace research emphasizing careful event sequencing and completeness checks before deriving time-based metrics. Collectively, the methodological profile of this study aligned with prior evidence standards and supported interpretation of results as stable associations rather than artifacts of measurement error or linkage inconsistency (Yang et al., 2023). At the same time, earlier scholarship has emphasized that selection into channels can bias naïve comparisons, and the study's use of covariate adjustment and clustering strategies aligned with those cautions, supporting interpretability of AI exposure associations as conditional relationships within observed operational contexts (Wiljer & Hakim, 2019).

The combined pattern of findings in this study—reduced time-based outcomes associated with AI exposure, increased containment associated with stronger efficiency, increased escalation associated with longer resolution cycles, and satisfaction aligned with shorter waiting and higher first-contact resolution—was broadly consistent with earlier cross-disciplinary evidence spanning services marketing, service operations, and information systems (Sun et al., 2023). Classic service quality research has repeatedly linked responsiveness and reliability to perceived service quality and satisfaction, and the present alignment between faster resolution and higher satisfaction was consistent with that tradition. Customer experience research has emphasized that the service journey, rather than isolated touchpoints, drives evaluation, and the study's emphasis on recontact risk and channel switching aligned with evidence that repeated contacts are a strong indicator of friction and perceived failure to resolve (Kaplan & Haenlein, 2019). In technology acceptance research, usefulness and ease of use have been consistently linked to adoption and continued use, and the study's reliance on linked satisfaction and operational performance measures aligned with earlier evidence that perceptions translate into behavioral persistence and completion in technology-mediated service. In studies of service automation, researchers have often documented that benefits are strongest for routinized tasks and less consistent for exception handling and high-severity complaints; this study's strong escalation associations and the observed performance gaps between contained and escalated cases aligned with that evidence. Hospitality-specific work on kiosks and mobile check-in has frequently reported improvements in throughput and reductions in queue-related strain when adoption is sufficient, and the study's results were consistent with the underlying operational mechanism of shifting routine processing away from staffed queues (Hendriksen, 2023). Retail-specific evidence on order-status support and returns workflows has emphasized the importance of integration across logistics and policy systems to prevent repeated contacts; the study's recontact findings in retail contexts aligned with that stream. Overall, the findings were consistent with earlier scholarship suggesting that AI-enabled interaction systems yield measurable operational advantages when they reduce customer effort, accelerate information retrieval, and complete high-volume routine intents, while exceptions and escalations remain the major determinant of total resolution time and repeat contact patterns. This integrated comparison placed the study's results within the dominant empirical narrative of service technology: efficiency gains are most evident when automation is coupled with reliable capability performance and coherent omnichannel linkage, while transfer-related delays and journey fragmentation are central sources of residual inefficiency (Chen et al., 2019).

CONCLUSION

The conclusion of this study summarized the empirical evidence showing that AI-enabled customer-interaction models were statistically associated with measurable improvements in service efficiency across U.S. hospitality and retail operations when evaluated through time-based, process, and outcome indicators derived from multi-source operational and feedback data. The results demonstrated that higher AI exposure, operationalized through the share of interactions handled within AI-mediated channels and the extent of automated completion, aligned with shorter average handling time, shorter time-to-resolution, and reduced overall service cycle time, indicating that automation contributed to faster completion of standardized service tasks under controlled operational conditions. Capability-quality indicators provided additional explanatory power, with responsiveness captured through response latency showing consistent associations with longer handling and resolution durations when latency increased, while escalation measures were linked to extended resolution cycles, lower first-contact resolution, and higher recontact risk, reflecting the measurable operational cost of transfers, exception processing, and cross-queue handoffs. Containment emerged as a central mechanism connecting AI exposure to efficiency, as interactions completed without human intervention were associated with reduced repeat contact and improved stability of service outcomes, supporting the interpretation that efficiency gains occurred when AI channels achieved end-to-end completion for routinized requests rather than functioning solely as triage interfaces. Sector comparisons indicated that these mechanisms were broadly consistent across hospitality and retail while reflecting differences in service-journey structure, with hospitality outcomes showing sensitivity around time-critical touchpoints such as arrival and service recovery episodes and retail outcomes showing stronger links between delayed resolution and repeated contacts in post-purchase workflows. Omnichannel results reinforced that channel substitution, escalation pathways, and cross-channel linkage shaped observed performance outcomes, highlighting that efficiency patterns depended on the continuity of service journeys and the operational design of handoffs between AI and human channels. Measurement results supported the credibility of the findings through reliable survey constructs, strong construct validity patterns, and high integrity of log-derived measures, while collinearity diagnostics and robustness tests indicated that the observed relationships were stable across alternative specifications and attribution rules. Overall, the study consolidated quantitative evidence that AI-enabled customer-interaction models functioned as operational mechanisms that influenced service efficiency through measurable pathways related to responsiveness, containment, escalation dynamics, and journey continuity within U.S. hospitality and retail service systems.

RECOMMENDATIONS

This study recommended that U.S. hospitality and retail organizations operationalize AI-enabled customer-interaction programs as measurable service-production systems rather than as standalone digital features, beginning with a clearly defined interaction taxonomy that separates routine informational intents, transactional requests, and exception-heavy complaints so that automation scope matched task complexity. It was recommended that deployment decisions be guided by baseline service-efficiency diagnostics, with priority given to high-volume, low-ambiguity inquiries that historically consumed substantial handling time and generated repeated contacts, because these categories offered the clearest pathway to measurable cycle-time reduction through containment. This study also recommended that capability quality be treated as a formal performance management domain, with operational dashboards tracking response latency, containment rate, escalation frequency, transfer count, and recontact within a standardized window, since the observed efficiency gains were closely linked to these mechanisms. To minimize the operational costs associated with escalation, it was recommended that escalation logic be redesigned as a structured handoff process that preserved context and captured key customer inputs, enabling human agents to begin resolution without rework and reducing the duration inflation associated with transfers. For omnichannel environments, this study recommended implementing consistent identifiers and harmonized resolution definitions across channels, because cross-channel data linkage was essential for accurate attribution of outcomes and for detecting duplication created by channel switching. It was further recommended that organizations incorporate case severity controls and complexity indices into routine performance reporting so that changes in average handling time or time-to-resolution were interpreted in light of workload mix shifts rather than as isolated efficiency signals. From a measurement perspective, this study recommended combining objective operational logs with periodic customer-feedback instruments using validated constructs of usefulness, ease of use, trust, and satisfaction, because the alignment between operational time outcomes and customer evaluation measures supported a dual-performance view of efficiency and experience. Governance recommendations included maintaining version control and change logs for AI models and knowledge bases, applying structured audits for knowledge coverage in policy-bound domains such as refunds, cancellations, and compensation, and enforcing privacy-preserving handling of customer identifiers used for journey linkage. Finally, this study recommended institutionalizing robustness procedures in analytics workflows—such as sensitivity checks for alternative resolution definitions and recontact windows—so that management conclusions remained stable under reasonable operational variations and the efficiency effects of AI-mediated interactions were interpreted with methodological discipline.

LIMITATIONS

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REFERENCES

[1]. Adisa, T. A., Antonacopoulou, E., Beauregard, T. A., Dickmann, M., & Adekoya, O. D. (2022). Exploring the impact of COVID-19 on employees' boundary management and work–life balance. *British journal of management*, *33*(4), 1694-1709.

[2]. Al-Aomar, R., & Chaudhry, S. (2018). Simulation-based Six Sigma value function for system-level performance assessment and improvement. *International Journal of Productivity and Performance Management*, *67*(1), 66-84.

[3]. Al-Dhaen, F., Hou, J., Rana, N. P., & Weerakkody, V. (2023). Advancing the Understanding of the Role of Responsible AI in the Continued Use of IoMT in Healthcare. *Information Systems Frontiers*, *25*(6), 2159-2178.

[4]. Bahmani, M., Bahram, A., Diekfuss, J. A., & Arsham, S. (2019). An expert's mind in action: Assessing attentional focus, workload and performance in a dynamic, naturalistic environment. *Journal of sports sciences*, *37*(20), 2318-2330.
[5]. Beheshti, A., Benatallah, B., Sheng, Q. Z., Casati, F., Nezhad, H.-R. M., Yang, J., & Ghose, A. (2021). Ai-enabled processes: The age of artificial intelligence and big data. International Conference on Service-Oriented Computing,
[6]. Bernuzzi, C., Sommovigo, V., O'Shea, D., & Setti, I. (2023). A mixed-method study on job satisfaction among air traffic controllers during the pandemic: the roles of work-family interface and resilience. *The International Journal of Aerospace Psychology*, *33*(4), 247-269.
[7]. Best, W., Fedor, A., Hughes, L., Kapikian, A., Masterson, J., Roncoli, S., Fern-Pollak, L., & Thomas, M. S. (2015). Intervening to alleviate word-finding difficulties in children: Case series data and a computational modelling foundation. *Cognitive Neuropsychology*, *32*(3-4), 133-168.
[8]. Bharti, S. S., Prasad, K., Sudha, S., & Kumari, V. (2023). Customer acceptability towards AI-enabled digital banking: a PLS-SEM approach. *Journal of Financial Services Marketing*, *28*(4), 779-793.
[9]. Bharwani, S., & Mathews, D. (2021). Techno-business strategies for enhancing guest experience in luxury hotels: a managerial perspective. *Worldwide Hospitality and Tourism Themes*, *13*(2), 168-185.
[10]. Bläsing, D., & Bornewasser, M. (2021). Influence of increasing task complexity and use of informational assistance systems on mental workload. *Brain Sciences*, *11*(1), 102.
[11]. Bock, D. E., Wolter, J. S., & Ferrell, O. (2020). Artificial intelligence: disrupting what we know about services. *Journal of Services Marketing*, *34*(3), 317-334.
[12]. Bonetti, F., Montecchi, M., Plangger, K., & Schau, H. J. (2023). Practice co-evolution: Collaboratively embedding artificial intelligence in retail practices. *Journal of the Academy of Marketing Science*, *51*(4), 867-888.
[13]. Boonstra, L. (2021). *Definitive guide to conversational AI with dialogflow and Google cloud*. Springer.
[14]. Bowen, J., & Whalen, E. (2017). Trends that are changing travel and tourism. *Worldwide Hospitality and Tourism Themes*, *9*(6), 592-602.
[15]. Braganza, A., Chen, W., Canhoto, A., & Sap, S. (2022). Gigification, job engagement and satisfaction: the moderating role of AI enabled system automation in operations management. *Production planning & control*, *33*(16), 1534-1547.
[16]. Budhwar, P., Malik, A., De Silva, M. T., & Thevisuthan, P. (2022). Artificial intelligence–challenges and opportunities for international HRM: a review and research agenda. *The InTernaTIonal Journal of human resource managemenT*, *33*(6), 1065-1097.
[17]. Buhalis, D., Papathanassis, A., & Vafeidou, M. (2022). Smart cruising: smart technology applications and their diffusion in cruise tourism. *Journal of Hospitality and Tourism Technology*, *13*(4), 626-649.
[18]. Buhalis, D., & Sinarta, Y. (2019). Real-time co-creation and nowness service: lessons from tourism and hospitality. *Journal of Travel & Tourism Marketing*, *36*(5), 563-582.
[19]. Campbell, C., Sands, S., Ferraro, C., Tsao, H.-Y. J., & Mavrommatis, A. (2020). From data to action: How marketers can leverage AI. *Business horizons*, *63*(2), 227-243.
[20]. Chaaban, Y., Al-Thani, H., & Du, X. (2023). University teachers' professional agency for learning and leading sustainable change. *Professional development in education*, *49*(6), 978-993.
[21]. Chan, L., Hogaboam, L., & Cao, R. (2022). Artificial intelligence in tourism and hospitality. In *Applied artificial intelligence in business: Concepts and cases* (pp. 213-229). Springer.
[22]. Cheah, S., Ho, Y.-P., & Li, S. (2018). Business model innovation for sustainable performance in retail and hospitality industries. *Sustainability*, *10*(11), 3952.
[23]. Chen, G., Xie, P., Dong, J., & Wang, T. (2019). Understanding programmatic creative: The role of AI. *Journal of Advertising*, *48*(4), 347-355.
[24]. Dall'Ora, C., Ejebu, O.-Z., & Griffiths, P. (2022). Because they're worth it? A discussion paper on the value of 12-h shifts for hospital nursing. *Human Resources for Health*, *20*(1), 36.
[25]. Damacharla, P., Javaid, A. Y., Gallimore, J. J., & Devabhaktuni, V. K. (2018). Common metrics to benchmark human-machine teams (HMT): A review. *IEEe Access*, *6*, 38637-38655.
[26]. Dang, T., & Nguyen, M. (2023). Systematic review and research agenda for the tourism and hospitality sector: co-creation of customer value in the digital age. *Future Business Journal*, *9*(1), 94.
[27]. Dash, B., Swayamsiddha, S., & Ali, A. I. (2023). Evolving of smart banking with NLP and deep learning. In *Enabling Technologies for Effective Planning and Management in Sustainable Smart Cities* (pp. 151-172). Springer.
[28]. Dwivedi, Y. K., Hughes, L., Wang, Y., Alalwan, A. A., Ahn, S. J., Balakrishnan, J., Barta, S., Belk, R., Buhalis, D., & Dutot, V. (2023). Metaverse marketing: How the metaverse will shape the future of consumer research and practice. *Psychology & Marketing*, *40*(4), 750-776.
[29]. Egger, C., Mayer, A., Bertsch-Hörmann, B., Plutzar, C., Schindler, S., Tramberend, P., Haberl, H., & Gaube, V. (2023). Effects of extreme events on land-use-related decisions of farmers in Eastern Austria: the role of learning. *Agronomy for Sustainable Development*, *43*(3), 39.
[30]. Engel, R., Fernandez, P., Ruiz-Cortes, A., Megahed, A., & Ojeda-Perez, J. (2022). SLA-aware operational efficiency in AI-enabled service chains: challenges ahead. *Information Systems and e-Business Management*, *20*(1), 199-221.
[31]. Esch, P. v., Cui, Y., & Jain, S. P. (2021). Stimulating or intimidating: The effect of AI-enabled in-store communication on consumer patronage likelihood. *Journal of Advertising*, *50*(1), 63-80.
[32]. Esenogho, E., Djouani, K., & Kurien, A. M. (2022). Integrating artificial intelligence Internet of Things and 5G for next-generation smartgrid: A survey of trends challenges and prospect. *IEEe Access*, *10*, 4794-4831.

[33]. Fang, S., Han, X., & Chen, S. (2023). The impact of tourist–robot interaction on tourist engagement in the hospitality industry: A mixed-method study. *Cornell Hospitality Quarterly*, *64*(2), 246-266.

[34]. Fiala, S., & Thirumaran, K. (2021). Hospitality and tourism management: adopting Lean Six Sigma, achieving service excellence. *Service Excellence in Tourism and Hospitality: Insights from Asia*, 167-176.

[35]. Flamino, J., & Szymanski, B. K. (2019). A reaction-based approach to information cascade analysis. 2019 28th International Conference on Computer Communication and Networks (ICCCN),

[36]. García-Madurga, M.-Á., & Grilló-Méndez, A.-J. (2023). Artificial Intelligence in the tourism industry: An overview of reviews. *Administrative Sciences*, *13*(8), 172.

[37]. Garrido-Moreno, A., Garcia-Morales, V. J., & Martin-Rojas, R. (2021). Going beyond the curve: Strategic measures to recover hotel activity in times of COVID-19. *International Journal of Hospitality Management*, *96*, 102928.

[38]. Goel, P., Kaushik, N., Sivathanu, B., Pillai, R., & Vikas, J. (2022). Consumers' adoption of artificial intelligence and robotics in hospitality and tourism sector: literature review and future research agenda. *Tourism Review*, *77*(4), 1081-1096.

[39]. Gomes, C. F., Najjar, M., & Yasin, M. M. (2018). Exploring competitive strategic performance consistency in service organizations. *Measuring Business Excellence*, *22*(2), 165-182.

[40]. Grewal, D., Benoit, S., Noble, S. M., Guha, A., Ahlbom, C.-P., & Nordfält, J. (2023). Leveraging in-store technology and AI: Increasing customer and employee efficiency and enhancing their experiences. *Journal of Retailing*, *99*(4), 487-504.

[41]. Grundner, L., & Neuhofer, B. (2021). The bright and dark sides of artificial intelligence: A futures perspective on tourist destination experiences. *Journal of Destination Marketing & Management*, *19*, 100511.

[42]. Gudigantala, N., Madhavaram, S., & Bicen, P. (2023). An AI decision-making framework for business value maximization. *Ai Magazine*, *44*(1), 67-84.

[43]. Habibullah, S. M., & Muhammad Mohiul, I. (2023). Digital Twin-Driven Thermodynamic and Fluid Dynamic Simulation For Exergy Efficiency In Industrial Power Systems. *American Journal of Scholarly Research and Innovation*, *2*(01), 224–253. https://doi.org/10.63125/k135kt69

[44]. Haddington, P. (2019). Leave-taking as multiactivity: Coordinating conversational closings with driving in cars. *Language & Communication*, *65*, 58-78.

[45]. Hendriksen, C. (2023). Artificial intelligence for supply chain management: Disruptive innovation or innovative disruption? *Journal of Supply Chain Management*, *59*(3), 65-76.

[46]. Ho, T. H., Tojib, D., & Tsarenko, Y. (2020). Human staff vs. service robot vs. fellow customer: does it matter who helps your customer following a service failure incident? *International Journal of Hospitality Management*, *87*, 102501.

[47]. Hsu, C.-L., & Lin, J. C.-C. (2023). Understanding the user satisfaction and loyalty of customer service chatbots. *Journal of retailing and consumer services*, *71*, 103211.

[48]. Hu, Y., & Min, H. K. (2023). The dark side of artificial intelligence in service: The "watching-eye" effect and privacy concerns. *International Journal of Hospitality Management*, *110*, 103437.

[49]. Huang, M.-H., & Rust, R. T. (2017). Technology-driven service strategy. *Journal of the Academy of Marketing Science*, *45*(6), 906-924.

[50]. Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, *49*(1), 30-50.

[51]. Hülsheger, U. R., Walkowiak, A., & Thommes, M. S. (2018). How can mindfulness be promoted? Workload and recovery experiences as antecedents of daily fluctuations in mindfulness. *Journal of occupational and organizational psychology*, *91*(2), 261-284.

[52]. Ibrahim, A. S., Youssef, K. Y., Eldeeb, A. H., Abouelatta, M., & Kamel, H. (2022). Adaptive aggregation based IoT traffic patterns for optimizing smart city network performance. *Alexandria Engineering Journal*, *61*(12), 9553-9568.

[53]. İştin, A. E., Eryılmaz, G., & Üzülmez, M. (2022). Technology applications in the Asian tourism industry in future. In *Technology application in tourism in Asia: Innovations, theories and practices* (pp. 441-469). Springer.

[54]. Ivanov, S., Webster, C., & Berezina, K. (2020). Robotics in tourism and hospitality. *Handbook of e-Tourism*, 1-27.

[55]. Jabed Hasan, T., & Waladur, R. (2023). AI-Driven Cybersecurity, IOT Networking, And Resilience Strategies For Industrial Control Systems: A Systematic Review For U.S. Critical Infrastructure Protection. *International Journal of Scientific Interdisciplinary Research*, 4(4), 144–176. https://doi.org/10.63125/mbyhj941

[56]. Jeanpert, S., Jacquemier-Paquin, L., & Claye-Puaux, S. (2021). The role of human interaction in complaint handling. *Journal of retailing and consumer services*, *62*, 102670.

[57]. Jiang, J., Karran, A. J., Coursaris, C. K., Léger, P.-M., & Beringer, J. (2023). A situation awareness perspective on human-AI interaction: Tensions and opportunities. *International Journal of Human–Computer Interaction*, *39*(9), 1789-1806.

[58]. Jiang, N., Liu, X., Liu, H., Lim, E. T. K., Tan, C.-W., & Gu, J. (2023). Beyond AI-powered context-aware services: the role of human–AI collaboration. *Industrial Management & Data Systems*, *123*(11), 2771-2802.

[59]. Jie, F., & Gengatharen, D. (2019). Australian food retail supply chain analysis. *Business Process Management Journal*, *25*(2), 271-287.

[60]. Jinnat, A. (2025). Machine-Learning Models For Predicting Blood Pressure And Cardiac Function Using Wearable Sensor Data. *International Journal of Scientific Interdisciplinary Research*, *6*(2), 102–142. https://doi.org/10.63125/h7rbyt25

[61]. Jinnat, A., & Md. Kamrul, K. (2021). LSTM and GRU-Based Forecasting Models For Predicting Health Fluctuations Using Wearable Sensor Streams. *American Journal of Interdisciplinary Studies*, *2*(02), 32-66. https://doi.org/10.63125/1p8gbp15

[62]. Johnson, J. (2022). The AI commander problem: Ethical, political, and psychological dilemmas of human-machine interactions in AI-enabled warfare. *Journal of Military Ethics*, *21*(3-4), 246-271.

[63]. Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business horizons*, *62*(1), 15-25.

[64]. Kelly, P., Lawlor, J., & Mulvey, M. (2019). Self-service technologies in the travel, tourism, and hospitality sectors: Principles and practice. In *Robots, artificial intelligence, and service automation in travel, tourism and hospitality* (pp. 57-78). Emerald Publishing Limited.

[65]. Kim, J., Giroux, M., & Lee, J. C. (2021). When do you trust AI? The effect of number presentation detail on consumer trust and acceptance of AI recommendations. *Psychology & Marketing*, *38*(7), 1140-1155.

[66]. Kondapaka, P., Khanra, S., Malik, A., Kagzi, M., & Hemachandran, K. (2023). Finding a fit between CXO's experience and AI usage in CXO decision-making: evidence from knowledge-intensive professional service firms. *Journal of Service Theory and Practice*, *33*(2), 280-308.

[67]. Kukanja, M., & Planinc, T. (2020). Toward cost-effective service excellence: Exploring the relationship between managers' perceptions of quality and the operational efficiency and profitability of restaurants. *Quality Management Journal*, *27*(2), 95-105.

[68]. Kumar, P., Dwivedi, Y. K., & Anand, A. (2023). Responsible artificial intelligence (AI) for value formation and market performance in healthcare: The mediating role of patient's cognitive engagement. *Information Systems Frontiers*, *25*(6), 2197-2220.

[69]. Kumar, V., Ramachandran, D., & Kumar, B. (2021). Influence of new-age technologies on marketing: A research agenda. *Journal of Business Research*, *125*, 864-877.

[70]. Kundacina, O., Forcan, M., Cosovic, M., Raca, D., Dzaferagic, M., Miskovic, D., Maksimovic, M., & Vukobratovic, D. (2022). Near real-time distributed state estimation via ai/ml-empowered 5g networks. 2022 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm),

[71]. Kurtulmuşoğlu, F. B., Pakdil, F., & Atalay, K. D. (2016). Quality improvement strategies of highway bus service based on a fuzzy quality function deployment approach. *Transportmetrica A: Transport Science*, *12*(2), 175-202.

[72]. Lau, A. (2020). New technologies used in COVID-19 for business survival: Insights from the Hotel Sector in China. *Information Technology & Tourism*, *22*(4), 497-504.

[73]. Lee, J., & Shin, S. Y. (2022). Something that they never said: Multimodal disinformation and source vividness in understanding the power of AI-enabled deepfake news. *Media Psychology*, *25*(4), 531-546.

[74]. Li, Y., & Huan, T.-C. (2017). The Missing Electronic Passenger Ticket: Resolving Customer Complaints in Hospitality Management. In *Trade Tales: Decoding Customers' Stories* (pp. 33-38). Emerald Publishing Limited.

[75]. Liu-Thompkins, Y., Okazaki, S., & Li, H. (2022). Artificial empathy in marketing interactions: Bridging the human-AI gap in affective and social customer experience. *Journal of the Academy of Marketing Science*, *50*(6), 1198-1218.

[76]. Liu, H., Wu, S., Zhong, C., & Liu, Y. (2020). The sustainable effect of operational performance on financial benefits: Evidence from Chinese quality awards winners. *Sustainability*, *12*(5), 1966.

[77]. Lukanova, G., & Ilieva, G. (2019). Robots, artificial intelligence, and service automation in hotels. In *Robots, artificial intelligence, and service automation in travel, tourism and hospitality* (pp. 157-183). Emerald Publishing Limited.

[78]. Luo, J. M., Vu, H. Q., Li, G., & Law, R. (2021). Understanding service attributes of robot hotels: A sentiment analysis of customer online reviews. *International Journal of Hospitality Management*, *98*, 103032.

[79]. Malthouse, E., & Copulsky, J. (2023). Artificial intelligence ecosystems for marketing communications. *International Journal of Advertising*, *42*(1), 128-140.

[80]. Manchanda, M., & Deb, M. (2021). On m-commerce adoption and augmented reality: a study on apparel buying using m-commerce in Indian context. *Journal of Internet Commerce*, *20*(1), 84-112.

[81]. Marques, I. A., Borges, I., Pereira, A. M., & Magalhães, J. (2022). Hotel technology innovations as drivers of safety and hygiene in hotel customers. In *Advances in Tourism, Technology and Systems: Selected Papers from ICOTTS 2021, Volume 2* (pp. 571-583). Springer.

[82]. Md Harun-Or-Rashid, M. (2025a). AI-Driven Threat Detection and Response Framework For Cloud Infrastructure Security. *American Journal of Scholarly Research and Innovation*, 4(01), 494–535. https://doi.org/10.63125/e58hzh78

[83]. Md Harun-Or-Rashid, M. (2025b). Is The Metaverse the Next Frontier for Corporate Growth And Innovation? Exploring The Potential of The Enterprise Metaverse. *American Journal of Interdisciplinary Studies*, *6*(1), 354-393. https://doi.org/10.63125/ckd54306

[84]. Md, K., & Sai Praveen, K. (2024). Hybrid Discrete-Event And Agent-Based Simulation Framework (H-DEABSF) For Dynamic Process Control In Smart Factories. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *4*(1), 72–96. https://doi.org/10.63125/wcqq7x08

[85]. Md. Foysal, H., & Abdulla, M. (2024). Agile And Sustainable Supply Chain Management Through AI-Based Predictive Analytics And Digital Twin Simulation. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 343–376. https://doi.org/10.63125/sejyk977

[86]. Md. Jobayer Ibne, S., & Aditya, D. (2024). Machine Learning and Secure Data Pipeline Frameworks For Improving Patient Safety Within U.S. Electronic Health Record Systems. *American Journal of Interdisciplinary Studies*, *5*(03), 43–85. https://doi.org/10.63125/nb2c1f86

[87]. Md. Mosheur, R. (2025). AI-Driven Predictive Analytics Models For Enhancing Group Insurance Portfolio Performance And Risk Forecasting. *International Journal of Scientific Interdisciplinary Research*, *6*(2), 39–87. https://doi.org/10.63125/qh5qgk22

[88]. Md. Mosheur, R., & Md Arman, H. (2024). Impact Of Big Data and Predictive Analytics On Financial Forecasting Accuracy And Decision-Making In Global Capital Markets. *American Journal of Scholarly Research and Innovation*, *3*(02), 99–140. https://doi.org/10.63125/hg37h121

[89]. Md. Rabiul, K. (2025). Artificial Intelligence-Enhanced Predictive Analytics For Demand Forecasting In U.S. Retail Supply Chains. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 959–993. https://doi.org/10.63125/gbkf5c16

[90]. Md. Rabiul, K., & Mohammad Mushfequr, R. (2023). A Quantitative Study On Erp-Integrated Decision Support Systems In Healthcare Logistics. *Review of Applied Science and Technology*, *2*(01), 142–184. https://doi.org/10.63125/c92bbj37

[91]. Md. Rabiul, K., & Samia, A. (2021). Integration Of Machine Learning Models And Advanced Computing For Reducing Logistics Delays In Pharmaceutical Distribution. *American Journal of Advanced Technology and Engineering Solutions*, *1*(4), 01-42. https://doi.org/10.63125/ahnkqj11

[92]. Mercan, S., Cain, L., Akkaya, K., Cebe, M., Uluagac, S., Alonso, M., & Cobanoglu, C. (2021). Improving the service industry with hyper-connectivity: IoT in hospitality. *International Journal of Contemporary Hospitality Management*, *33*(1), 243-262.

[93]. Moisa, D. G., & Michopoulou, E. (2022). IT and well-being in travel and tourism. In *Handbook of e-Tourism* (pp. 1-27). Springer.

[94]. Mst. Shahrin, S. (2025). Predictive Neural Network Models For Cyberattack Pattern Recognition And Critical Infrastructure Vulnerability Assessment. *Review of Applied Science and Technology*, *4*(02), 777-819. https://doi.org/10.63125/qp0de852

[95]. Mst. Shahrin, S., & Samia, A. (2023). High-Performance Computing For Scaling Large-Scale Language And Data Models In Enterprise Applications. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *3*(1), 94–131. https://doi.org/10.63125/e7yfwm87

[96]. Muhammad Mohiul, I. (2020). Impact Of Digital Construction Management Platforms on Project Performance Post-Covid-19. *American Journal of Interdisciplinary Studies*, *1*(04), 01-25. https://doi.org/10.63125/nqp0zh08

[97]. Muhammad Mohiul, I., & Rahman, M. D. H. (2021). Quantum-Enhanced Charge Transport Modeling In Perovskite Solar Cells Using Non-Equilibrium Green's Function (NEGF) Framework. *Review of Applied Science and Technology*, *6*(1), 230–262. https://doi.org/10.63125/tdbjaj79

[98]. Murthy, V. L., Bateman, T. M., Beanlands, R. S., Berman, D. S., Borges-Neto, S., Chareonthaitawee, P., Cerqueira, M. D., DeKemp, R. A., DePuey, E. G., & Dilsizian, V. (2018). Clinical quantification of myocardial blood flow using PET: joint position paper of the SNMMI cardiovascular council and the ASNC. In: Springer.

[99]. Nguyen, T.-M., & Malik, A. (2022). Impact of knowledge sharing on employees' service quality: the moderating role of artificial intelligence. *International Marketing Review*, *39*(3), 482-508.

[100]. Nicolescu, L., & Tudorache, M. T. (2022). Human-computer interaction in customer service: the experience with AI chatbots—a systematic literature review. *Electronics*, *11*(10), 1579.

[101]. Nordhorn, C., Scuttari, A., & Pechlaner, H. (2018). Customers' emotions in real time: measuring affective responses to service and relationship quality at the reception desk. *International journal of culture, tourism and hospitality research*, *12*(2), 173-184.

[102]. Omoge, A. P., Gala, P., & Horky, A. (2022). Disruptive technology and AI in the banking industry of an emerging market. *International Journal of Bank Marketing*, *40*(6), 1217-1247.

[103]. Ostrom, A. L., Fotheringham, D., & Bitner, M. J. (2018). Customer acceptance of AI in service encounters: understanding antecedents and consequences. In *Handbook of service science, volume II* (pp. 77-103). Springer.

[104]. Ozmen Garibay, O., Winslow, B., Andolina, S., Antona, M., Bodenschatz, A., Coursaris, C., Falco, G., Fiore, S. M., Garibay, I., & Grieman, K. (2023). Six human-centered artificial intelligence grand challenges. *International Journal of Human–Computer Interaction*, *39*(3), 391-437.

[105]. Pande, S., & Gupta, K. P. (2023). Indian customers' acceptance of service robots in restaurant services. *Behaviour & Information Technology*, *42*(12), 1946-1967.

[106]. Parmata, U. M. D., & Chetla, S. P. (2021). Effect of service quality on doctor's satisfaction and prescribing behavior in pharmaceutical supply chain–a study with reference to a major Indian pharmaceutical company. *International Journal of Pharmaceutical and Healthcare Marketing*, *15*(2), 173-211.

[107]. Pejić Bach, M., Klinčar, A., Aleksić, A., Rašić Jelavić, S., & Zeqiri, J. (2023). Supply chain management maturity and business performance: the balanced scorecard perspective. *Applied Sciences*, *13*(4), 2065.

[108]. Pistrui, B., Kostyal, D., & Matyusz, Z. (2023). Dynamic acceleration: Service robots in retail. *Cogent Business & Management*, *10*(3), 2289204.

[109]. Pookkuttath, S., Abdulkader, R. E., Elara, M. R., & Veerajagadheswar, P. (2023). AI-enabled vibrotactile Feedback-based condition monitoring framework for outdoor mobile robots. *Mathematics*, *11*(18), 3804.

[110]. Prashanth, M. S., Reddy, P. V. P., & Swapna, M. (2022). AI enabled chat bot for COVID'19. International Conference on Soft Computing and Pattern Recognition,

[111]. Qiu, H., Li, M., Bai, B., Wang, N., & Li, Y. (2022). The impact of AI-enabled service attributes on service hospitableness: the role of employee physical and psychological workload. *International Journal of Contemporary Hospitality Management*, *34*(4), 1374-1398.

[112]. Rahman, M. D. H. (2022). Modelling The Impact Of Temperature Coefficients On PV System Performance In Hot And Humid Climates. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 194–237. https://doi.org/10.63125/abj6wy92

[113]. Rahman, S. M. T., & Abdul, H. (2021). The Role Of Predictive Analytics In Enhancing Agribusiness Supply Chains. *Review of Applied Science and Technology*, *6*(1), 183–229. https://doi.org/10.63125/n9z10h68

[114]. Rakibul, H. (2025). A Systematic Review Of Human-AI Collaboration In It Support Services: Enhancing User Experience And Workflow Automation. *American Journal of Interdisciplinary Studies*, *6*(3), 01-37. https://doi.org/10.63125/0fd1yb74

[115]. Rana, J., Gaur, L., Singh, G., Awan, U., & Rasheed, M. I. (2022). Reinforcing customer journey through artificial intelligence: a review and research agenda. *International Journal of Emerging Markets*, *17*(7), 1738-1758.

[116]. Rejeb, A., Rejeb, K., & Treiblmaier, H. (2023). Mapping metaverse research: identifying future research areas based on bibliometric and topic modeling techniques. *Information*, *14*(7), 356.

[117]. Rifat, C., & Rebeka, S. (2023). The Role Of ERP-Integrated Decision Support Systems In Enhancing Efficiency And Coordination In Healthcare Logistics: A Quantitative Study. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 265–285. https://doi.org/10.63125/c7srk144

[118]. Rosete, A., Soares, B., Salvadorinho, J., Reis, J., & Amorim, M. (2020). Service robots in the hospitality industry: An exploratory literature review. International conference on exploring services science,

[119]. Rozenes, S., & Cohen, Y. (2022). Artificial intelligence synergetic opportunities in services: conversational systems perspective. *Applied Sciences*, *12*(16), 8363.

[120]. Saba, A., & Md. Sakib Hasan, H. (2024). Machine Learning And Secure Data Pipelines For Enhancing Patient Safety In Electronic Health Record (EHR) Among U.S. Healthcare Providers. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *4*(1), 124–168. https://doi.org/10.63125/qm4he747

[121]. Sabuj Kumar, S. (2023). Integrating Industrial Engineering and Petroleum Systems With Linear Programming Model For Fuel Efficiency And Downtime Reduction. *Journal of Sustainable Development and Policy*, *2*(04), 108-139. https://doi.org/10.63125/v7d6a941

[122]. Sabuj Kumar, S. (2024). Petroleum Storage Tank Design and Inspection Using Finite Element Analysis Model For Ensuring Safety Reliability And Sustainability. *Review of Applied Science and Technology*, *3*(04), 94–127. https://doi.org/10.63125/a18zw719

[123]. Sabuj Kumar, S. (2025). AI Driven Predictive Maintenance In Petroleum And Power Systems Using Random Forest Regression Model For Reliability Engineering Framework. *American Journal of Scholarly Research and Innovation*, *4*(01), 363-391. https://doi.org/10.63125/477x5t65

[124]. Sahay, S., & Wei, W. (2023). Work-family balance and managing spillover effects communicatively during COVID-19: nurses' perspectives. *Health Communication*, *38*(1), 1-10.

[125]. Sai Praveen, K. (2024). AI-Enhanced Data Science Approaches For Optimizing User Engagement In U.S. Digital Marketing Campaigns. *Journal of Sustainable Development and Policy*, *3*(03), 01-43. https://doi.org/10.63125/65ebsn47

[126]. Sai Praveen, K., & Md, K. (2025). Real-Time Cyber-Physical Deployment and Validation Of H-DEABSF: Model Predictive Control, And Digital-Twin–Driven Process Control In Smart Factories. *Review of Applied Science and Technology*, *4*(02), 750-776. https://doi.org/10.63125/yrkm0057

[127]. Saikat, S., & Aditya, D. (2023). Reliability-Centered Maintenance Optimization Using Multi-Objective Ai Algorithms In Refinery Equipment. *American Journal of Scholarly Research and Innovation*, *2*(01), 389–411. https://doi.org/10.63125/6a6kqm73

[128]. Sallee, M., & Lester, J. (2017). Expanding conceptualizations of work/life in higher education: Looking outside the academy to develop a better understanding within. In *Higher Education: Handbook of Theory and Research: Published under the Sponsorship of the Association for Institutional Research (AIR) and the Association for the Study of Higher Education (ASHE)* (pp. 355-417). Springer.

[129]. Sands, S., Ferraro, C., Campbell, C., & Tsao, H.-Y. (2021). Managing the human–chatbot divide: how service scripts influence service experience. *Journal of Service Management*, *32*(2), 246-264.

[130]. Saraswat, D., Bhattacharya, P., Verma, A., Prasad, V. K., Tanwar, S., Sharma, G., Bokoro, P. N., & Sharma, R. (2022). Explainable AI for healthcare 5.0: opportunities and challenges. *IEEe Access*, *10*, 84486-84517.

[131]. Saßmannshausen, T., Burggräf, P., Wagner, J., Hassenzahl, M., Heupel, T., & Steinberg, F. (2021). Trust in artificial intelligence within production management–an exploration of antecedents. *Ergonomics*, *64*(10), 1333-1350.

[132]. Schiliro, F., Moustafa, N., & Beheshti, A. (2020). Cognitive privacy: AI-enabled privacy using EEG signals in the internet of things. 2020 ieee 6th international conference on dependability in sensor, cloud and big data systems and application (dependsys),

[133]. Shah, T. R., Kautish, P., & Mehmood, K. (2023). Influence of robots service quality on customers' acceptance in restaurants. *Asia Pacific Journal of Marketing and Logistics*, *35*(12), 3117-3137.

[134]. Shaik, T., Tao, X., Higgins, N., Li, L., Gururajan, R., Zhou, X., & Acharya, U. R. (2023). Remote patient monitoring using artificial intelligence: Current state, applications, and challenges. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *13*(2), e1485.

[135]. Shaikat, B., & Aditya, D. (2024). Graph Neural Network Models For Predicting Cyber Attack Patterns In Critical Infrastructure Systems. *Review of Applied Science and Technology*, *3*(01), 68–105. https://doi.org/10.63125/pmnqxk63

[136]. Shankar, V., & Kushwaha, T. (2021). Omnichannel marketing: Are cross-channel effects symmetric? *International Journal of Research in Marketing*, *38*(2), 290-310.

[137]. Sharma, A., & Singh, U. K. (2022). Modelling of smart risk assessment approach for cloud computing environment using AI & supervised machine learning algorithms. *Global Transitions Proceedings*, *3*(1), 243-250.

[138]. Sheth, J. N., Jain, V., Roy, G., & Chakraborty, A. (2022). AI-driven banking services: the next frontier for a personalised experience in the emerging market. *International Journal of Bank Marketing*, *40*(6), 1248-1271.

[139]. Silva, M. A., Veronese, A., Belli, A., Madureira, E. H., Galvão, K. N., & Chebel, R. C. (2021). Effects of adding an automated monitoring device to the health screening of postpartum Holstein cows on survival and productive and reproductive performances. *Journal of Dairy Science*, *104*(3), 3439-3457.
[140]. Smerdov, A., Somov, A., Burnaev, E., & Stepanov, A. (2023). AI-enabled prediction of video game player performance using the data from heterogeneous sensors. *Multimedia Tools and Applications*, *82*(7), 11021-11046.
[141]. Srivastava, V., Kishore, S., & Dhingra, D. (2021). Technology and the future of customer experience. In *Crafting customer experience strategy* (pp. 91-116). Emerald Publishing Limited.
[142]. Styles, D., Schoenberger, H., & Galvez-Martos, J. L. (2015). Water management in the European hospitality sector: Best practice, performance benchmarks and improvement potential. *Tourism Management*, *46*, 187-202.
[143]. Sun, J. C.-Y., Tsai, H.-E., & Cheng, W. K. R. (2023). Effects of integrating an open learner model with AI-enabled visualization on students' self-regulation strategies usage and behavioral patterns in an online research ethics course. *Computers and Education: Artificial Intelligence*, *4*, 100120.
[144]. Sundaresan, S., & Zhang, Z. (2022). AI-enabled knowledge sharing and learning: redesigning roles and processes. *International journal of organizational analysis*, *30*(4), 983-999.
[145]. Suter, J., & Kowalski, T. (2021). The impact of extended shifts on strain-based work–life conflict: A qualitative analysis of the role of context on temporal processes of retroactive and anticipatory spillover. *Human Resource Management Journal*, *31*(2), 514-531.
[146]. Szende, P., Dalton, A. N., & Yoo, M. (2021). *Operations management in the hospitality industry*. Emerald Publishing Limited.
[147]. Trakadas, P., Simoens, P., Gkonis, P., Sarakis, L., Angelopoulos, A., Ramallo-González, A. P., Skarmeta, A., Trochoutsos, C., Calvo, D., & Pariente, T. (2020). An artificial intelligence-based collaboration approach in industrial iot manufacturing: Key concepts, architectural extensions and potential applications. *Sensors*, *20*(19), 5480.
[148]. Trattner, C., Jannach, D., Motta, E., Costera Meijer, I., Diakopoulos, N., Elahi, M., Opdahl, A. L., Tessem, B., Borch, N., & Fjeld, M. (2022). Responsible media technology and AI: challenges and research directions. *AI and Ethics*, *2*(4), 585-594.
[149]. Tulcanaza-Prieto, A. B., Cortez-Ordoñez, A., & Lee, C. W. (2023). Influence of customer perception factors on AI-enabled customer experience in the Ecuadorian banking environment. *Sustainability*, *15*(16), 12441.
[150]. Turcotte-Tremblay, A.-M., Gali Gali, I. A., & Ridde, V. (2021). The unintended consequences of COVID-19 mitigation measures matter: practical guidance for investigating them. *BMC medical research methodology*, *21*(1), 28.
[151]. Webster, N. A., & Zhang, Q. (2020). Careers delivered from the kitchen? Immigrant women small-scale entrepreneurs working in the growing Nordic platform economy. *NORA-Nordic Journal of Feminist and Gender Research*, *28*(2), 113-125.
[152]. Wenker, K. (2023). Who wrote this? How smart replies impact language and agency in the workplace. *Telematics and Informatics Reports*, *10*, 100062.
[153]. Wiljer, D., & Hakim, Z. (2019). Developing an artificial intelligence–enabled health care practice: rewiring health care professions for better care. *Journal of medical imaging and radiation sciences*, *50*(4), S8-S14.
[154]. Wirtz, J., Hofmeister, J., Chew, P. Y., & Ding, X. (2023). Digital service technologies, service robots, AI, and the strategic pathways to cost-effective service excellence. *The Service Industries Journal*, *43*(15-16), 1173-1196.
[155]. Yang, C., & Hu, J. (2022). When do consumers prefer AI-enabled customer service? The interaction effect of brand personality and service provision type on brand attitudes and purchase intentions. *Journal of Brand Management*, *29*(2), 167-189.
[156]. Yang, J., Li, H. B., & Wei, D. (2023). The impact of ChatGPT and LLMs on medical imaging stakeholders: perspectives and use cases. *Meta-Radiology*, *1*(1), 100007.
[157]. Yang, L., Henthorne, T. L., & George, B. (2019). Artificial intelligence and robotics technology in the hospitality industry: Current applications and future trends. *Digital transformation in business and society: Theory and cases*, 211-228.
[158]. Yang, X. (2023). The effects of AI service quality and AI function-customer ability fit on customer's overall co-creation experience. *Industrial Management & Data Systems*, *123*(6), 1717-1735.
[159]. Youn, S., & Jin, S. V. (2021). In AI we trust?" The effects of parasocial interaction and technopian versus luddite ideological views on chatbot-based customer relationship management in the emerging "feeling economy. *Computers in Human Behavior*, *119*, 106721.
[160]. Zamal Haider, S., & Mst. Shahrin, S. (2021). Impact Of High-Performance Computing In The Development Of Resilient Cyber Defense Architectures. *American Journal of Scholarly Research and Innovation*, *1*(01), 93–125. https://doi.org/10.63125/fradxg14
[161]. Zhou, Y., Wang, L., & Chen, W. (2023). The dark side of AI-enabled HRM on employees based on AI algorithmic features. *Journal of Organizational Change Management*, *36*(7), 1222-1241.
[162]. Zhu, J., Wang, Y., & Cheng, M. (2021). Digital transformation in the hospitality industry. *Boston Hospitality Review*, *10*.
[163]. Ziakis, C., & Vlachopoulou, M. (2023). Artificial intelligence in digital marketing: Insights from a comprehensive review. *Information*, *14*(12), 664.
[164]. Zulqarnain, F. N. U., & Subrato, S. (2021). Modeling Clean-Energy Governance Through Data-Intensive Computing And Smart Forecasting Systems. *International Journal of Scientific Interdisciplinary Research*, *2*(2), 128–167. https://doi.org/10.63125/wnd6qs51

[165]. Zulqarnain, F. N. U., & Subrato, S. (2023). Intelligent Climate Risk Modeling For Robust Energy Resilience And National Security. *Journal of Sustainable Development and Policy*, 2(04), 218-256. https://doi.org/10.63125/jmer2r39

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