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From service failures to customer acceptance: the role of managerial response and adaptive innovation in AI-enabled service systems

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Abstract: This study examines how service failures in AI-enabled hospitality systems relate to customer acceptance, managerial response, organisational adaptation, and workforce pressures. Using a multi-method design combining customer survey data (N = 308), organisational survey data (N = 65), and semi-structured interviews (N = 19), the study distinguishes customer-level acceptance mechanisms from organisational response and adaptation processes. Customer-level analysis shows that trust and perceived service performance are positively associated with acceptance, while fear is negatively associated with acceptance. Organisational and qualitative evidence indicates that service disruptions require situational interpretation, human intervention, operational adjustment, and continued learning. Workforce pressure emerges as an important contextual condition associated with service instability and response capacity. Integrating these complementary sources of evidence, the study advances a process-oriented understanding of AI-enabled service transformation and highlights the importance of aligning technological performance, managerial action, workforce capacity, and customer evaluation.

Keywords: digital transformation; service innovation; adaptive innovation; workforce pressure; customer acceptance; AI-enabled services.

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1 Introduction

The rapid integration of AI-enabled service systems in hospitality has transformed service delivery, promising increased efficiency, consistency, and cost reduction (Ivanov and Webster, 2019; Huang and Rust, 2021). AI-powered technologies, including service robots and automated service systems, can support the automation of service tasks and improve service productivity (Wirtz et al., 2018; Huang and Rust, 2018). Despite these advantages, implementation can introduce service failures, including system malfunctions, interaction breakdowns, and customer discomfort during human-technology encounters (Wirtz et al., 2018; Čaić et al., 2018).

Such disruptions can shape customer perceptions and acceptance, particularly in high-contact contexts where trust and experience are central (Parasuraman et al., 2000; Lu et al., 2019). Recent evidence further shows that customer responses to AI-enabled service technologies are influenced by trust, interaction quality, service context, and human–robot encounters (Chi et al., 2023; Kao and Huang, 2023).

Beyond their immediate operational impact, these disruptions represent moments of instability within broader digital transformation and service innovation processes. Their management therefore becomes an important organisational challenge, particularly under uncertainty, resource constraints, and continuous customer interaction. Evidence that service robots influence customer evaluations and satisfaction while their effects depend on the conditions in which they are deployed reinforces the need to examine the organisational mechanisms through which AI-enabled services are managed after disruptions occur (Wu and Huo, 2023).

AI-enabled service implementation is a dynamic and uncertainty-driven process involving continuous adjustment and iterative decision-making (Vial, 2019; Verhoef et al., 2021). This challenge is particularly pronounced in hospitality, where technological systems operate within high-contact environments shaped by workforce conditions, service routines, and customer expectations. Service outcomes therefore depend not only on system functionality but also on the organisation's capacity to interpret disruptions, coordinate responses, and maintain service continuity.

Prior research on technology acceptance and AI adoption in hospitality has primarily examined perceived usefulness, trust, anxiety, interaction quality, and behavioural intention (Davis, 1989; Venkatesh et al., 2003; Gursoy et al., 2019; Chi et al., 2023; Kao and Huang, 2023). Customer adoption and resistance may also depend on context-specific motives extending beyond conventional acceptance variables (Rasheed et al., 2023). Meanwhile, project management research has examined implementation challenges, governance, and performance in technology-driven initiatives (Too and Weaver, 2014; Petrovic et al., 2026). These streams provide only partial explanations of what occurs after an AI-enabled service disruption: acceptance research focuses primarily on individual responses, service-failure research on recovery, and digital transformation and innovation research on organisational capabilities and implementation processes.

This fragmentation reveals an important theoretical and empirical gap. Existing literature provides substantial evidence that customer acceptance depends on perceptions of AI-enabled technologies, yet offers less insight into how managers interpret service disruptions and translate responses into adaptive practices. Similarly, studies of implementation and project adaptation explain organisational responses to uncertainty but rarely consider these processes alongside customer-level acceptance outcomes (Too and Weaver, 2014). Research therefore lacks an integrated understanding of organisational

responses to AI-enabled service disruptions alongside the customer perceptions associated with acceptance. This limitation is increasingly important as digital innovation research calls for greater integration of technological, organisational, and capability-based perspectives (Felicetti et al., 2024).

The study addresses this gap through a process-oriented perspective grounded primarily in dynamic capability theory. Dynamic capabilities describe the organisational capacity to sense changes, seize opportunities or respond to threats, and reconfigure resources and routines under changing conditions (Teece, 2007; Eisenhardt and Martin, 2000). Applied to AI-enabled services, critical incidents provide signals requiring interpretation and action; managerial responses address emerging disruptions; and subsequent adjustments to processes, workflows, and human-technology configurations represent adaptive reconfiguration. Adaptive innovation is therefore understood not as a one-time reaction to service failure but as a process through which disruptions can generate learning and operational adjustment. A complementary socio-technical perspective recognises that these processes involve technological capabilities, workforce conditions, managerial practices, and customer-facing service requirements (Vial, 2019; Verhoef et al., 2021).

This process perspective is particularly relevant because disruptions, responses, and adaptations may unfold dynamically over time (Edmondson, 2011; Eisenhardt, 1989). Static acceptance models identify factors associated with willingness to use technology but provide limited insight into organisational responses to implementation problems. Similarly, treating service failures as isolated episodes overlooks their potential to stimulate learning and changes in service routines. A process-oriented perspective can therefore complement customer-level acceptance models by explaining how disruptions generate managerial interpretation, response, and adaptive practices.

Against this background, the study pursues three interrelated research objectives. First, it examines how critical incidents in AI-enabled hospitality services are interpreted and addressed through managerial responses. Second, it investigates how managerial responses can develop into adaptive innovation through adjustments to operational processes and service delivery. Third, it examines customer-level factors associated with acceptance of AI-enabled services and uses qualitative evidence to explain the sensemaking, decision-making, and learning mechanisms underlying organisational response and adaptation. Together, these objectives distinguish customer-level quantitative analysis from organisational and qualitative evidence while enabling their integration within a common process-oriented framework.

To address these objectives, the study develops a multi-level incident-response-adaptation framework and draws on customer surveys (N = 308), organisational survey responses (N = 65), and in-depth interviews (N = 19). The sources serve distinct analytical purposes: customer data examine perceptual factors associated with acceptance, organisational survey data provide evidence on workforce pressures and service-consistency conditions, and qualitative interviews explain how disruptions are interpreted and translated into adaptive practices. The datasets are analysed separately and integrated at the interpretation stage rather than combined within a single structural model.

This study makes three contributions. First, it advances service innovation and digital transformation research by conceptualising service disruptions as potential triggers of managerial response, organisational learning, and adaptive innovation rather than solely as negative technological outcomes. Second, it extends technology acceptance research

by considering customer acceptance alongside the organisational processes surrounding AI implementation. Third, by integrating customer, organisational, and qualitative evidence while maintaining their analytical distinction, it provides a multi-level perspective in which technological performance, managerial agency, workforce conditions, organisational adaptation, and customer responses represent complementary dimensions of AI-enabled service transformation. This process-oriented perspective responds to calls for more context-sensitive approaches to digital transformation, project environments, and service innovation (Felicetti et al., 2024).

2 Literature review and hypotheses

2.1 Critical incidents in AI-enabled service environments

The increasing adoption of AI-enabled technologies in hospitality has introduced new forms of service interactions as well as novel types of service failures. These failures, conceptualised as critical incidents, represent unexpected disruptions that significantly affect service delivery and customer experience (Bitner et al., 1990; Edvardsson and Roos, 2001). In technology-mediated service contexts, such incidents may include system errors, delays, incorrect outputs, communication failures, or breakdowns in human-machine interaction (Wirtz et al., 2018; Huang and Rust, 2021). As AI applications become increasingly embedded in organisational activities, understanding their implementation and adoption requires attention not only to technological functionality but also to the organisational conditions surrounding their use (Tuffaha and Perello-Marin, 2023).

Unlike traditional service failures caused primarily by human error, AI-related incidents often involve ambiguity, reduced emotional responsiveness, and limited recovery flexibility, which can amplify customer dissatisfaction (Čaić et al., 2018; van Doorn et al., 2017). Moreover, in hospitality settings characterised by high customer contact, even relatively minor disruptions can significantly influence perceptions of service quality and trust (Parasuraman et al., 2000). Critical incidents therefore extend beyond isolated operational events. They can reveal mismatches between technological capabilities, service routines, workforce practices, and customer expectations, making them potential triggers for managerial interpretation and organisational adjustment.

From a dynamic capabilities perspective, unexpected incidents can be understood as signals that activate organisational sensing processes. Dynamic capabilities become particularly important when organisations face uncertainty and must identify changes, mobilise resources, and reconfigure existing routines (Eisenhardt and Martin, 2000; Teece, 2007). Research on resource leverage similarly emphasises that dynamic capabilities enable organisations to respond to changing conditions through the recombination and deployment of available resources (Pham Thi et al., 2023). In AI-enabled hospitality services, critical incidents may therefore provide operational signals that reveal deficiencies in existing service configurations and create a need for managerial interpretation and response.

2.2 Managerial response to service failures

Managerial responses to service failures play a critical role in mitigating negative outcomes and restoring service performance. Service recovery literature emphasises that timely, appropriate, and adaptive responses can reduce customer dissatisfaction and improve overall service evaluations (Tax et al., 1998; Smith et al., 1999). In project-based environments, managerial responses extend beyond direct customer recovery and may involve operational adjustments, resource reallocation, employee coordination, escalation decisions, and process redesign.

In the context of AI-enabled services, managerial responses become more complex because managers must balance technological constraints, employee capabilities, operational requirements, and customer expectations (Huang and Rust, 2021). Managers must interpret the nature and severity of incidents, determine whether human intervention is required, coordinate corrective actions, and decide whether the disruption indicates a temporary malfunction or a more fundamental weakness in service design. Consequently, managerial responses are not merely reactive recovery actions but may constitute the first organisational step toward learning and adaptation.

This interpretation is consistent with the dynamic capabilities perspective. Following the sensing of a disruption, organisations must seize an appropriate response by mobilising resources and selecting corrective actions (Teece, 2007). The effectiveness of this process depends on the organisation's ability to coordinate resources and convert information about emerging problems into action. Evidence from innovation research further suggests that technological capability and absorptive capacity are important mechanisms through which organisations transform knowledge and resources into innovation outcomes (Lestari and Sunyoto, 2023). Managerial response can therefore function as a bridge between recognising an operational disruption and initiating adaptive changes in the service system.

2.3 Adaptive innovation in dynamic service environments

Project adaptation can be defined as the organisational capacity to adjust processes, structures, resources, and decisions in response to changing conditions and unexpected events. In complex and uncertain environments, such as technology-driven hospitality systems, adaptation is critical for sustaining performance and achieving intended outcomes. In this study, project adaptation is conceptualised as an operational manifestation of adaptive innovation: the iterative modification of service processes, human-technology configurations, and managerial routines in response to implementation experience.

Adaptive project management emphasises flexibility, learning, and responsiveness to emerging challenges rather than strict adherence to predetermined plans. In the presence of critical incidents, managerial responses may result in process modifications, service redesign, changes in human intervention, resource reallocation, or revised operational procedures. When such adjustments are incorporated into subsequent service delivery, they move beyond immediate service recovery and constitute adaptive innovation. This distinction is important because innovation in AI-enabled service environments may emerge incrementally through repeated operational learning rather than exclusively through planned technological change.

Dynamic capabilities theory provides a theoretical basis for this process. Whereas sensing identifies emerging problems and seizing mobilises managerial responses, reconfiguration involves modifying organisational resources and routines to maintain alignment with changing conditions (Teece, 2007). From this perspective, adaptive innovation reflects the organisational capacity to translate experience with disruption into adjustments in existing processes, resources, and service configurations. Innovation research further emphasises that organisational processes and information-system strategies can support innovation ambidexterity by enabling firms to adapt existing activities while developing new ones (Yoshikuni, 2024). Adaptive innovation can therefore be understood as an organisational process through which managerial responses to disruption are translated into subsequent changes in service delivery and human-technology configurations.

2.4 Customer acceptance of AI-enabled services

Customer acceptance of AI-enabled services has been widely examined through models such as the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT) (Davis, 1989; Venkatesh et al., 2003). In hospitality contexts, acceptance is shaped by factors such as trust, perceived performance, anxiety, and privacy concerns (Gursoy et al., 2019; Belanche et al., 2020). Recent research continues to demonstrate that customer acceptance of AI-enabled service technologies depends strongly on trust and contextual characteristics of human-technology interaction (Chi et al., 2023; Kao and Huang, 2023).

Trust in AI systems has been identified as a particularly important determinant of acceptance when customers depend on technology for service delivery (Lu et al., 2019). Research integrating trust with TAMs similarly demonstrates that trust can strengthen behavioural intentions toward digital services (Hassan et al., 2024). Conversely, fear and discomfort associated with AI, including uncertainty about system behaviour and the perceived absence of human interaction, can reduce willingness to engage with technology (Čaić et al., 2018). Research on automation adoption further demonstrates that technology acceptance is influenced not only by expected benefits but also by perceived implementation barriers and user concerns (Katke and Babu, 2024).

Perceived performance provides another important basis for acceptance because customers are more likely to engage with technologies that improve service speed, consistency, convenience, or effectiveness. Privacy and data-security concerns may also create resistance when customers perceive that the benefits of AI-enabled services are accompanied by risks related to personal information or reduced control (Parasuraman et al., 2000). These customer-level variables complement the organisational process examined in this study. Whereas the organisational perspective explains how disruptions may stimulate managerial interpretation, response, and adaptation, the customer perspective examines the perceptual factors associated with willingness to accept AI-enabled services.

2.5 Organisational process of incident response and adaptive innovation

The preceding literature suggests that critical incidents, managerial responses, and adaptive innovation should not be treated as unrelated organisational phenomena. Dynamic capabilities theory provides an integrating process logic: disruptions provide

signals that must be sensed; managerial intervention represents the mobilisation of organisational responses; and subsequent modification of routines and resources represents adaptive reconfiguration (Eisenhardt and Martin, 2000; Teece, 2007). This process perspective enables service failures to be understood not only as negative operational outcomes but also as potential triggers of organisational learning and adaptation.

Critical incidents interrupt established service routines and create discrepancies between expected and actual service performance. Such disruptions may require managerial attention, interpretation, coordination, and corrective intervention, particularly when they involve interactions among technology, employees, customers, and service procedures. From a dynamic capabilities perspective, critical incidents can therefore function as sensing signals that stimulate managerial action. The organisational significance of these incidents lies not simply in their occurrence but in how managers interpret them and mobilise resources in response.

Managerial response, in turn, may extend beyond the immediate restoration of service. Corrective actions can reveal deficiencies in existing procedures and generate changes in resource allocation, employee roles, technological configurations, or service routines. Dynamic capabilities theory conceptualises this transition as movement from recognising and responding to environmental signals toward reconfiguring organisational resources and activities (Teece, 2007). Research on dynamic capabilities and innovation similarly suggests that the ability to mobilise and recombine resources facilitates organisational adaptation and innovation (Pham Thi et al., 2023; Lestari and Sunyoto, 2023). When managerial responses generate adjustments that become incorporated into subsequent service delivery, immediate recovery can therefore develop into a broader process of adaptive innovation.

In this study, the relationships among critical incidents, managerial response, and adaptive innovation are consequently treated as an organisational process framework rather than as a single statistically estimated causal chain. The organisational survey and qualitative interviews are used to examine the contextual conditions and managerial mechanisms associated with this process, while customer acceptance is examined separately through customer-level quantitative evidence. The two analytical perspectives are subsequently integrated to explain how organisational adaptation and customer evaluation coexist within AI-enabled service transformation.

2.6 Customer-level antecedents of AI-enabled service acceptance

The organisational process described above explains how AI-enabled service systems may respond to disruption through managerial interpretation and adaptive change. Customer acceptance, however, also depends on individual perceptions of the technology and its service performance. These relationships are examined separately as customer-level antecedents of acceptance rather than as additional stages of the organisational incident-response-adaptation process.

Trust reduces perceived uncertainty and increases customers' willingness to rely on an AI-enabled service system. This is particularly important when customers cannot directly evaluate the technological processes underlying service delivery. Prior technology-acceptance and hospitality research consistently identifies trust as an important determinant of willingness to interact with AI-enabled services (Lu et al., 2019; Gursoy et al., 2019; Chi et al., 2023). Evidence from IJBIR also supports the integration

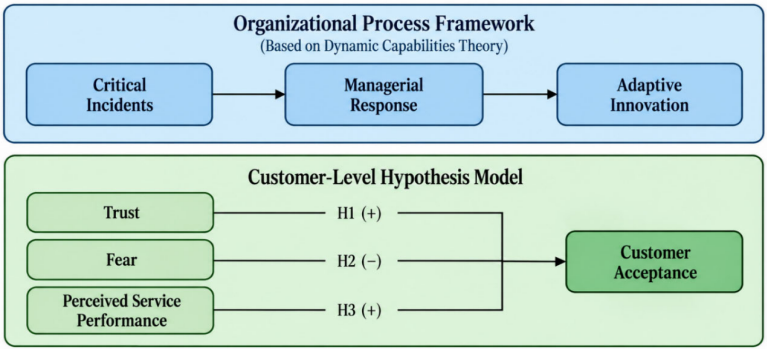
of trust with technology-acceptance mechanisms in explaining digital service usage (Hassan et al., 2024). Therefore:

H1 Trust positively influences customer acceptance.

Fear represents an affective barrier to technology acceptance. Customers may experience uncertainty, discomfort, or concern when interacting with autonomous systems, particularly when system behaviour is unfamiliar or human assistance appears limited (Čaić et al., 2018). Such negative emotional responses can outweigh perceived functional benefits and reduce willingness to engage with AI-enabled services. Recent research also suggests that adoption and resistance to AI-enabled service technologies are shaped by distinct reasons and concerns rather than by perceived utility alone (Rasheed et al., 2023). Therefore:

H2 Fear negatively influences customer acceptance.

Figure 1 Conceptual framework of organisational adaptation and customer acceptance in AI-enabled service systems (see online version for colours)



Notes: The upper panel presents the organisational process framework, grounded in dynamic capabilities theory, in which critical incidents provide signals for managerial response and adaptive innovation. These relationships represent a process-oriented conceptual framework and are not modelled as statistically tested causal paths. The lower panel presents the customer-level hypothesis model tested using customer survey data (N = 308). H1 predicts a positive effect of trust on customer acceptance; H2 predicts a negative effect of fear on customer acceptance; and H3 predicts a positive effect of perceived performance on customer acceptance.

Perceived performance reflects the extent to which customers believe that an AI-enabled service system delivers useful, efficient, reliable, or improved service outcomes. Both TAM and UTAUT emphasise performance-related beliefs as central determinants of technology adoption (Davis, 1989; Venkatesh et al., 2003). In hospitality, customers are therefore more likely to accept AI-enabled services when the technology provides observable service benefits and performs its intended functions effectively (Belanche et al., 2020; Kao and Huang, 2023). Therefore:

H3 Perceived performance positively influences customer acceptance.

Together, H1–H3 represent the customer-level relationships examined quantitatively in this study. They complement, rather than form part of, the organisational

incident-response-adaptation process developed in the preceding sections. This analytical distinction enables the study to examine customer acceptance and organisational adaptation as related dimensions of AI-enabled service transformation without treating them as a single causal chain. The conceptual framework of the study is presented in Figure 1.

3 Methodology

3.1 Research design

This study employs a multi-method research design to examine customer acceptance and organisational adaptation in AI-enabled hospitality environments. Given the complexity of the research problem and the need to capture both customer perceptions and organisational processes, quantitative and qualitative data sources are utilised (Creswell and Plano Clark, 2011).

The quantitative component comprises two independent surveys with distinct analytical purposes. The customer survey examines perceptual antecedents of acceptance of AI-enabled services, whereas the organisational survey provides evidence on workforce pressures, service-consistency challenges, technology use, and organisational response priorities. The qualitative component complements these surveys by examining how hospitality professionals interpret service disruptions, formulate responses, and translate implementation experience into adaptive practices. This design enables customer-level relationships and organisational mechanisms to be examined separately while contributing to a broader understanding of AI-enabled service transformation, consistent with recommendations for multi-source research in organisational and service settings (Edmondson and McManus, 2007; Eisenhardt, 1989).

The three data sources were therefore designed to address distinct but complementary analytical purposes rather than to represent a single pooled sample or a single structural model. Customer survey data were used to examine customer-level acceptance and its perceptual antecedents. Organisational survey data were used to characterise workforce-related operational pressures, perceived effects on service consistency, technology use, and organisational response priorities. Semi-structured interviews were used to examine the managerial sensemaking, human intervention, operational adjustment, and learning processes through which disruptions were addressed in practice. Each component was analysed separately, and the findings were subsequently integrated at the interpretation stage within the broader process-oriented framework. This approach maintains the analytical distinction between customer-level quantitative relationships and organisational process evidence while allowing their implications for AI-enabled service transformation to be considered together.

3.2 Data collection and sample

Data were collected from three independent sources to provide complementary perspectives on AI-enabled service implementation. Each source addressed a distinct component of the research framework and was analysed separately before the findings were integrated at the interpretation stage.

Table 1 Profile of interviewed hospitality managers (N = 19)

Interview ID	*Position*	*Management level*	*Department*	*Hotel category*	*Country*
E1	General Manager	Top management	General Management	4★	Kazakhstan
E2	General Manager	Top management	General Management	4★	Serbia
E3	General Manager/Owner	Top management	Executive Management	4★	Europe
E4	General Manager	Top management	Executive Management	5★ casino resort	North Cyprus
E5	Hotel Director	Top management	Executive Management	5★ resort	Turkey
E6	General Manager	Top management	General Management	5★	Montenegro
E7	General Manager	Top management	General Management	5★ city hotel	Russia
E8	General Manager	Top management	General Management	5★	Croatia
E9	Director of Engineering	Middle management	Engineering	4–5★	Kazakhstan
E10	Chief Accountant	Middle management	Finance	4–5★	Kazakhstan
E11	Executive Chef	Middle management	Food Production	4★	Kazakhstan
E12	F&B Manager	Middle management	Food & Beverage	4–5★	Kazakhstan
E13	Front Office Manager	Middle management	Front Office	4–5★	Kazakhstan
E14	Assistant Front Office Manager	Operational management	Front Office	4–5★	Kazakhstan
E15	HR Specialist	Middle management	Human Resources	4–5★	Kazakhstan
E16	Restaurant Service Administrator	Operational management	Food & Beverage	4–5★	Kazakhstan
E17	Restaurant Administrator	Operational management	Food & Beverage	4–5★	Kazakhstan
E18	Housekeeping Manager	Middle management	Housekeeping	4–5★	Kazakhstan
E19	Operations/Service Manager	Middle management	Operations	4–5★	Kazakhstan

Notes: The qualitative dataset includes 19 semi-structured interviews with hospitality professionals across strategic, departmental, and operational management levels. Participants represent multiple functional areas, including executive management, finance, human resources, engineering, front office, housekeeping, and food and beverage operations. Interviews were anonymised and coded (E1–E19) to ensure confidentiality while enabling systematic thematic analysis.

First, customer data were obtained through a structured survey administered to hospitality service users (N = 308). The survey captured customer perceptions of AI-enabled service systems, including trust, fear, perceived service performance, safety, privacy concerns, and acceptance. The customer dataset provides the quantitative basis for examining the hypothesised relationships between trust, fear, perceived performance, and customer acceptance. Safety and privacy were measured separately and are not treated as multi-item reflective constructs in the hypothesised model.

Second, organisational survey data were obtained from hospitality personnel (N = 65) representing managerial, supervisory, and operational roles. The survey focused on workforce pressure and service-consistency conditions, including the frequency and perceived effects of staff shortages, operational areas affected by workforce pressure, the use of digital tools and automation, and organisational priorities for improving service consistency. This dataset was used to provide descriptive organisational context rather than to estimate the hypothesised customer-level model or the incident-response-adaptation process as a structural causal model.

Third, qualitative insights were gathered through in-depth interviews with hospitality professionals (N = 19), representing senior, middle, and operational management levels. The interviews provided contextual evidence on how service disruptions were interpreted, how managerial responses were formulated, and how implementation experience contributed to operational adjustment and adaptive practices.

Table 2 Sample characteristics and analytical purpose of data sources

Data source	*Sample*	*Key characteristics*	*Primary analytical purpose*
Customer survey	N = 308	Hospitality service users; diverse demographic and behavioural profiles; users of AI-enabled hospitality services	Quantitative assessment of customer-level perceptual antecedents and their relationships with acceptance
Organisational survey	N = 65	Hospitality personnel representing managerial, supervisory, and operational roles; respondents exposed to workforce and service-consistency challenges	Descriptive examination of workforce pressure, its perceived effects on service consistency, technology use, and organisational response priorities
Semi-structured interviews	N = 19	8 top-management, 8 middle-management, and 3 operational-management participants; multiple hotel functions and geographical contexts	Qualitative examination of how service disruptions are interpreted, managed, and translated into adaptive practices

Notes: The three datasets were collected independently and represent complementary sources of evidence. Customer survey data capture customer perceptions associated with acceptance of AI-enabled services; organisational survey data provide contextual evidence on workforce pressure, service-consistency challenges, technology use, and organisational response priorities; and semi-structured interviews provide explanatory insights into managerial interpretation, decision-making, operational adjustment, and adaptation. The datasets were analysed separately according to their respective analytical purposes and integrated at the interpretation stage; they were not pooled or treated as components of a single structural model.

The qualitative component was therefore used to examine the managerial mechanisms underlying the organisational process framework and to complement the quantitative evidence.

Table 1 presents the profile of interviewed hospitality professionals, including their positions, organisational roles, functional areas, and geographic distribution.

The use of multiple data sources strengthens the study by enabling complementary analytical perspectives to be compared and integrated (Jick, 1979). The three datasets represent independent sources of evidence and were not pooled into a single sample or analysed as a single causal model. Rather, the customer survey provides evidence on perceptual antecedents of AI-enabled service acceptance, the organisational survey describes workforce and service-consistency conditions surrounding implementation, and the interviews explain managerial response and adaptation processes.

To provide a transparent overview of the empirical setting, Table 2 presents the structure, characteristics, and analytical purpose of the three data sources used in this study.

Table 3 Customer-level variables and measurement structure

Variable	*Conceptual meaning*	*Measurement structure*	*Role in analysis*
Trust	Confidence in and willingness to rely on AI-enabled service systems	Three Likert-scale items	Hypothesised predictor of customer acceptance (H1)
Fear	Emotional discomfort, anxiety, and concern associated with AI-enabled services	Three Likert-scale items	Hypothesised predictor of customer acceptance (H2)
Perceived service performance	Perceived speed, efficiency, and accuracy of AI-enabled service delivery	Two Likert-scale items assessing fast and efficient service and accurate and error-free service	Hypothesised predictor of customer acceptance (H3)
Acceptance	Willingness to use and engage with AI-enabled hospitality services	Three Likert-scale items	Dependent construct
Design preference	Preferences concerning the appearance and interaction characteristics of AI-enabled systems	Three Likert-scale items	Supplementary customer perception
Safety	Perceived safety when interacting with AI-enabled systems	Single Likert-scale item	Supplementary observed variable
Privacy concerns	Concern regarding privacy when interacting with AI-enabled systems	Single Likert-scale item	Supplementary observed variable

Notes: Trust, fear, perceived service performance, and acceptance constitute the customer-level variables used in the hypothesised model. Design preference was measured as an additional multi-item customer perception, whereas safety and privacy concerns were measured using separate single items and were therefore not modelled as reflective latent constructs. Organisational survey and qualitative interview data were analysed separately and were not included in the customer-level measurement model.

3.3 Measurement of constructs

Customer-level variables were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire assessed customer perceptions of AI-enabled hospitality services across trust, fear, design preference, perceived service performance, safety, privacy concerns, and acceptance.

The hypothesised customer-level model included trust, fear, perceived service performance, and acceptance. Trust and fear were each measured using three items, while acceptance was measured using three items. Perceived service performance was operationalised using two items assessing whether AI-enabled service provides fast and efficient service and accurate and error-free service. A third item included in the broader service-quality block addressed the perceived lack of emotional understanding compared with human employees. Because this item captures an interpersonal rather than performance-related dimension of service, it was not included in the perceived performance construct used for hypothesis testing.

The questionnaire additionally included three items addressing design preferences and separate single-item measures of perceived safety and privacy concerns. These variables were retained as supplementary customer perceptions but were not specified as reflective latent constructs in the hypothesised model. In particular, privacy concerns were treated as a single observed variable rather than as a multi-item construct. This distinction avoids imposing reflective measurement assumptions on conceptually distinct individual indicators.

The organisational survey (N = 65) and qualitative interview data (N = 19) were analysed separately and were not incorporated into the customer-level measurement model. Their analytical roles were to provide organisational context and explanatory evidence concerning workforce pressures, managerial response, and adaptive practices.

3.4 Analytical approach

Customer survey data (N = 308) were analysed in two stages. First, the internal consistency of the multi-item customer-level measures was assessed using Cronbach's alpha. Composite scores were then calculated for trust, fear, perceived service performance, and customer acceptance. Trust, fear, and acceptance were based on their respective three-item measures, while perceived service performance was calculated from the two items assessing fast and efficient service and accurate and error-free service. Design preference was retained as a supplementary multi-item measure, whereas safety and privacy concerns were treated as separate single-item observed variables.

Second, the hypothesised customer-level relationships were examined using multiple regression analysis, with customer acceptance as the dependent variable and trust, fear, and perceived service performance as predictors. Standardised coefficients were used to assess the direction and relative strength of the relationships specified in H1–H3. This analytical specification reflects the revised conceptual framework, in which customer-level hypotheses are tested independently from the organisational incident-response-adaptation process.

Table 4 presents the descriptive statistics and internal consistency results for the multi-item customer measures used in the analysis.

Table 4 Descriptive statistics and internal consistency of customer-level measures

Measure	*Items*	*Mean*	*Cronbach's alpha*
Trust	3	3.38	0.885
Fear	3	2.49	0.902
Perceived service performance	2	3.34	0.825
Design preference	3	3.53	0.791
Acceptance	3	3.49	0.942

Notes: Means are based on five-point Likert scales. Cronbach's alpha is reported for multi-item measures. Safety and privacy concerns were measured using separate single items and are therefore not included in the internal-consistency assessment.

The results indicate satisfactory internal consistency across all multi-item measures. Cronbach's alpha ranges from 0.791 for design preference to 0.942 for acceptance, exceeding the commonly applied threshold of 0.70. Trust ($\alpha = 0.885$), fear ($\alpha = 0.902$), and perceived service performance ($\alpha = 0.825$) therefore demonstrate adequate reliability for the subsequent customer-level analysis.

Before estimating the regression model, bivariate associations among the customer-level variables were examined to assess the direction of relationships and identify potential overlap among predictors. The hypothesised regression model was then estimated using trust, fear, and perceived service performance as simultaneous predictors of customer acceptance. Design preference, safety, and privacy concerns were not included in the confirmatory hypothesis model because they were not specified as hypothesised antecedents in the revised theoretical framework. Their descriptive patterns were retained as supplementary information where relevant.

Organisational survey data (N = 65) were analysed independently from the customer-level analysis using descriptive techniques. The analysis focused on workforce pressure and service-consistency conditions, including the frequency and perceived consequences of staff shortages, operational areas affected by workforce pressure, the use of digital tools and automation, and organisational priorities for improving service consistency. These data were used to provide organisational context for AI-enabled service implementation rather than to estimate causal relationships among critical incidents, managerial response, adaptive innovation, and customer acceptance.

Finally, qualitative interview data (N = 19) were analysed separately using thematic analysis to identify recurring patterns related to disruption interpretation, managerial decision-making, human intervention, operational adjustment, and organisational learning (Braun and Clarke, 2006). The qualitative findings were used to examine and explain the organisational processes represented in the incident-response-adaptation framework. These findings were subsequently integrated with the customer and organisational survey results at the interpretation stage, while maintaining the analytical distinction among the three independent sources of evidence.

4 Results

4.1 Descriptive statistics and reliability assessment

Customer-level measures demonstrated satisfactory internal consistency. As reported in Table 4, Cronbach's alpha values ranged from 0.791 to 0.942 across the multi-item measures, exceeding the commonly applied threshold of 0.70. Acceptance demonstrated the highest internal consistency (α = 0.942), followed by fear (α = 0.902), trust (α = 0.885), perceived service performance (α = 0.825), and design preference (α = 0.791).

The descriptive results indicate generally moderate to positive customer evaluations of AI-enabled hospitality services. Design preference recorded the highest mean (M = 3.53), followed by acceptance (M = 3.49), trust (M = 3.38), and perceived service performance (M = 3.34). Fear was comparatively lower (M = 2.49), indicating that negative emotional responses were less pronounced than positive evaluations of the technology within the sample.

Taken together, the reliability results support the use of trust, fear, perceived service performance, and acceptance in the subsequent customer-level analysis. Design preference was retained as a supplementary customer perception but was not included in the hypothesised regression model. Safety and privacy concerns were measured as separate single-item variables and were therefore not subject to internal-consistency assessment or modeled as reflective latent constructs.

4.2 Customer-level hypothesis testing

The hypothesised customer-level relationships were examined using multiple regression analysis, with customer acceptance as the dependent variable and trust, fear, and perceived service performance as simultaneous predictors. The overall regression model was statistically significant, $F(3, 304) = 173.40$, $p < 0.001$, and explained 63.1% of the variance in customer acceptance ($R^2 = 0.631$; adjusted $R^2 = 0.628$).

Trust demonstrated the strongest positive association with customer acceptance ($\beta = 0.549$, $p < 0.001$), providing support for H1. This result indicates that customers who reported greater confidence in and willingness to rely on AI-enabled service systems were substantially more likely to express acceptance of their use in hospitality settings.

Fear showed a statistically significant negative association with customer acceptance ($\beta = -0.090$, $p = 0.018$), supporting H2. Although the magnitude of this relationship was smaller than those observed for trust and perceived service performance, the result indicates that greater discomfort and unease toward AI-powered humanoid robots were associated with lower customer acceptance.

Perceived service performance was positively associated with customer acceptance ($\beta = 0.282$, $p < 0.001$), supporting H3. Customers who perceived AI-powered humanoid robots as capable of providing fast, efficient, accurate, and error-free service were more likely to accept their use in hospitality environments.

Multicollinearity diagnostics indicated no problematic overlap among the predictors. Variance inflation factor (VIF) values were 1.98 for trust, 1.18 for fear, and 1.75 for perceived service performance, all well below conventional thresholds. Taken together, the results show that all three hypothesised customer-level relationships were supported,

with trust emerging as the strongest predictor of acceptance, followed by perceived service performance and fear.

The regression results are summarised in Table 5.

Table 5 Customer-level regression results

Hypothesis	*Relationship*	*Standardised β*	*p-value*	*VIF*	*Result*
H1	Trust → Acceptance	0.549	< 0.001	1.98	Supported
H2	Fear → Acceptance	−0.090	0.018	1.18	Supported
H3	Perceived service performance → Acceptance	0.282	< 0.001	1.75	Supported

Notes: N = 308. Customer acceptance is the dependent variable. Standardised regression coefficients are reported. Model statistics: $R^2 = 0.631$; adjusted $R^2 = 0.628$; $F(3, 304) = 173.40$, $p < 0.001$.

4.3 Organisational context: workforce pressure and service consistency

The organisational survey (N = 65) provides complementary evidence on the operational conditions surrounding AI-enabled service implementation. Workforce shortages were a recurring issue across the sample: 41.5% of respondents reported experiencing staff shortages sometimes, 35.4% often, and 6.2% almost always. Taken together, 83.1% of respondents experienced workforce shortages at least sometimes during regular operations.

The perceived consequences for service quality were also substantial. More than half of respondents reported that staff shortages affected service quality significantly (50.8%) or critically (6.2%), while a further 30.8% reported a moderate effect. Thus, 87.7% of respondents perceived at least a moderate impact of workforce shortages on service quality.

Workforce pressure was not evenly distributed across operational functions. Housekeeping was identified most frequently as an affected area (63.1%), followed by kitchen operations (52.3%), F&B service (47.7%), front desk (32.3%), and maintenance (27.7%). These results indicate that workforce pressure is concentrated particularly in labour-intensive operational departments.

Technology was already being used as part of the operational response environment. Approximately 30.8% of respondents reported extensive use of digital tools or automation, while 43.1% reported using them to some extent. By contrast, 24.6% described technology use as very limited and 1.5% reported no use. Overall, 73.8% of respondents indicated at least some use of digital tools or automation in daily operations.

When asked what would most improve service consistency, 35.4% selected better use of digital tools and automation, followed by better coordination between departments (30.8%), better workforce planning (12.3%), and clearer operational procedures (9.2%). A further 12.3% indicated that no significant improvement was needed. These findings suggest that respondents viewed both technological and organisational coordination measures as relevant to improving service consistency.

Table 6 Organisational survey results

Indicator	*Response/area*	*n*	*%*
Staff shortages	Never	3	4.6
	Rarely	8	12.3
	Sometimes	27	41.5
	Often	23	35.4
	Almost always	4	6.2
Impact on service quality	Not at all	3	4.6
	Slightly	5	7.7
	Moderately	20	30.8
	Significantly	33	50.8
	Critically	4	6.2
Areas most affected*	Housekeeping	41	63.1
	Kitchen	34	52.3
	F&B service	31	47.7
	Front desk	21	32.3
	Maintenance	18	27.7
Use of digital tools/automation	To some extent	28	43.1
	Extensively	20	30.8
	Very limited	16	24.6
	Not at all	1	1.5
Priority for improving service consistency	Better use of digital tools/automation	23	35.4
	Better coordination between departments	20	30.8
	Better workforce planning	8	12.3
	Clearer operational procedures	6	9.2
	No significant improvement needed	8	12.3

Notes: N = 65. Percentages are based on the full sample. *Multiple responses were permitted for operational areas affected by workforce pressure; therefore, percentages do not sum to 100%.

The organisational survey findings therefore show that workforce pressure represents a substantial operational condition within the sampled hospitality settings, particularly in labour-intensive departments. At the same time, respondents identified both digital tools and cross-departmental coordination as important mechanisms for improving service consistency. These findings provide the organisational context for the managerial sensemaking and adaptation mechanisms examined through the qualitative interviews in the following section.

4.4 Qualitative insights from interviews

The thematic analysis of interview data (N = 19) provided deeper insight into how hospitality professionals interpret and respond to disruptions in AI-enabled service environments. Three dominant themes emerged from the analysis: *sensemaking under*

uncertainty, *balancing technology and human intervention*, and *continuous adaptation and learning*.

First, *sensemaking under uncertainty* reflects the need for managers to interpret ambiguous and evolving situations when technological systems do not perform as expected. Respondents emphasised the importance of experience, situational judgment, and timely decision-making when information is incomplete or the appropriate response is not immediately evident.

Second, *balancing technology and human intervention* captures the continuing need to combine AI-enabled service delivery with human oversight. Respondents indicated that technological systems may support service operations but cannot fully replace human judgment in customer-sensitive or operationally critical situations. Managerial or staff intervention therefore remains important when technological capabilities are insufficient or when service continuity is at risk.

Third, *continuous adaptation and learning* reflects the learning-oriented nature of organisational responses. Respondents described disruptions as opportunities to reconsider procedures, refine service processes, improve coordination, and adjust the interaction between employees and AI-enabled technologies. This indicates that organisational response may extend beyond immediate problem resolution and contribute to subsequent adaptation of service routines.

Table 7 Qualitative insights: managerial interpretation, responses, and adaptation mechanisms

Theme	*Managerial interpretation*	*Typical response*	*Link to incident-response-adaptation process*
Sensemaking under uncertainty	Managers interpret ambiguous or unexpected technology-related disruptions under conditions of incomplete information	Situational judgment, rapid decision-making, reliance on managerial experience	Illustrates how disruptions generate managerial interpretation and response
Balancing technology and human intervention	Technology can support service delivery but human oversight remains necessary in customer-sensitive or operationally critical situations	Staff intervention, human oversight, adjustment of technology-supported service delivery	Illustrates how managerial response supports operational adjustment
Continuous adaptation and learning	Operational problems provide information that can be used to improve service processes and technology integration	Process refinement, workflow adjustment, improved human-technology coordination	Illustrates how experience with disruption can contribute to continuing adaptation

Notes: Themes were identified through thematic analysis of semi-structured interviews (N = 19). The table illustrates how managerial interpretation and response relate to the organisational incident-response-adaptation framework. The qualitative findings complement, rather than statistically test, the organisational survey and customer-level quantitative results.

These qualitative findings complement the organisational survey results reported in Section 4.3. Whereas the organisational survey identifies workforce pressure, service-consistency challenges, technology use, and improvement priorities, the interviews provide explanatory insight into how managers interpret operational problems

and translate experience into response and adaptation. The qualitative evidence therefore helps clarify the mechanisms represented in the organisational incident-response-adaptation framework.

The qualitative findings provide an explanatory layer to the organisational evidence by showing how managers interpret disruptions, exercise judgment under uncertainty, determine when human intervention is required, and translate operational experience into adaptive practices. The interview findings are not treated as a separate test of causal relationships; instead, they provide contextual evidence concerning the mechanisms through which organisational response and adaptation occur in AI-enabled service environments. Integration of these findings with the customer-level quantitative results is developed further in the discussion section.

5 Discussion

5.1 Interpretation of key findings

The findings reveal complementary customer-level and organisational processes associated with AI-enabled service transformation. Rather than treating customer acceptance as an isolated technological outcome, the results indicate that customer perceptions operate within an organisational environment characterised by workforce pressures, service-consistency challenges, managerial interpretation, and continuing adaptation. This process-oriented perspective is consistent with the view of service innovation as an ongoing adaptive process in which organisations respond to changing conditions by modifying resources, routines, and service practices (Ostrom et al., 2015; Felicetti et al., 2024).

At the customer level, the quantitative findings demonstrate that acceptance is associated with trust, perceived service performance, and fear. Trust showed the strongest positive relationship with acceptance ($\beta = 0.549$, $p < 0.001$), followed by perceived service performance ($\beta = 0.282$, $p < 0.001$), whereas fear showed a smaller but statistically significant negative relationship ($\beta = –0.090$, $p = 0.018$). The overall model explained 63.1% of the variance in customer acceptance. These findings indicate that acceptance depends strongly on whether customers perceive AI-enabled services as trustworthy and capable of delivering effective service, while negative emotional responses can reduce willingness to accept such technologies. The comparatively smaller effect of fear further suggests that positive evaluations of trust and service performance may play a more prominent role in customer acceptance than negative emotional reactions within the present sample.

The organisational survey provides important context for interpreting these customer-level findings. Workforce shortages were experienced at least sometimes by 83.1% of respondents, while 87.7% reported that staffing shortages had at least a moderate effect on service quality. Housekeeping, kitchen operations, and F&B service were identified as the operational areas most frequently affected by workforce pressure. At the same time, 73.8% of respondents reported at least some use of digital tools or automation, and better use of such technologies was the most frequently selected priority for improving service consistency. These findings indicate that AI-enabled service implementation occurs within operational environments in which organisations

simultaneously confront workforce constraints, service-quality pressures, and the need to coordinate technological and human resources.

The interview findings provide an explanatory organisational layer to these contextual conditions. Three mechanisms emerged from the thematic analysis: sensemaking under uncertainty, balancing technology and human intervention, and continuous adaptation and learning. Respondents described the need to interpret disruptions under incomplete information, determine when human intervention was necessary, and use operational experience to refine processes and improve human-technology coordination. These findings suggest that organisational adaptation is not simply a technological adjustment but involves managerial judgment, human oversight, and continuing modification of service routines.

Viewed through dynamic capabilities theory, the organisational findings are consistent with a process of sensing, responding, and reconfiguring. Operational disruptions and service pressures provide signals that require interpretation; managerial action mobilises human and organisational responses; and accumulated experience can contribute to subsequent adjustments in workflows, responsibilities, and human-technology interaction practices. The qualitative evidence therefore illustrates mechanisms through which dynamic capabilities may operate at the service-delivery level, while the organisational survey identifies the workforce and service-consistency conditions within which such capabilities become particularly relevant.

Integration of the three evidence streams consequently suggests that customer acceptance and organisational adaptation represent distinct but complementary dimensions of AI-enabled service transformation. The customer analysis identifies the perceptual factors associated with acceptance, whereas the organisational survey and interviews illuminate the operational context and adaptive mechanisms surrounding technology-enabled service delivery. The study therefore extends technology-acceptance perspectives by situating customer evaluation within a broader service system in which technological capabilities, workforce conditions, managerial judgment, and organisational processes coexist. This interpretation is consistent with socio-technical perspectives emphasising that successful digital transformation depends on the alignment of technological capabilities with human and organisational processes (Vial, 2019; Verhoef et al., 2021).

5.2 Managerial response and adaptive capacity

The organisational and qualitative findings indicate that managerial response plays an important role in how organisations address service disruptions and develop adaptive capacity in AI-enabled service environments. Consistent with project governance research, effective responses require managers to coordinate resources, responsibilities, and corrective actions under conditions of uncertainty (Müller and Turner, 2010; Too and Weaver, 2014). From a dynamic capabilities perspective, these responses can be understood as mechanisms through which organisations mobilise and reconfigure resources and operational processes in response to emerging challenges (Teece, 2007).

The organisational survey showed that workforce pressure and service-consistency challenges form an important operational context for adaptation, while respondents identified both digital tools and improved cross-departmental coordination as important priorities for maintaining service consistency. The interviews explain how adaptation occurs within this context. Managers described interpreting uncertain situations,

determining when human intervention was required, and using experience with disruption to refine workflows, service procedures, and human-technology coordination.

This distinction between immediate response and sustained adaptation is theoretically important. Rapid corrective action may restore service continuity, but adaptive capacity requires organisations to learn from disruptions and incorporate that learning into subsequent processes and routines. Managerial response should therefore not be understood simply as reactive problem solving; its longer-term value lies in whether operational experience contributes to organisational learning and the reconfiguration of service practices.

This interpretation extends the concept of adaptive capacity by highlighting the transition from incident-specific intervention to organisational reconfiguration. In AI-enabled service environments, effective adaptation depends not only on rapid response but also on maintaining human oversight, learning from disruption, and progressively modifying organisational routines. This is consistent with resilience perspectives that distinguish immediate adaptive responses from more sustained organisational capacity (Zwikael and Smyrk, 2019) and with the dynamic capabilities view of adaptation as an ongoing process.

5.3 Adaptation, performance, and technology acceptance

The findings indicate that organisational adaptation and customer acceptance represent complementary dimensions of AI-enabled service transformation. The qualitative evidence shows that responses to service disruptions can develop from immediate corrective actions into modifications of workflows, human oversight, and service processes. Such adaptation is consistent with research that conceptualises organisational responses to disruption as part of broader processes of resilience, innovation, and digital transformation (Williams et al., 2017; Chen et al., 2016).

At the customer level, acceptance was positively associated with trust and perceived service performance and negatively associated with fear. These findings suggest that AI-enabled service transformation cannot be evaluated solely through operational adaptation. Customers must also perceive the service system as trustworthy, effective, and sufficiently comfortable to use. Organisational adaptation and customer acceptance therefore represent distinct but complementary dimensions: the former concerns how organisations adjust service delivery, whereas the latter reflects how customers evaluate AI-enabled service experiences.

This interpretation moves beyond a static view of technology acceptance. AI-enabled service implementation can be understood as an iterative process in which organisations respond to disruptions, learn from operational experience, and adjust technological and human components of service delivery. This perspective is consistent with technology-acceptance research emphasising contextual influences on adoption (Venkatesh et al., 2012) and service-innovation perspectives that conceptualise innovation as an evolving process of resource integration and value creation (Ostrom et al., 2015; Kindermann et al., 2021).

From a dynamic capabilities perspective, adaptation reflects the capacity to reconfigure operational routines and resources in response to changing service conditions (Teece, 2007). Its significance therefore extends beyond immediate incident recovery: learning from disruption and adjusting service processes can support alignment among technological systems, human intervention, and operational requirements.

5.4 Workforce pressure as an organisational context

The organisational and qualitative evidence identifies workforce pressure as an important contextual condition surrounding AI-enabled service implementation. In the organisational survey, 83.1% of respondents reported experiencing staff shortages at least sometimes, while 87.7% indicated that shortages had at least a moderate effect on service quality. Housekeeping, kitchen operations, and F&B service were the areas most frequently affected. The interview evidence further indicated that staffing constraints and operational workload can increase service pressure and complicate the maintenance of consistent service delivery.

This interpretation is consistent with hospitality research highlighting workforce vulnerabilities and the effects of crisis-related pressures on employees' well-being and attendance (Baum et al., 2020; Karatepe et al., 2021). It is also compatible with the job demands-resources perspective, according to which excessive demands combined with insufficient resources can generate strain and impair organisational functioning (Demerouti et al., 2001). In AI-enabled service environments, these conditions may be particularly relevant because technological implementation requires organisations to coordinate new technological capabilities with existing human resources and service responsibilities.

Workforce pressure should therefore be understood as a contextual condition rather than as a quantitatively established antecedent in the customer-level model. Organisations implementing AI-enabled services require sufficient human and organisational capacity to maintain service continuity, provide human oversight, and adapt operational routines. This reinforces socio-technical perspectives emphasising that the effectiveness of digital technologies depends on their integration with human actors and organisational processes (Davenport et al., 2020). Future research could formally examine whether workforce-related conditions influence service disruption, organisational adaptation, and customer acceptance.

6 Implications

6.1 Theoretical implications

This study offers three main theoretical contributions to research on AI-enabled service transformation.

First, it extends technology acceptance research by situating customer acceptance within a broader organisational context. Rather than treating acceptance solely as an outcome of individual perceptions, the findings show that customer evaluations of trust, perceived service performance, and fear coexist with workforce pressures, service-consistency challenges, and organisational adaptation. This extends established technology acceptance perspectives by highlighting the organisational environment within which customer acceptance develops (Venkatesh et al., 2012).

Second, the study extends Dynamic Capabilities Theory to AI-enabled hospitality service environments by illustrating how service disruptions can activate processes of managerial interpretation, response, learning, and operational reconfiguration (Teece, 2007). The qualitative findings suggest that adaptive capacity develops not simply through immediate problem resolution but through the ability to translate operational

experience into modified workflows, human oversight, and service routines. This provides a process-oriented explanation of how dynamic capabilities may operate during AI-enabled service transformation.

Third, the study contributes a multi-level perspective by integrating customer-level quantitative evidence, organisational survey evidence, and qualitative insights within a common analytical framework. This approach distinguishes customer acceptance from organisational adaptation while showing how both can be examined as complementary dimensions of AI-enabled service transformation. It also identifies workforce pressure as an important contextual condition surrounding technology-enabled service delivery. The resulting perspective conceptualises AI-enabled service transformation as a socio-technical and adaptive process involving technological performance, managerial agency, human resources, and customer evaluation (Ostrom et al., 2015).

6.2 Managerial implications

The findings suggest that managers should approach AI-enabled service transformation as a continuous process of monitoring, response, and adaptation rather than as a one-time technology implementation. Service disruptions can provide important signals for organisational learning, requiring mechanisms for identifying operational problems, determining when human intervention is necessary, and translating recurring issues into adjustments to workflows and operating procedures.

Customer acceptance also requires attention beyond technical implementation. Because trust and perceived service performance were positively associated with acceptance, while fear was negatively associated with it, managers should prioritise reliable service delivery, transparent customer communication, and accessible human support when AI-enabled systems create uncertainty or fail to meet service expectations. Maintaining appropriate human oversight can therefore support both operational continuity and customer confidence.

Finally, workforce capacity should be incorporated into implementation planning. The organisational findings show that staff shortages and workforce pressure can create substantial service-consistency challenges, particularly in labour-intensive operational areas. Training, clear responsibilities, phased implementation, cross-departmental coordination, feedback mechanisms, and flexible human–AI operating arrangements can strengthen organisational capacity and support more sustainable service improvement.

7 Limitations and future research

This study has several limitations that also provide directions for future research. First, the empirical evidence was collected within specific hospitality contexts and organisational environments, which may limit the generalisability of the findings to other industries and geographical settings. Although the multi-source design incorporates customer, organisational, and qualitative perspectives, the quantitative evidence relies on self-reported and cross-sectional data. Consequently, the observed customer-level relationships should not be interpreted as establishing temporal causality. Future research could replicate the framework across countries and service sectors and employ longitudinal designs, objective performance indicators, and behavioural data to examine

how customer perceptions and organisational adaptation develop over time (Podsakoff et al., 2003; Rindfleisch et al., 2008).

Second, the qualitative component is based on 19 interviews with hospitality professionals representing different managerial levels, functions, and organisational contexts. Although this diversity provides complementary perspectives, larger qualitative samples or longitudinal interviews, ethnographic observation, and diary studies could provide additional insight into how managers interpret service disruptions and translate immediate responses into sustained organisational adaptation.

Third, safety and privacy concerns were measured using separate single-item indicators and were therefore retained as supplementary customer perceptions rather than modelled as reflective latent constructs. This limits the extent to which their roles in customer acceptance can be assessed in the present study. Future research should employ validated multi-item measures of safety and privacy concerns to examine their relationships with acceptance and their potential interaction with trust, fear, and perceived service performance.

Finally, workforce pressure emerged from the organisational and qualitative evidence as an important contextual condition surrounding service consistency and adaptation, but it was not formally modelled within the customer-level quantitative framework. Future studies could operationalise workforce-related constructs and examine their relationships with service disruption, adaptive capacity, and customer outcomes. Additional research could also investigate AI maturity, organisational digital readiness, and different configurations of human-AI collaboration as contextual or moderating conditions influencing adaptation and acceptance (Huang and Rust, 2018; Verhoef et al., 2021).

8 Conclusions

This study examined customer acceptance and organisational adaptation as complementary dimensions of AI-enabled hospitality service transformation. At the customer level, acceptance was positively associated with trust and perceived service performance and negatively associated with fear. The organisational survey showed that workforce pressure and service-consistency challenges form an important context for technology-enabled service delivery, while the qualitative evidence revealed how managers interpret disruptions, determine when human intervention is required, and translate operational experience into adaptive practices.

By integrating these complementary sources of evidence, the study demonstrates the value of examining customer acceptance alongside the organisational processes surrounding AI-enabled service implementation. Service disruptions require managerial interpretation and response, while accumulated experience can contribute to adjustments in workflows, human oversight, and human–technology coordination. At the same time, customer acceptance depends on perceptions of trust, service performance, and emotional discomfort. These findings support a process-oriented understanding of AI-enabled service transformation in which customer evaluation and organisational adaptation represent distinct but complementary components of the broader service system.

The central contribution of the study is therefore to connect customer-level technology acceptance with organisational adaptation within a common analytical perspective without treating them as a single causal process. Viewed through Dynamic Capabilities Theory, AI-enabled service transformation involves the continuing

interpretation of operational challenges, mobilisation of responses, organisational learning, and adjustment of service practices. For hospitality organisations, sustainable AI integration consequently depends on aligning technological capabilities with human oversight, adaptive managerial practices, workforce capacity, and customer expectations.

Declarations

Artificial intelligence (AI) tools were used solely for language editing and to improve the clarity of the manuscript. The author takes full responsibility for the content of the article.

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