https://doi.org/10.65166/6szjng64
© The Author(s). Published by SLSI Press

Journal of Enterprise Strategy & Management Innovation
Volume I, Issue 4, November 2026
ISSN: 3116-4277 (Online)
https://journal.ijhba.com/index.php/jesmi
https://slsipress.com

Automate the Back, Humanize the Front: Hybrid Intelligence and the Strategic Value of Human Frontline Service under AI Commoditization

Reina Gamasan, MBA[1]; Ramon George Atento, PhD[1]
[1]Lyceum of the Philippines University - Manila
Reina.Gamasan@lpu.edu.ph

Abstract

Firms across service industries are replacing customer-facing employees with chatbots, voice agents, and other AI systems, usually on the grounds of labour savings and throughput. This paper examines whether, and under what conditions, human frontline interaction remains a source of competitive value as AI service capabilities spread. Using a conceptual design built on an integrative literature review, it synthesises five bodies of research that have developed largely separately: frontline service automation, algorithm aversion, relationship marketing and the resource-based view, the digital exclusion of vulnerable consumers, and human–AI collaboration. The synthesis indicates that automation does not generally improve customer outcomes. Automated agents perform reliably in routine, structured encounters but fall short where tasks are ambiguous, emotionally charged, or consequential. Customers tend to judge algorithmic errors harshly, hold the deploying firm responsible for them, and generalise failures across automated systems. A resource-based reading suggests that as AI service capabilities become widely accessible and are perceived as interchangeable, they tend toward competitive parity. Human frontline service, by contrast, may meet the conditions of a strategic resource where firms invest in it as a capability. The paper develops a front-stage/back-stage hybrid intelligence framework that classifies service touchpoints by task ambiguity, consequence stakes, emotional intensity, and customer vulnerability, and it advances seven propositions for empirical testing. Implications are drawn for Southeast Asian service economies, including the Philippine IT-BPM sector and ASEAN retail banking, without treating the region as homogeneous. The analysis is conceptual and does not establish causal effects on firm performance. For practitioners, it offers a structured basis for deciding where automation belongs and where human capability should remain at the point of customer contact.

Keywords: *hybrid intelligence; service automation; algorithm aversion; resource-based view; frontline employees; digital exclusion; Southeast Asia*

1. Introduction

Across service industries, artificial intelligence has moved from the back office to the customer's ear. Quick-service restaurants are piloting voice-recognition systems at drive-through lanes. Retail banks are channelling enquiries through automated phone trees and conversational agents while rationalizing branch networks. Insurers and healthcare intermediaries are routing billing and claims questions through chatbots and self-service portals. The managerial case for these deployments is familiar and, on its face, persuasive: lower labour costs, standardized transactions, consistent upselling, extended service hours, and shorter wait times (Ding et al., 2025; George et al., 2025; Gnewuch et al., 2023). Measured against cost-per-transaction and throughput, replacing frontline personnel with AI looks like a straightforward productivity gain.

That framing rests on an assumption that deserves scrutiny: that customer-facing interaction is mainly a cost to be minimised rather than a capability that creates value. Recent corporate experience suggests the assumption is fragile. McDonald's ended an automated order-taking test conducted with IBM at about 100 drive-through locations in 2024, after roughly two and a half years of trials and with a stated aim of reaching order accuracy above 95% before any broader adoption (Nation's Restaurant News, 2024). In contrast, Chick-fil-A's chief executive stated in 2026 that the company would not pursue AI voice ordering in its drive-through lanes. He said its use of AI would instead focus on operations behind the scenes, so that hospitality could remain "human to human" (Gray News, 2026). Practitioner commentators, including caregiving researcher and health-technology entrepreneur Neal K. Shah, have argued that the broader rush to automate customer touchpoints may be eroding customer trust and excluding older and vulnerable consumers from essential services (Shah, 2026). These cases and commentaries are not evidence of a general rule, since each firm's outcomes reflect many

factors beyond its automation choices. They do, however, show a strategic divergence among comparable firms facing the same technology, and that divergence calls for theoretical explanation.

Three lines of scholarly work point to why the divergence matters. First, research on algorithm aversion indicates that people may lose confidence in an algorithm after seeing it err, even when the algorithm outperforms human judgment overall, and that machine errors may be judged more harshly than equivalent human errors (Han & Ko, 2025; Renier et al., 2021). If that asymmetry holds in service encounters, a single automated failure may cost more relationally than its operational size suggests. Second, long-standing work in relationship marketing and service management links service experience to retention, loyalty, and willingness to pay, so cost savings at the frontline may be offset by revenue effects that never appear in a labour-cost spreadsheet (Fam et al., 2021; Kotze & Mostert, 2025; Makki et al., 2026). Third, research on digital exclusion shows that automated service channels can disadvantage older, less digitally fluent, and financially vulnerable customers. These are the customers for whom a human intermediary may be the difference between a resolved problem and a cascading one (Cheung et al., 2026; Kaye, 2026; Money et al., 2023). The literature on algorithm appreciation, which finds that people sometimes prefer algorithmic advice, cautions against assuming customers uniformly reject automation (X. Jin & Li, 2025). The relevant question is therefore conditional rather than categorical.

These strands converge on a strategic problem that remains underdeveloped in management scholarship. Most research on AI in services examines adoption intentions, technology acceptance, or customer satisfaction with specific interfaces. Far less work asks the competitive-strategy question: under what conditions does frontline AI create sustainable advantage, and under what conditions does human interaction become the scarcer and more valuable resource? The resource-based view holds that advantage comes from resources that are valuable, rare, and costly to imitate. As AI service capabilities become accessible through cloud platforms and third-party vendors, a firm's chatbot or voice agent may increasingly resemble those of its rivals. To that extent, automated service may become a competitive necessity rather than a differentiator. Human service, if it is well trained, empowered, and deployed where it matters most, may meet the criteria of a strategic resource better under AI diffusion than before it. This is a conditional argument, not an established finding, and the paper treats it as such.

Framing the question this way moves the managerial problem from a binary choice (automate or not) to an allocation choice: which touchpoints should be automated, which should remain human, and how the two should be combined. Service management has long distinguished front-stage activities, visible to and co-produced with the customer, from back-stage activities that support them out of view (Wirtz et al., 2023). That distinction offers a useful starting point. It suggests a hybrid intelligence configuration in which automation handles repetitive, rule-bound, and computationally intensive back-stage work, such as inventory, scheduling, routing, and kitchen logistics. Human staff, in turn, concentrate on front-stage moments characterised by ambiguity, emotional intensity, high stakes, or customer vulnerability. Managers currently have little theory-informed guidance for drawing that boundary, and the costs of drawing it badly fall on firms and customers alike.

The problem is especially pressing in Southeast Asia, for structural reasons that set the region apart from the North American contexts in which the motivating cases arose. The Philippines has built one of the world's largest IT-business process management sectors largely on human customer interaction. Its strategic exposure to customer-service automation is therefore a national competitiveness concern, not only a firm-level one. Banking systems across ASEAN are digitalizing quickly, with mobile wallets and digital banks expanding access while raising questions about customers left behind by branch rationalisation. In the Philippines, for example, recent prudential rules for digital-centric banks have been assessed as lacking explicit inclusion-sensitive transition provisions for underserved island and rural communities (Geca et al., 2026). Several ASEAN economies are ageing, at markedly different speeds, which enlarges the population for whom human-mediated service carries both commercial and ethical weight. Many service encounters in the region also take place in multilingual, code-switching environments, which plausibly add to the speech-recognition difficulties seen in noisy automated ordering. ASEAN is not homogeneous on any of these dimensions. Singapore's digital maturity, the Philippines' services-export dependence, and the demographic profiles of Thailand and Vietnam imply different strategic calculations. That heterogeneity is part of why a contingent allocation framework is more useful to regional managers than a universal prescription.

Since the question concerns strategic logic across sectors and contexts rather than one measurable outcome, this paper uses a conceptual design built on an integrative review of the literature. The evidence on algorithm aversion, service automation, retention economics, vulnerable consumers, and human–AI collaboration is spread across marketing, information systems, operations, and strategy, and has rarely been integrated around the competitive-advantage question. An integrative conceptual approach allows these literatures to be synthesized, their tensions examined, and a framework with testable propositions developed for future empirical work. The paper does not claim to establish causal effects of automation on firm performance, and it uses the corporate cases only as illustrations.

Within this design, the paper pursues four interrelated objectives. It synthesizes the evidence on how customers respond to AI-mediated service, including the conditions under which algorithmic failure provokes disproportionate loss of trust and those under which automation is welcomed. It evaluates, through a resource-based lens, whether human frontline interaction meets the conditions of a strategic resource as AI service capabilities diffuse. It examines the exclusion risks that automated service architectures create for vulnerable customers, and the reputational, ethical, and regulatory exposures these imply. Building on these analyses, it develops a front-stage/back-stage hybrid intelligence framework that classifies service touchpoints by ambiguity, stakes, emotional intensity, and customer vulnerability, and derives propositions on where human presence is most likely to create durable value.

The paper speaks to two audiences. For scholars, it extends resource-based reasoning to the competitive consequences of AI diffusion in services and connects behavioural evidence on algorithm aversion to strategic outcomes. For practitioners, including executives in quick-service restaurants, banking, healthcare, retail, and contact-centre operations across Southeast Asia, it offers a structured way to make deployment decisions that weighs labour savings against trust, retention, inclusion, and differentiation. The central claim is not that firms should resist AI. Rather, the source of advantage may lie less in how much a firm automates than in how deliberately it decides where people should remain.

2. Review of Related Literature

2.1 AI and Automation in Frontline Service Encounters

AI now operates at the customer interface in several forms: text-based chatbots, voice agents, service robots, virtual assistants, and a broad family of self-service technologies. These can support employees, augment them, or replace them outright (Castelo et al., 2023; George et al., 2025). The managerial reasons for deployment are consistent across sectors. Firms cite round-the-clock availability, speed, scalability, cost reduction, relief from labour constraints, and the chance to redirect employees toward higher-value work (Ding et al., 2025; Gnewuch et al., 2023). Survey evidence from commercial banks likewise associates AI applications in customer service, fraud detection, and decision support with gains in process automation, cost efficiency, and transaction accuracy (Ying & Encio, 2026). These motives are framed almost entirely from the firm's side. They describe what automation saves, not what customers gain. That framing matters for the paper's central question, because a deployment logic built on cost efficiency need not match the drivers of customer value.

Task typologies give the clearest conceptual basis for judging what frontline AI can plausibly do. Several frameworks converge on a common boundary: AI is strongest in mechanical and analytical tasks, while humans keep a relative advantage in intuitive, creative, and empathetic work (Bagozzi et al., 2022; Pavone et al., 2022; Wirtz & Stock-Homburg, 2025). Tuomi and Ascenção (2021) applied this logic to frontline food service and found that most tasks were mechanical (58.8%) or analytical (26.8%), with only 11.3% classified as intuitive and 3.1% as empathetic. This distribution explains why automation has clustered in standardized interactions. It also prompts an interpretive point that the study does not test directly: the small share of intuitive and empathetic tasks may carry a disproportionate share of an encounter's relational consequences. If so, task frequency is a poor guide to task strategic weight.

The evidence on customer evaluations does not support the assumption that replacing human employees with automated agents improves satisfaction. Two recent meta-analyses report that, holding service quality constant, automated agents generally do not produce better customer evaluations than human agents (De Oliveira Santini et al., 2025; Gelbrich et al., 2025). Castelo et al. (2023) offer a mechanism. Customers tend to infer that service bots serve the firm's cost-cutting interests more than their own, and this inference lowers evaluations unless firms visibly pass benefits on to customers or the bot delivers clearly better service. Meta-analytic work on anthropomorphism shows that design features shape acceptance as well (Blut et al., 2021). The underlying difficulty is not purely technical, however. It is attributional: customers read automation as a signal of firm priorities.

The literature is not uniformly negative, and its contingencies are analytically useful. Routine requests that are resolved accurately tend to produce satisfactory chatbot experiences (Nicolescu & Tudorache, 2022). A natural field experiment in call-centre service found that voice-based AI reduced complaints over time when it replaced an interactive voice response system (L. Wang et al., 2023). In that case, however, the comparison was with an earlier automated channel, not with human agents. For embarrassing or purely utilitarian services, robots can outperform humans, plausibly because machine interaction lowers social discomfort (De Oliveira Santini et al., 2025). In complex or emotionally charged encounters, by contrast, customers usually prefer human agents, and satisfaction with automated service falls as complexity rises (De Oliveira Santini et al., 2025; Hasan, 2025).

Performance on non-routine requests sharpens this pattern. AI agents do not, overall, match human performance when customers need contextual judgment, emotional understanding, or creative problem-solving rather than information retrieval or scripted resolution (Gnewuch et al., 2023; Wirtz & Stock-Homburg, 2025). Field evidence from Alibaba's customer service operations, reported in a preprint, shows the trade-off in practice. Agentic AI shortened chats, yet customer

ratings fell, and emotionally escalated interactions were the hardest for human intervention to recover (Y.-W. Wang et al., 2026). Other studies find that hybrid routing, where AI handles common requests and humans take exceptions, performs more reliably (Gnewuch et al., 2023). Visible coordination between human and digital employees can also raise satisfaction by making the service process appear coherent (Le et al., 2024).

The literature in this theme is methodologically uneven. Scenario-based experiments and systematic reviews dominate, while field experiments are few and come mostly from Chinese platform settings (L. Wang et al., 2023; Y.-W. Wang et al., 2026). Outcomes are measured mainly as satisfaction, complaints, or usage intention. Retention, pricing power, and firm-level performance, the outcomes most relevant to competitive strategy, are rarely observed. For the present paper, the main contribution of this literature is to reframe the managerial question. The evidence does not show that automation fails or succeeds in general. It shows an efficiency boundary that runs through task type, complexity, and emotional intensity. The strategic problem is therefore where that boundary lies in a given service architecture, not whether to automate.

2.2 Algorithm Aversion, Trust, and Customer Responses to AI Service Failure

A central claim in the public debate on frontline automation is that people forgive human error more readily than machine error. The literature partly supports this claim, but with significant qualifications. In evaluative and advisory tasks, algorithmic mistakes provoke harsher immediate reactions and lower acceptance than equivalent human mistakes, and this holds across variations in error severity and system maturity (Renier et al., 2021). Trust in algorithmic agents can drop sharply after a single observed error (Candrian & Scherer, 2023; Han & Ko, 2025). One proposed explanation is that people hold algorithms to unrealistic expectations of perfection, so any error violates those expectations more severely than the same error from a human (Han & Ko, 2025; Maasland & Weißmüller, 2022). Evidence from industrial service recovery also suggests that AI-enabled recovery efforts can erode trust and customer engagement (Naidoo, 2026).

A second body of work complicates the simple asymmetry. When algorithmic errors cause brand-harm crises, consumers sometimes react less negatively toward the brand than when a human caused the harm. This appears to be because algorithms are seen as lacking intentionality and self-serving motives (Srinivasan & Sarial-Abi, 2021). In a related finding, consumers respond less negatively to unfavourable offers delivered by AI than to the same offers delivered by humans (Garvey et al., 2021). The apparent contradiction resolves once two dimensions are separated. Customers judge algorithmic competence harshly but assign moral culpability to algorithms leniently. Responsibility does not disappear in the second case. Instead, it shifts upward: when an AI agent fails, customers attribute greater responsibility to the deploying firm, because the machine is not seen as an agent capable of blame (Cai et al., 2024; Pavone et al., 2022). For strategy, this shift is the key point. In an automated encounter, there is no frontline employee to absorb, personalise, and repair a failure, so the firm itself becomes the target of attribution.

Research on moderators shows when aversion is strongest. It intensifies in subjective or unstructured tasks, where human flexibility is valued (X. Jin & Li, 2025). It increases with the gravity of the decision (Filiz et al., 2023). Errors that occur early in a relationship produce more persistent distrust, although giving users some control can soften this timing effect (Kim et al., 2022). Cross-country evidence suggests that algorithm aversion is not confined to Western, educated, industrialised, rich, and democratic populations, although its intensity varies with individual differences (Liu et al., 2023). Longoni et al. (2022) document algorithmic transference: people generalise one algorithm's failures to other algorithms because they see automated systems as homogeneous. This finding bears directly on the commoditization argument. If customers see AI service agents as largely interchangeable, a widely publicized failure may lower trust in automated service across an industry, not only at the firm that failed.

Recovery research shows that trust lost to automated failure can be partly restored, and that the mechanisms differ from those used in human service recovery. Showing that a system learns from its mistakes reduces aversion and restores reliance, which counters the common assumption that algorithms cannot improve (Reich et al., 2022). Explanations and explainable system designs strengthen trust resilience after failure (Han & Ko, 2025; Xu & Wang, 2024). Describing a system as self-learning "AI" rather than a rule-based "algorithm" can also make responses more forgiving by changing perceptions of the error's stability (Candrian & Scherer, 2023). Interpersonal tactics carry over to automated agents to some degree. Chatbots that use a socially oriented communication style lower dissatisfaction after failure (Cai et al., 2024), and self-deprecating humour can raise tolerance (Yang et al., 2023). Generative AI introduces a new risk, however. When customers recognise recovery messages as machine-generated, trust can fall unless visible human oversight is present (Naidoo, 2026; Tan et al., 2024).

The methodological profile of this literature limits how directly it applies to frontline service. Much of the foundational evidence comes from laboratory and online experiments on forecasting, advisory, or evaluation tasks rather than live service encounters. Samples are often drawn from online panels or student populations, and outcomes are usually measured right after a single manipulated error. Extending these findings to ongoing customer relationships in restaurants, banks, or contact centres is therefore an inference, not an established result. Even so, the literature supports a conditional proposition relevant

to this paper. Automated failure is especially costly where tasks are unstructured, stakes are high, and customers expect perfection. In these conditions, firms bear the attributional consequences directly, and a human intermediary may serve as a buffer for both trust and blame.

2.3 Human Interaction as a Strategic Resource

Human frontline interaction is consistently associated with loyalty and retention across a range of service settings. Personal encounters with employees build interpersonal trust and relational capital, which appear to buffer against defection (Fam et al., 2021; Jiménez-Jiménez et al., 2025; Kotze & Mostert, 2025). In high-contact services, employee relationships support repeat patronage, and cultural expectations shape how strictly customers judge relational delivery (Fam et al., 2021). This point matters for the culturally diverse service markets of Southeast Asia. At the level of individual encounters, frontline employees' relational communication, including matching intimacy and task orientation while staying composed, drives customer satisfaction even in online service interactions (Grewal et al., 2026). Customer orientation among service employees supports retention through satisfaction and commitment (Nafisah et al., 2025). Interaction quality shapes customer experience and, through it, behavioural loyalty (Eskiler & Safak, 2022). Store-level evidence indicates that frontline employees enhance store loyalty in physical retail (Kotze & Mostert, 2025), and employee–customer identification supports trust and loyalty in online shopping contexts (Sachdev & Sauber, 2023).

A second strand places the source of this value inside the organization. Internal marketing investments are associated with customer attraction and retention, which suggests that how a firm treats its frontline workforce carries through to customer outcomes (Makki et al., 2026). Employee loyalty appears to support service quality and customer retention in culturally embedded retail settings (Hemo et al., 2026). Service orientation also links managerial, employee, and customer perspectives to performance (Yi et al., 2022). The interpretation that follows is important for the paper's argument. The strategic value of human interaction does not come from headcount alone. It depends on organizational investment in selection, training, retention, and empowerment. A frontline staffed by under-resourced employees would not be expected to yield the relational benefits this literature describes.

The willingness of customers to pay more for human service is more conditional than the loyalty evidence. In restaurant settings, consumers pay a premium for human chefs working with robots when the service is personalised, but prefer robotic or self-service delivery without any human premium when the task is standardized (Kazakova et al., 2025). Consumer innovativeness moderates these preferences. Less innovative consumers pay more for human co-production, while more innovative consumers pay more for robotic co-production (Wu et al., 2021). Technology-infused encounters can also raise willingness to pay when frontline staff display competence with the technology (Röding et al., 2023). In multi-touchpoint service environments, customer engagement and dependence contribute to loyalty (Chen et al., 2023). Taken together, these findings do not support a blanket claim that customers will pay more for human service. They suggest that a human premium is earned where personalization, complexity, or risk reduction is visible to the customer.

Explicit resource-based arguments about frontline interaction remain relatively scarce. Asakdiyah (2026) argues that relational frontline capabilities meet the conditions of value, rarity, and imperfect imitability, while efficiency gained purely through digital self-service diffuses quickly among competitors and erodes as a source of advantage. The mechanism proposed is path dependency: interpersonal service routines and relational capital build up through social exchange over time and are hard for rivals to copy. Empirical work offers partial support. Face-to-face employee engagement gives physical retailers a differentiation advantage over online competitors (Kotze & Mostert, 2025). In service triads that include robots, customers, and employees, high-quality employees compensate for technological shortfalls and preserve repatronage intentions (Odekerken-Schröder et al., 2021). Relationship marketing research in contractual services similarly links relational investment to brand loyalty (Chatzi et al., 2024).

This theme's literature is dominated by cross-sectional surveys analysed with structural equation or partial least squares modelling. It is concentrated in fitness, hospitality, and retail settings, and it relies heavily on self-reported loyalty intentions rather than observed retention or financial performance. The resource-based application to human frontline service under AI diffusion is mostly argued conceptually, often in less established outlets, rather than tested. The theme therefore establishes a strong association between human interaction and loyalty and a conditional basis for price premiums. It does not establish that human service causes superior firm performance, or that it will continue to be a source of advantage as AI capabilities spread. That second proposition is the one this paper aims to develop.

2.4 Digital Exclusion and Vulnerable Consumers in Automated Service Systems

The literature broadly agrees that older adults face significant barriers when essential services move to digital and automated channels. In healthcare, a substantial share of older patients, between 57% and 64% according to one synthesis, do not use patient portals at all, and between 23% and 29% lack compatible devices (Kaye, 2026). In mobile banking, usability evaluations reveal deficiencies in error prevention and in the visibility of system status. Usability declines with

age, from a mean score of 54.2 among adults aged 60 to 63 to 45.3 among those aged 72 to 75 (Amouzadeh et al., 2026). Qualitative work with adults over 75 identifies barriers that combine capability, confidence, and trust (Money et al., 2023). Research on the post-lockdown shift to contactless services documents experiences of isolation and diminished agency among older adults (Morrison et al., 2023).

The mechanisms of exclusion operate on several levels at once. Cognitive and interface frictions include complex login procedures, password requirements, and multi-factor authentication (Kaye, 2026). Psychological barriers centre on fear of scams and anxiety about making irreversible mistakes. These lead older consumers to use only some channels and to avoid digital fund transfers (Cheung et al., 2026; Money et al., 2023). Older adults are not a homogeneous group, since physical and motor capacities decline progressively across age cohorts (Amouzadeh et al., 2026; Cheung et al., 2026). Socioeconomic vulnerability intersects with age through income constraints, gendered disadvantage, and limited device ownership (Morrison et al., 2023; S & Sengupta, 2025). Unequal digital access also corresponds to measurable differences among Philippine firms, where manufacturers with low digital access reported lower digital financial inclusion than those with high access (R. G. O. Atento et al., 2026). The documented consequences reach beyond the customer. Login friction is associated with higher call-centre loads and poorer medication adherence (Kaye, 2026), and some older customers remain wholly dependent on human tellers (Cheung et al., 2026).

Evidence from Asian contexts adds an important nuance. In Hong Kong and mainland China, older consumers often rely on family members to complete digital transactions, or ask frontline staff to operate their smartphones for them during branch visits (Cheung et al., 2026; X.-F. Jin & Fan, 2022). This reliance on family intermediaries intersects with broader scholarship on caregiving for older adults, which highlights the psychosocial demands that support roles place on caregivers (Quinto et al., 2026). Older users in these settings report preferring human interaction because automated voice systems lack empathy and patience (X.-F. Jin & Fan, 2022). A review of older adults' adoption of digital banking finds that barriers and motivations coexist (Dizon & Ebardo, 2025). This implies that exclusion is not inevitable, but that adoption depends on support structures that automated channels alone do not provide. A global synthesis of fintech and older adults reaches a similar conclusion: inclusive digital finance depends on enabling conditions beyond the technology itself (S & Sengupta, 2025). Evidence from the Global Findex 2025 across Asia similarly suggests that connectivity alone does not explain financial inclusion, which also depends on demand-side conditions such as digital literacy, trust, and income, and on the regulatory and institutional environment (A. G. Atento et al., 2026). These findings bear on the paper's argument. In some markets, human intermediaries do not just complement digital channels. They are the channel through which digital services become usable at all.

Research on bank branch closures extends the analysis to physical access. Branch "desertification" reduces financial accessibility for elderly, immobile, and low-income groups (Baldassarre et al., 2025). Rural and non-affluent communities face the greatest increases in travel friction (Aversa et al., 2022; Clark et al., 2023). Spatial modelling in Wales shows that reductions in public transport compound the effects of branch closures for consumers without cars (Higgs et al., 2022; Langford et al., 2022). In Hungary, online banking use among adults aged 65 to 74 lags far behind that of younger adults, at 34% compared with 75%. This suggests that digital channels cannot fully replace in-person banking for less educated or isolated pensioners (El-Meouch et al., 2023). Closures improve institutional profitability, but those gains depend largely on younger, digitally active customers (Cho et al., 2023; El-Meouch et al., 2023). In Italy, branch closures are associated with reduced new firm creation (Cardamone & Trivieri, 2024), which links service-channel decisions to local entrepreneurial activity.

The evidence on closures is not uniform. In the United States, branch counts fell by 19% between 2014 and 2024, yet average travel distances rose only marginally, by 0.02 to 0.28 miles. This indicates that the spatial effects of consolidation depend on national geography (Adams & Sherlund, 2025). Physical frictions can also nudge digitally capable consumers toward adoption (Choi & Loh, 2023). The harm therefore appears concentrated among less digitally active and more vulnerable segments rather than spread across the whole customer base. Methodologically, this literature relies on geographic and spatial analysis, usability testing, and qualitative inquiry, mostly in European and North American settings, with Asian evidence centred on Greater China. For the present paper, the theme establishes customer vulnerability as a legitimate criterion for deciding which touchpoints to automate. It also suggests that exclusion creates reputational, regulatory, and commercial exposure: firms that remove human access may be discarding a dependent customer segment rather than simply cutting costs.

2.5 Hybrid Intelligence and Human–AI Task Allocation in Service Operations

The literature on hybrid service models broadly agrees that combining AI with human employees outperforms full automation on customer outcomes. The size of that advantage depends on how handoffs, escalation, and customer expectations are managed (Ding et al., 2025; Gnewuch et al., 2023). The underlying reason is consistent with the evidence in Section 2.1: AI often struggles with complex, novel, or emotionally charged interactions, and human involvement

preserves resolution quality in exactly those cases. Field evidence from Alibaba's platform, reported in a preprint, shows that unassisted agentic AI shortened chat duration by 64.6% while customer ratings fell by 0.858 points, and that human oversight reduced this decline in quality (Y.-W. Wang et al., 2026). The same study found that human intervention was least effective once interactions had already escalated emotionally. This implies that when humans enter an interaction matters as much as whether they enter it. A conceptual analysis of AI in manufacturing and marketing reaches a parallel conclusion beyond customer service: fully automated deployment architectures frequently underperform calibrated human–AI collaboration, and whether AI substitutes for or augments human work depends on task composition and on how organizations design task allocation, human capital investment, and governance (Tolentino et al., 2026).

Hybrid design involves trade-offs that make the hybrid model a set of configurations rather than a single solution. Tiered escalation, where AI triages standard queries and humans handle exceptions, preserves capacity for emotional and complex work (Ding et al., 2025; Gnewuch et al., 2023). Transparency has competing effects. Signalling collaboration between human and digital employees improves perceived team cohesion and satisfaction (Le et al., 2024), yet disclosing human involvement behind a chatbot can change customer behaviour in ways that add to employees' workload (Gnewuch et al., 2023). Ding et al. (2025) show that the economics of hybrid configurations depend on labour costs: the net advantage of collaboration varies across labour-cost levels rather than rising steadily. This finding is directly relevant to lower-wage service economies in Southeast Asia, where the cost calculus for keeping human staff differs from that in high-wage markets. In financial services, blending automated platforms with physical advisory touchpoints ("phygitalization") reduces operational friction and supports both customer and employee well-being (Roederer et al., 2026).

The evidence on augmentation, meaning AI that assists employees rather than replacing them, is among the strongest in this literature. In a study of 5,172 customer-support agents, access to a generative AI assistant increased issues resolved per hour by 15% on average, accelerated skill acquisition, and reduced escalations to managers (Brynjolfsson et al., 2023). The gains were concentrated among novice and lower-skilled workers, with little effect on the most experienced staff (Brynjolfsson et al., 2023). Because a large share of the agents in that study were based in the Philippines, it is among the most directly relevant pieces of evidence for the region's contact-centre sector. Chatbots can provide employees with informational and emotional support that improves role clarity and task performance (Lin et al., 2024). Organizational AI adoption has also been linked to employee innovation performance (Hu et al., 2026). Augmentation has costs, however. AI adoption can be a double-edged influence on service performance (Quan et al., 2025), and pervasive deployment can provoke anxiety or a sense of obsolescence when poorly managed (Blaurock et al., 2025). Effective collaborative intelligence systems require process control, transparency of system logic, and verification of outputs, so that automation bias is avoided and employees retain ownership of the work (Blaurock et al., 2025; Costa & Ghosh, 2025). Qualitative evidence from Philippine accounting practitioners points in the same direction: AI is adopted most comfortably in low-risk assistive uses, verification overhead can reduce net efficiency gains where outputs lack traceability, and practitioners anticipate workforce recomposition rather than immediate displacement (Bendal et al., 2026).

The distinction between front-stage and back-stage work has become an explicit organizing principle in this literature. Wirtz et al. (2023) describe strategic pathways to cost-effective service excellence that assign different human–AI combinations to customer-facing and back-office processes. In back-stage workflows, AI handles standardized data processing, anomaly detection, predictive classification, and routine troubleshooting efficiently (Babar et al., 2025; Wirtz et al., 2023). Front-stage encounters, by contrast, require human oversight to provide situational empathy, ethical accountability, and contextual judgment when unscripted problems arise (Costa & Ghosh, 2025; Wirtz & Stock-Homburg, 2025). In business-to-business service recovery, managers see analytical AI as suited to early fault prediction, with relational and conversational AI working alongside human managers during active resolution (Ameen et al., 2024). Frontline roles are accordingly shifting from executing transactions toward advisory work, triage, and oversight (Hlembytskyi, 2025; Wirtz & Stock-Homburg, 2025).

The methodological base of this theme is mixed. A small number of rigorous field studies (Brynjolfsson et al., 2023; Y.-W. Wang et al., 2026) and analytical models (Ding et al., 2025) sit alongside conceptual frameworks and systematic reviews of varying quality, some of them in less established outlets. Most evidence comes from contact centres, IT support, and platform-based customer service. Physical service settings such as quick-service restaurants, bank branches, and pharmacies are much less studied. For the present paper, this theme supplies the design vocabulary for the allocation framework: tiered escalation, timing of intervention, augmentation rather than substitution, and the front-stage/back-stage boundary. It also shows that these elements have been examined largely in isolation. They have not yet been integrated with the trust, resource, and exclusion considerations discussed in the preceding themes.

2.6 Synthesis of Literature

Read together, the five themes point to a consistent pattern: the value of frontline automation is contingent rather than general, and the contingencies line up across literatures that have developed largely in isolation from one another. The

service automation literature places the efficiency boundary at task type. AI performs well in mechanical, analytical, and routine encounters and falls short in complex, intuitive, and empathetic ones (De Oliveira Santini et al., 2025; Tuomi & Ascenção, 2021; Wirtz & Stock-Homburg, 2025). The algorithm aversion literature identifies largely the same conditions, namely unstructured tasks, high stakes, and expectations of perfection, as those under which automated failure is judged most harshly (Filiz et al., 2023; X. Jin & Li, 2025; Renier et al., 2021). The strategic resource literature finds that customers place the most value on human interaction, including willingness to pay a premium, where personalization, complexity, or risk reduction are visible (Kazakova et al., 2025; Wu et al., 2021). The exclusion literature shows that the cost of removing human access falls most heavily on customers who are older, less digitally capable, or financially exposed (Cheung et al., 2026; Kaye, 2026). The hybrid intelligence literature converges on a front-stage/back-stage division of labour that matches these boundaries (Wirtz et al., 2023).

Four cross-cutting insights follow from this convergence. First, the managerial question is better framed as one of allocation than of adoption. No theme supports either wholesale automation or wholesale resistance to it. Each supports a contingent distribution of human and machine roles across touchpoints. Second, attribution is a strategic variable, not only a psychological one. Customers read automation as a sign of firm priorities (Castelo et al., 2023), shift blame for automated failure to the firm (Cai et al., 2024; Pavone et al., 2022), and generalize failures across automated systems they see as interchangeable (Longoni et al., 2022). Automation therefore changes where relational risk sits in the firm. Third, the strategic value of human service depends on organizational investment. The loyalty benefits documented in the literature are tied to internal marketing, employee retention, and empowerment (Makki et al., 2026), and the largest productivity gains from AI come when it augments workers rather than replaces them (Brynjolfsson et al., 2023). Human frontline service is thus best understood as a capability that firms must build, not as a residual cost that remains after automation. Fourth, the literatures diverge on how much the customer base matters. Studies of automation and aversion generally treat customers as a homogeneous population responding to experimental manipulations, whereas the exclusion literature shows strong heterogeneity by age, digital capability, and geography. Customer segmentation, and not only task type, therefore has to inform allocation decisions.

These themes also share an important tension. The evidence on customer reactions favours keeping human presence at consequential touchpoints, yet the labour-cost economics of hybrid configurations differ across contexts (Ding et al., 2025). Customers' willingness to pay for human service is conditional, not assured (Kazakova et al., 2025). Any strategic argument for human frontline service must therefore be conditional on context, segment, and touchpoint. It cannot rest on a universal claim about human superiority.

2.7 Gaps in the Literature

The first gap is conceptual. The literature has not combined behavioural evidence on algorithm aversion with resource-based reasoning about competitive advantage. Studies of customer responses to AI rarely ask what those responses mean for sustainable differentiation. The few resource-based treatments of frontline interaction are mostly conceptual, appear in less established outlets, and do not address how the diffusion of AI capabilities might change the relative scarcity of human service (Asakdiyah, 2026). Whether, and under what conditions, human interaction becomes more strategically valuable as AI becomes a commodity is therefore asserted in practitioner discourse but has not been theorized.

The second gap concerns allocation logic. Hybrid intelligence research describes configurations such as escalation, augmentation, and front-stage/back-stage separation, but it offers managers no integrated criteria for deciding which specific touchpoints should be human, automated, or hybrid. Task typologies classify activities by cognitive type, and exclusion research identifies vulnerable segments, but no framework yet combines task ambiguity, stakes, emotional intensity, and customer vulnerability into a single basis for allocation decisions.

The third gap is methodological. The evidence relies heavily on scenario experiments, online panels, and cross-sectional surveys of loyalty intentions. Observed retention, pricing power, and firm-level performance are rarely measured. Field evidence is scarce and concentrated in platform-based contact centres. Physical frontline settings such as quick-service restaurants, bank branches, pharmacies, and healthcare billing remain understudied, even though these are the settings where automation decisions are currently most visible.

The fourth gap is geographic. Evidence on aversion and branch closures comes mainly from North America and Europe, and Asian evidence on vulnerable consumers centres on Hong Kong and mainland China. Southeast Asian service markets, including the Philippine contact-centre sector, ASEAN retail banking, and the region's multilingual service environments, are almost absent from the literature as research settings. This is so even though a key augmentation study drew heavily on Philippine-based agents (Brynjolfsson et al., 2023). The literature has not examined how differences in labour costs, digital maturity, demographic ageing, and cultural expectations of hospitality across ASEAN economies might change the calculus of frontline automation.

The fifth gap concerns practitioner relevance. Managers making deployment decisions have little guidance that weighs labour savings against attribution risk, retention effects, exclusion exposure, and differentiation potential within a single decision frame.

2.8 Contribution of the Present Paper

This paper makes three contributions. The first is theoretical. It extends resource-based reasoning to the competitive consequences of AI diffusion in customer-facing services, arguing conditionally that as automated service capabilities become widely accessible and seen as interchangeable, they lose their capacity to differentiate firms. Under these conditions, well-resourced human frontline interaction may better satisfy the requirements of a strategic resource. Connecting this argument to evidence on attributional asymmetry and algorithmic transference provides a behavioural mechanism for the resource-based claim, which has so far been missing.

The second contribution is integrative. The paper synthesises five literatures that have developed largely separately into a front-stage/back-stage hybrid intelligence framework. The framework classifies service touchpoints by ambiguity, stakes, emotional intensity, and customer vulnerability, and from this classification it derives propositions that empirical research can test.

The third contribution is contextual and practical. The paper places the analysis in Southeast Asian service economies without treating them as homogeneous, and it considers the distinct implications for the Philippine contact-centre sector, ASEAN retail banking, ageing consumer segments, and multilingual service settings. For practitioners, it provides a structured decision frame for frontline automation that weighs cost efficiency against trust, retention, inclusion, and differentiation. The paper does not claim to establish causal effects. Its aim is to give scholars a theoretically grounded agenda and to give managers a disciplined way to decide where people should remain at the point of customer contact.

3. Methodology

3.1 Research Design

The paper uses a conceptual research design built on an integrative literature review. This design suits the research problem because the central question concerns strategic logic. It asks under what conditions human frontline interaction is a source of competitive advantage as AI service capabilities diffuse, and how firms should allocate human and automated roles across service touchpoints. Answering it requires integrating evidence from service marketing, consumer psychology, information systems, operations management, financial access, and strategic management. These literatures have developed largely in parallel, use different constructs and methods, and have not previously been combined around the competitive-advantage question. An integrative conceptual design makes it possible to synthesise them, examine their tensions, and develop a framework and propositions for later empirical testing. The paper collects no primary data and makes no causal claims. Its analytical output consists of a synthesis, a classification framework, and a set of formal propositions.

3.2 Source Orientation and Retrieval

Literature was identified through structured searches of a large-scale academic search index covering peer-reviewed journal literature across the management, marketing, information systems, operations, and social science disciplines. Retrieval followed the five-theme framework set out in Section 2. For each theme, two closed-form (yes/no) research questions were developed to target the evidentiary claim most relevant to the paper's argument. Examples include whether customers react more negatively to service failures caused by AI agents than to identical failures caused by human employees, and whether hybrid service models outperform fully automated ones on customer outcomes. Framing the searches as testable questions directed retrieval toward studies that test or bear directly on a specific proposition, rather than toward broad topical coverage. Searches were not restricted by date. The returned corpus is nonetheless concentrated in 2021 to 2026, which reflects the recent growth of research on conversational AI, service robots, and generative AI in customer service. Across the five themes, retrieval yielded 85 unique records after removing studies that appeared under more than one theme.

3.3 Inclusion and Appraisal Logic

A record was retained for synthesis if it met three conditions. It had to address customer-facing service, frontline employees, or service operations, rather than AI or automation in general. It had to report empirical findings, meta-analytic estimates, or developed conceptual arguments relevant to at least one guide question. And it had to be traceable through a digital object identifier or equivalent persistent reference. Records that addressed the topic only tangentially were not cited.

Retained sources were weighted according to the strength of their evidence rather than treated as equivalent. Meta-analyses, field experiments, and studies in established peer-reviewed service, marketing, information systems, and

management journals carried primary evidentiary weight. Sources in less established outlets were used only to corroborate patterns found in stronger studies, and their claims were stated with hedged language. Quantitative figures reported in such sources were excluded when they could not be corroborated elsewhere in the corpus. Preprints were retained where they offered rare field evidence, but they are identified as preprints wherever they are cited. Findings were extracted as reported by the retrieved records. Where studies reached divergent conclusions, both positions were kept and the divergence was analysed rather than resolved by selective citation.

3.4 Thematic Grouping Logic

The five themes follow an analytical sequence that moves from phenomenon to mechanism to strategic value to risk to managerial response. Theme 1 establishes what frontline automation does and does not achieve. Theme 2 examines the customer-side mechanism through which automated failure affects trust and attribution. Theme 3 assesses whether human interaction produces the loyalty, pricing, and differentiation outcomes associated with a strategic resource. Theme 4 examines how automated service architectures distribute costs across customer segments, with particular attention to vulnerable consumers. Theme 5 reviews the organizational designs available for combining human and machine capabilities. This sequence ensures that the framework developed in Section 4 rests on demonstrated customer responses and strategic outcomes, rather than on design principles proposed in the abstract.

3.5 Analytical Procedure and Evaluative Criteria

The analysis proceeds in three stages. In the first, cross-thematic synthesis, findings were compared across themes to identify convergent boundary conditions, meaning the conditions under which automation's value changes direction, together with recurring tensions and differences in method and context. The results of this stage are reported in Section 2.6.

In the second stage, resource-based evaluation, the evidence was assessed against the established resource-based criteria of value, rarity, and inimitability. Two questions were asked: whether automated service capabilities can sustain differentiation as they diffuse, and whether human frontline interaction can meet these criteria and under what organizational conditions. Evidence on algorithmic transference and on customers' perception of automated systems as homogeneous was treated as behavioural input to the imitability criterion. Evidence on internal marketing and workforce investment was treated as input to the conditions under which human service capability becomes costly to imitate.

In the third stage, framework and proposition development, touchpoints were classified along four dimensions identified through the synthesis: task ambiguity, consequence stakes, emotional intensity, and customer vulnerability. Each dimension is anchored in the reviewed evidence. Ambiguity draws on task-typology and complex-request research. Stakes draw on decision-gravity and failure-attribution research. Emotional intensity draws on research on escalation and empathetic tasks. Vulnerability draws on research on digital exclusion. These dimensions form the basis of a front-stage/back-stage hybrid intelligence framework, from which formal propositions were derived. Each proposition was required to trace to identifiable evidence in the reviewed literature and to be stated in a form that permits empirical test.

3.6 Illustrative Cases and Contextual Focus

The analysis draws on publicly reported corporate cases in quick-service restaurants, including drive-through automation trials and a contrasting decision to keep human order-taking, along with sectoral examples from retail banking, healthcare billing, pharmacy services, and contact centres. These cases serve only as illustrations. They clarify the strategic choices the framework addresses and show how its dimensions apply in practice. They are not treated as evidence for the propositions, and no performance outcome is attributed to any firm's automation decision, since such outcomes reflect many organizational and market factors beyond frontline design. Practitioner commentary that motivated the research question is used only to identify the problem and is not cited as evidence.

The literature base is international, but the evaluative focus is on Southeast Asian service economies. When the analysis considers regional implications, ASEAN economies are not treated as homogeneous. Differences in labour costs, digital maturity, demographic ageing, the scale of the services-export sector (particularly the Philippine contact-centre industry), and multilingual service environments are treated as contextual variables that may moderate how the framework applies. Because the reviewed literature contains little Southeast Asian evidence, regional implications are presented as reasoned inferences from the general evidence, not as established regional findings.

3.7 Limitations

The design has several limitations. The review is integrative rather than systematic. It did not follow a registered protocol, exhaustive multi-database searching, or formal reporting standards for systematic reviews, so relevant studies outside the retrieved corpus may have been missed. Reliance on a single search index means that retrieval reflects that index's coverage and relevance-ranking procedures. Findings were extracted as reported by the retrieved records, and the

analysis depends on the accuracy of those reports. The corpus is limited to English-language literature and is concentrated in recent publications, which may underrepresent earlier foundational work and regional scholarship published in other languages. Synthesis and appraisal were carried out by a single analytical process without independent double coding. Finally, because the paper is conceptual, its framework and propositions are theoretically grounded but untested. Its claims concern plausible mechanisms and conditions, not demonstrated effects on firm performance.

4. Analytical Synthesis

4.1 The Commoditization Argument through a Resource-Based Lens

Under the resource-based view, a capability supports sustained advantage only if it is valuable, rare, and costly to imitate. Applying these criteria to automated customer service produces a conditional but clear conclusion. The evidence establishes that automated service creates value: it lowers costs, extends availability, and performs routine and structured tasks reliably (Ding et al., 2025; Gnewuch et al., 2023; Nicolescu & Tudorache, 2022). Value alone, however, yields only competitive parity. The rarity and imitability criteria are where automated service becomes vulnerable. Frontline AI is increasingly bought from common vendors and built on shared foundation models. The capabilities available to one firm are therefore, to a large and growing extent, available to its rivals. This is an inference about the trajectory of the technology rather than a documented market outcome. It is consistent with the argument that efficiency gained through digital self-service spreads quickly among competitors and does not form a lasting basis for differentiation (Asakdiyah, 2026). A comparable pattern has been described for big data capabilities, which appear to generate competitive value only through organizational mediators such as dynamic capabilities, learning, governance, and culture, rather than through technology investment alone (Chen & Atento, 2026).

The behavioural literature adds a dimension that resource-based reasoning usually omits: customers' own perceptions of how interchangeable automated systems are. The finding that people generalize one algorithm's failures to other algorithms because they see automated systems as homogeneous (Longoni et al., 2022) suggests that customers may already treat AI service agents as a single category rather than as firm-specific assets. If so, automated service is imitable both technically and perceptually. Firms that deploy similar agents may find that these agents add little distinctiveness to the brand, while the firms share exposure to category-wide reputational shocks. Automated service thus tends toward the status of a competitive necessity: firms incur costs for lacking it but gain little distinction from having it.

Human frontline interaction fares differently against the same criteria, though only under specific organizational conditions. Its value is well supported for loyalty and retention (Fam et al., 2021; Grewal et al., 2026; Kotze & Mostert, 2025) and supported conditionally for price premiums (Kazakova et al., 2025; Wu et al., 2021). Its rarity is plausibly *endogenous to competitor behaviour*. As rivals withdraw human staff from customer contact, well-staffed frontline service becomes scarcer in the market. This mechanism is inferred, not observed. Its inimitability comes from social complexity and path dependence. Relational routines, a service culture, workforce retention, and internal marketing build up over time and cannot be bought from a vendor (Asakdiyah, 2026; Hemo et al., 2026; Makki et al., 2026). The analysis therefore distinguishes human service as a capability from human service as headcount. An under-trained, under-empowered, high-turnover frontline is neither valuable nor hard to imitate. Only a frontline that the firm has invested in meets the resource-based conditions. The commoditization argument does not imply that keeping people confers advantage. It implies that a firm's capacity to build superior human service becomes relatively more strategic as automated capability becomes common.

4.2 The Trust Asymmetry: Why Automated Failure Is Strategically Costly

The reviewed evidence supports a more precise account of the "humans are forgiven, machines are not" claim than practitioner discourse usually gives. The synthesis identifies three distinct components, which together make up a trust asymmetry with strategic consequences.

The first is a *competence penalty*. Customers judge algorithmic errors more harshly in evaluative tasks, and trust can drop sharply after a single error, apparently because people expect algorithms to be perfect (Han & Ko, 2025; Renier et al., 2021). The second is a *responsibility upshift*. Customers excuse the algorithm of moral intent but assign greater responsibility to the firm that deployed it (Cai et al., 2024; Pavone et al., 2022). The third is *category spillover*, the generalization of failures across automated systems (Longoni et al., 2022). A fourth element, documented elsewhere, sits alongside these: customers tend to read automation as a cost-saving signal of firm priorities (Castelo et al., 2023). This means that failures of automated agents may confirm a suspicion customers already hold.

The strategic implication is that automated and human service produce differently shaped risk profiles. Within the efficiency boundary identified in Section 2.1, automation offers modest and dependable gains in routine transactions. Outside that boundary, its failures are concentrated, attributed directly to the firm, and potentially amplified across a

category. A human employee plays a structural role that this asymmetry makes visible. The employee can contain blame at the level of the individual encounter, apologise, and personalise recovery. The analysis refers to this as the employee's *mediating function*: absorbing ambiguity and error before they become failures attributed to the organization.

The recovery literature shows that this function can be partly replicated by automated means. Systems can demonstrate that they learn, explain their failures, or adopt socially oriented communication (Cai et al., 2024; Reich et al., 2022; Xu & Wang, 2024). Two boundaries remain, however. Recovery is hardest once an interaction has escalated emotionally, even when a human intervenes (Y.-W. Wang et al., 2026, preprint). Recovery communication that customers recognize as generated by AI can lower trust unless visible human oversight is present (Naidoo, 2026; Tan et al., 2024). The inference is that the mediating function is most valuable when exercised *before* failure, at touchpoints where error is likely and costly, rather than as a recovery mechanism after the fact.

4.3 A Touchpoint Classification for Allocation Decisions

Taken together, the preceding analyses suggest that allocation decisions should be made touchpoint by touchpoint rather than across the enterprise as a whole. The synthesis identifies four dimensions along which touchpoints differ in ways that change the relative value of human and automated service. Each dimension is anchored in convergent evidence from at least two themes (Table 1).

Table 1. *Touchpoint classification dimensions for human–AI allocation*

Dimension	Definition	Evidence basis	Allocation implication when high
Task ambiguity	Degree to which the request is unstructured, non-routine, or requires contextual interpretation	Complex-request performance gaps; stronger aversion in unstructured tasks (Gnewuch et al., 2023; X. Jin & Li, 2025; Tuomi & Ascenção, 2021)	Human-led or human-escalated handling
Consequence stakes	Magnitude and reversibility of harm if the encounter fails	Aversion rises with decision gravity; failure attribution to firm (Filiz et al., 2023; Pavone et al., 2022)	Human verification before irreversible action
Emotional intensity	Degree of customer distress, frustration, or need for reassurance	Human preference in emotional encounters; difficulty of recovering escalated interactions (De Oliveira Santini et al., 2025; Hasan, 2025; Y.-W. Wang et al., 2026)	Early human involvement, before escalation
Customer vulnerability	Extent to which the customer segment faces digital, cognitive, physical, or financial barriers	Exclusion of older and low-capability users; dependence on human intermediaries (Cheung et al., 2026; X.-F. Jin & Fan, 2022; Kaye, 2026)	Guaranteed human access as a channel option

Note. Dimensions derived by the author from the integrative review in Section 2. Sources indicate the evidentiary basis of each dimension; no study cited tests the classification as a whole.

Three features of the classification matter analytically. First, the dimensions are separate from one another. A balance enquiry is low on all four, whereas a request by an older customer to transfer savings urgently may be low in ambiguity yet high in stakes and vulnerability. Second, the vulnerability dimension belongs to the *customer* rather than the *task*. This reflects the exclusion literature's finding that the same touchpoint can be routine for one segment and a barrier for another (Amouzadeh et al., 2026; El-Meouch et al., 2023). Third, the classification identifies the conditions under which human value rises. It does not on its own determine allocation, because cost structure and capability investment also enter the decision (Ding et al., 2025).

4.4 The Front-Stage/Back-Stage Hybrid Intelligence Framework

Combining the touchpoint classification with the front-stage/back-stage distinction (Wirtz et al., 2023) yields an allocation framework with one back-stage domain and four front-stage zones (Table 2).

Table 2. *Hybrid intelligence allocation framework*

Domain or zone	Touchpoint profile	Allocation	Illustrative touchpoints
Back stage	No direct customer contact	Automate extensively	Inventory forecasting, scheduling, routing, kitchen logistics, data processing
Zone 1: Automated front stage	Low on all four dimensions	AI-led, with an always-available human option	Order status, balance enquiry, appointment confirmation
Zone 2: AI-led with escalation	Usually low; occasionally high ambiguity or emotion	AI triage with early, rule-based human escalation	Billing questions, order modifications, standard complaints
Zone 3: Human-led, AI-augmented	High ambiguity or emotional intensity	Human agent supported by AI tools	Disputes, complex claims, technical troubleshooting, distressed customers
Zone 4: Human-protected	High stakes combined with high vulnerability	Guaranteed human handling and verification	Large or unusual transfers by older customers, coverage denials, medication counselling

Note. Framework developed by the author from the synthesis in Sections 2.6 and 4.3; back-stage/front-stage distinction adapted from Wirtz et al. (2023).

The framework includes four design principles drawn from the reviewed evidence. *Escalation should be timed before escalation of emotion*, because human intervention appears least effective once an interaction has already escalated (Y.-W. Wang et al., 2026, preprint). *Collaboration should be visible where it signals coherence*, because cues of human–AI teamwork can raise satisfaction (Le et al., 2024). Firms should still keep in mind that disclosing human involvement changes customer behaviour (Gnewuch et al., 2023). *Channel choice should be preserved for vulnerable segments*, because in some markets human intermediaries are the route through which digital services become usable at all (Cheung et al., 2026; X.-F. Jin & Fan, 2022). *Back-stage savings should be reinvested in frontline capability.* This principle follows from the resource-based argument: the advantage-generating potential of human service depends on the investment documented in the internal-marketing and augmentation literatures (Brynjolfsson et al., 2023; Makki et al., 2026). The fourth principle is a strategic recommendation built on inference, not an empirically demonstrated effect.

4.5 Sectoral Illustrations

In *quick-service restaurants*, the task-automatability evidence suggests that most frontline food-service tasks can be automated in principle (Tuomi & Ascenção, 2021). The drive-through order, however, combines noisy acoustic conditions, mid-order changes, and wide variation in accents, which raises task ambiguity well above what the task's mechanical classification implies. The end in 2024 of an automated order-taking test at about 100 locations, which the company had expected to reach order accuracy above 95% before broader adoption (Nation's Restaurant News, 2024), illustrates how a touchpoint that appears to belong in Zone 1 on paper may in operation require the support associated with Zones 2 or 3. The company did not attribute its decision to a single cause and stated that voice ordering would remain part of its future, so the case illustrates the difficulty without establishing its source. The contrasting decision to keep human drive-through order-taking while using AI behind the scenes (Gray News, 2026) fits the framework's separation of back stage from front stage. Neither case shows that one approach is superior, since restaurant performance depends on many factors beyond frontline design. Related work on full-service dining treats chronic service delivery failure as a compounding strategic liability that erodes customer tolerance and accelerates defection, and argues that durable resolution requires process redesign and human capital strategy rather than operational adjustment alone (Mendoza et al., 2026).

In *retail banking*, routine enquiries fit Zone 1. The evidence on scam anxiety, irreversible errors, and older customers' dependence on tellers (Cheung et al., 2026; Money et al., 2023), together with the evidence on branch desertification (Baldassarre et al., 2025; El-Meouch et al., 2023), places high-value transactions by vulnerable customers in Zone 4. The association between branch closures and lower rates of new firm creation (Cardamone & Trivieri, 2024) suggests that channel decisions may have consequences for local entrepreneurial ecosystems as well. Given the rapid digitalization of ASEAN retail banking, the framework implies that regional banks should treat assisted channels for older and less digitally capable customers as a planned design choice rather than a residual cost. This is an inference that has not yet been tested in regional data.

In *healthcare billing and pharmacy services*, high stakes and high vulnerability frequently occur together. Low engagement with patient portals among older patients, and its links to call-centre load and medication adherence (Kaye, 2026), indicate that billing disputes and medication counselling belong in Zones 3 and 4. Evidence from Filipino healthcare workers shows that compassionate practice, including empathetic listening and the simplification of complex information, is deliberately exercised but constrained by workload, fatigue, and limited institutional psychosocial support (Papasin, 2026). This underscores that human capability at these touchpoints depends on organizational investment. The cost of exclusion here falls on the customer's health as well as on the firm's revenue. In Philippine retail pharmacy, the market leader's nationwide branch network and consumer trust have been identified as enduring strengths, even as digital-first competitors expose weaknesses in digital adoption (A. G. Atento & Atento, 2025). Physical, human-staffed access and digital capability may therefore need to be developed together rather than traded against each other.

In *contact centres*, augmentation evidence is especially relevant to the Philippine IT-BPM sector. Generative AI assistance raised productivity and was most beneficial to less experienced agents, in a study whose workforce was substantially Philippine-based (Brynjolfsson et al., 2023). The framework implies a repositioning pathway. Routine Zone 1 volume is likely to be automated, but Zone 3 work (complex, emotional, and high-judgment service delivered by AI-augmented human agents) matches the conditions under which human service retains value. The finding that the economics of hybrid configurations depend on labour cost (Ding et al., 2025) suggests that lower-wage service economies may face a different, and possibly more favourable, cost calculus for hybrid models than high-wage markets. This, too, is a reasoned inference requiring empirical verification. Variation across ASEAN economies in wages, sector scale, and digital maturity means the pathway will not be the same throughout the region.

4.6 Propositions

The analysis yields seven propositions for empirical testing.

Proposition 1. As AI customer-service capabilities diffuse through common vendors and shared models, automated frontline service will be associated with competitive parity rather than sustained differentiation.

Proposition 2. Human frontline service will be associated with differentiation and retention outcomes only where firms invest in the selection, training, retention, and empowerment of frontline employees. Human headcount without such investment will show no such association.

Proposition 3. Customer-attributed responsibility for service failure will be greater for automated than for human-delivered failure at touchpoints high in consequence stakes, and this difference will be associated with lower subsequent loyalty toward the firm.

Proposition 4. Widely publicized failures of automated service agents will be associated with reduced trust in automated service across firms in the same category, not only at the firm that failed.

Proposition 5. At touchpoints high in task ambiguity or emotional intensity, hybrid configurations that involve humans before emotional escalation will outperform fully automated configurations on customer satisfaction and resolution outcomes.

Proposition 6. Removing human access at touchpoints high in customer vulnerability will be associated with disproportionate service exclusion and attrition among older and less digitally capable customers.

Proposition 7. In lower-wage service economies, including segments of the Southeast Asian IT-BPM sector, AI-augmented human service at Zone 3 touchpoints will offer a more favourable cost–quality trade-off than full automation, relative to higher-wage markets.

5. Discussion of Findings

5.1 Implications for Strategic Management Theory

The analysis has three implications for theory. First, it suggests that resource-based reasoning about technology needs to take account of how *customers* perceive whether resources are interchangeable, alongside the usual attention to competitors' ability to copy them. Conventional resource-based analysis assesses imitability from the supply side, asking whether rivals can acquire or replicate a capability. The evidence on algorithmic transference (Longoni et al., 2022) points to a demand-side counterpart: customers may treat technically distinct automated systems as one category, which erodes differentiation even when firms' implementations differ. If so, rarity and inimitability are partly properties of perception as well as of resource endowment. This extension is offered as a theoretical inference that remains to be tested.

Second, the analysis shifts where competitive advantage is located in the debate about service technology. The prevailing framing treats AI adoption as a capability race in which firms that automate faster and more extensively gain an advantage. The synthesis suggests that advantage is more likely to come from the *allocation* of human and machine roles than from the *extent* of automation. This aligns the question with research on organizational design and complementary assets: the strategic value of a widely available technology depends on the organization-specific capabilities it is combined with. The finding that AI augmentation benefits less experienced workers most (Brynjolfsson et al., 2023) supports this view. Technology raised the performance floor of the workforce, while the organization's human capability remained the variable that distinguished firms.

Third, the analysis connects behavioural research on algorithm aversion to strategic outcomes in a way that neither literature has done on its own. Algorithm aversion has mostly been studied as a problem for individual decisions, and strategy research has rarely considered customers' differing attributions to human and automated agents. The responsibility upshift, in which blame for automated failure moves from the agent to the firm (Cai et al., 2024; Pavone et al., 2022), has organizational consequences. It concentrates relational risk at the level of the firm and removes the mediating layer that frontline employees have historically provided. Treating attribution as a strategic variable gives service-strategy theory a mechanism that helps explain why cost-efficient automation may not translate into value capture.

5.2 Relevance for Southeast Asian and Emerging-Market Contexts

The framework's implications vary across Southeast Asian economies, which reinforces the analytical rule that ASEAN should not be treated as a single context. For the Philippines, the most important implication concerns the IT-BPM sector. The augmentation evidence, drawn substantially from Philippine-based agents (Brynjolfsson et al., 2023), together with the conditional cost advantages of hybrid configurations at different labour-cost levels (Ding et al., 2025), suggests that the sector's strategic position may depend less on defending routine call volume than on moving toward complex, emotionally demanding, AI-augmented service. That is a reasoned inference, not a forecast. Its realisation would depend on workforce development, client demand, and investment decisions that this analysis cannot assess.

For ASEAN retail banking, the vulnerability dimension is especially relevant. The exclusion literature, including evidence from older consumers in Hong Kong and mainland China who rely on family members and branch staff to use digital services (Cheung et al., 2026; X.-F. Jin & Fan, 2022), suggests that rapid digitalization may leave behind segments that are commercially significant and socially vulnerable. Since ageing proceeds at very different speeds across the region, the size of the Zone 4 customer population will also differ by market. The finding that branch closures are associated with less new firm creation in other settings (Cardamone & Trivieri, 2024) indicates that channel decisions may also affect local entrepreneurial ecosystems. Whether that association holds in ASEAN has not been tested.

The region's linguistic and cultural characteristics add a further consideration. Multilingual and code-switching service encounters plausibly raise task ambiguity for speech-based automation. Evidence that cultural expectations shape how strictly customers evaluate relational service (Fam et al., 2021) suggests that the value of human interaction may itself vary with cultural norms of hospitality. Both points identify contextual moderators for regional research rather than established findings.

5.3 Theoretical and Practical Meaning for Management Practice

The practical meaning of the findings lies in how they reframe decisions rather than in prescribing outcomes. For managers, the analysis suggests that the business case for frontline automation, usually built on labour savings and throughput, leaves out several costs that do not appear on an operating budget. These include attributional exposure when automated agents fail, potential spillover of trust across the category, the loss of segments that depend on human access, and the gradual loss of the human capability that might otherwise differentiate the firm as automation spreads. Including these costs does not necessarily change the decision to automate a given touchpoint. It does change the analysis that the decision should rest on.

The framework also suggests that frontline workforce strategy and technology strategy are interdependent rather than separate domains. If human service creates advantage only when the firm has invested in it, then decisions on training, retention, and empowerment become part of technology strategy rather than a separate human-resource matter. The productivity gains documented under augmentation (Brynjolfsson et al., 2023) indicate that this interdependence can work in both directions: technology can strengthen the human capability that sustains differentiation, rather than replacing it. Philippine retail evidence is consistent with this interdependence: a legacy retailer's established brand and nationwide physical access were found to anchor its relevance, while its sustainability was judged to depend on strengthening its digital customer experience and omnichannel integration (A. G. Atento & Atento, 2026).

5.4 Boundaries of Inference

The conclusions this analysis can support are limited. As a conceptual paper built on an integrative review, it identifies plausible mechanisms, boundary conditions, and testable propositions. It does not show that human frontline service causes better firm performance, and it does not show that any firm's automation choices determined its outcomes. The illustrative cases clarify strategic choices but do not test them.

The commoditization argument is explicitly conditional. It depends on the continued spread of AI capabilities through common vendors and shared models. A different technological path, such as substantial firm-specific differentiation in proprietary AI systems, would weaken it. Much of the behavioural evidence comes from experimental settings and from Western or Chinese populations, so applying it to live service relationships in Southeast Asia is an inference. The evidence on willingness to pay is conditional, so the analysis does not support a general claim that customers will pay more for human service. Finally, the evidence base comes from a single search index and an integrative rather than systematic review, so it may not capture all relevant literature. These boundaries define the scope within which the framework and propositions should be read and tested.

6. Conclusions and Recommendations

6.1 Conclusions

This paper set out to examine a strategic question that cost-driven automation of customer-facing service has largely overlooked: under what conditions does human frontline interaction remain a source of competitive value as AI service capabilities spread? Using an integrative review of five literatures, the paper reaches four conclusions, each held within the boundaries of a conceptual design.

First, the evidence does not support the assumption that automating frontline service improves customer outcomes in general. Automated agents perform reliably in routine, structured, and low-stakes encounters, but they fall short where tasks are ambiguous, emotionally charged, or consequential. The managerial question is therefore one of allocation, not adoption.

Second, automated failure carries a distinctive strategic cost. Customers tend to judge algorithmic errors harshly on competence, shift responsibility for those errors to the deploying firm, and generalize failures across automated systems they see as similar. Automation thus changes where relational risk sits, removing the mediating layer that frontline employees have historically provided.

Third, a resource-based reading suggests a conditional reversal of strategic value. As automated service capabilities become widely accessible and are perceived as interchangeable, they tend toward competitive parity. Human frontline service may meet the conditions of a strategic resource more fully under these circumstances, but only when firms invest in it as a capability rather than retaining it as headcount.

Fourth, automated service architectures distribute their costs unevenly. Older, less digitally capable, and financially vulnerable customers bear a disproportionate share. In some markets, human intermediaries are the channel through which digital services become usable at all.

From these conclusions, the paper developed a front-stage/back-stage hybrid intelligence framework that classifies touchpoints by task ambiguity, consequence stakes, emotional intensity, and customer vulnerability, along with seven propositions for empirical testing. The framework's central principle is that firms should automate extensively where customers do not see the work, and should place human capability deliberately at the touchpoints where it matters most.

6.2 Recommendations

For management practice. Service firms should evaluate frontline automation touchpoint by touchpoint rather than across the enterprise as a whole. They should assess each touchpoint against the four classification dimensions before deciding on its allocation. Business cases for automation should account for attributional exposure, potential trust spillover, and segment attrition alongside labour savings. Where hybrid configurations are used, escalation to human agents should be designed to occur before customer frustration escalates, not after. Firms that keep human frontline service should treat it as a capability that needs sustained investment in training, retention, and empowerment. Redirecting part of the savings from back-stage automation toward frontline capability is consistent with the resource-based logic developed here, though its performance effects remain to be tested.

For Southeast Asian service sectors. Stakeholders in the Philippine IT-BPM sector, including firms, industry associations, and training institutions, should consider workforce development aimed at complex, AI-augmented service work rather than relying on routine call volume. Retail banks across ASEAN should treat assisted channels for older and

less digitally capable customers as a deliberate design choice, scaled to each market's demographic profile, rather than as a legacy cost to be phased out.

For institutional and regulatory design. In essential services such as banking, insurance, healthcare billing, and pharmacy, regulators and industry bodies may wish to consider whether customers in vulnerable segments should have guaranteed access to a human channel for high-stakes transactions. This recommendation is offered as a matter for policy deliberation rather than a prescription, because its costs and enforcement implications fall outside this analysis.

For future research. The propositions call for empirical testing using designs this paper could not employ. Priorities include field studies that link touchpoint-level allocation choices to observed retention and pricing outcomes, rather than stated intentions. Longitudinal work could test whether automated service capabilities converge toward competitive parity as they diffuse. Studies of category-level trust spillover after publicized automation failures would test the transference proposition. Above all, Southeast Asian evidence is needed: research on Philippine contact centres, ASEAN retail banking, and multilingual service settings would test whether the framework's dimensions and their weights hold across the region's diverse labour-cost, demographic, and cultural conditions.

6.3 Closing Statement

The rapid spread of AI into customer service has encouraged firms to treat each human touchpoint as a cost awaiting elimination. The evidence reviewed here supports a more measured view. As intelligent automation becomes widely available, it is likely to become a baseline expectation rather than a source of distinction. Firms that use it well behind the scenes, and that invest in skilled, well-supported people where customers need judgment, reassurance, and accountability, may be better placed to build durable trust than firms that automate indiscriminately. Whether this holds in practice is an empirical question, and this paper has aimed to frame that question precisely enough to be tested.

References

Adams, R., & Sherlund, S. (2025). *Where's the bank? Banking access in the era of branch consolidation* (Finance and Economics Discussion Series). Board of Governors of the Federal Reserve System. https://doi.org/10.17016/feds.2025.086

Ameen, N., Pagani, M., Pantano, E., Cheah, J., Tarba, S., & Xia, S. (2024). The rise of human–machine collaboration: Managers' perceptions of leveraging artificial intelligence for enhanced B2B service recovery. *British Journal of Management*. https://doi.org/10.1111/1467-8551.12829

Amouzadeh, E., Dianat, I., Faradmal, J., Khalili, M., & Babamiri, M. (2026). What makes mobile banking difficult for older adults? A multi-layer usability investigation. *Health Promotion Perspectives, 16*, 74–84. https://doi.org/10.34172/hpp.44884

Asakdiyah, S. (2026). Relationship marketing as a driver of competitive advantage in service industries. *Jurnal Manajemen, Bisnis dan Kewirausahaan*. https://doi.org/10.55606/jumbiku.v6i1.6863

Atento, A. G., & Atento, R. G. (2025). A case study of Mercury Drug Corporation: Strategic adaptation to universal healthcare and digital disruption in the Philippines. *International Journal of Health & Business Analytics, 1*(1). https://doi.org/10.65166/zhw7dd39

Atento, A. G., & Atento, R. G. (2026). Legacy retail under digital disruption: Strategic insights from National Book Store's omnichannel transition in the Philippines. *Journal of Enterprise Strategy and Management Innovation, 1*(1). https://doi.org/10.65166/nny9z718

Atento, A. G., Atento, R. G. O., Espelita, C. A. M. H., & Lantin-Magana, L. M. (2026). Digital connectivity and financial inclusion in Asia: A thematic review of mobile infrastructure, account ownership, and policy implications using Global Findex 2025 evidence. *Asian Financial Economics and Policy, 1*(1). https://doi.org/10.65166/9h1wkj82

Atento, R. G. O., Quinto, L. F., Espelita, C. A. M. H., & Atento, A. G. (2026). Digital financial inclusion and supply chain resilience in manufacturing: A comparative analysis across the digital access divide. *Journal of Enterprise Strategy and Management Innovation, 1*(3). https://doi.org/10.65166/dg5t7027

Aversa, J., Shaker, R., Cleave, E., & Salooja, N. (2022). Determinants of bank closures: Exploring the relationship between neighborhood characteristics and bank branch locations. *Papers in Applied Geography, 8*, 393–413. https://doi.org/10.1080/23754931.2022.2072232

Babar, Z., Paul, R., Rahman, M. A., & Barua, T. (2025). A systematic review of human–AI collaboration in IT support services: Enhancing user experience and workflow automation. *Journal of Sustainable Development and Policy*. https://doi.org/10.63125/grqtf978

Bagozzi, R., Brady, M. K., & Huang, M.-H. (2022). AI service and emotion. *Journal of Service Research, 25*, 499–504. https://doi.org/10.1177/10946705221118579

Baldassarre, S., Cavola, M., & Pipicelli, E. (2025). Bank branch desertification and the design of a postal banking network. *Socio-Economic Planning Sciences*. https://doi.org/10.1016/j.seps.2025.102216

Bendal, A., Planas-Sabasa, S. A., Atento, R. G. O., & Espelita, C. A. M. H. (2026). Artificial intelligence as disruptive technology in accounting: A qualitative study of practitioner perceptions on automation, judgment, and decision support. *Journal of Enterprise Strategy and Management Innovation, 1*(1). https://doi.org/10.65166/0sdayg70

Blaurock, M., Büttgen, M., & Schepers, J. (2025). Designing collaborative intelligence systems for employee–AI service co-production. *Journal of Service Research, 28*, 544–562. https://doi.org/10.1177/10946705241238751

Blut, M., Wang, C., Wünderlich, N., & Brock, C. (2021). Understanding anthropomorphism in service provision: A meta-analysis of physical robots, chatbots, and other AI. *Journal of the Academy of Marketing Science, 49*, 632–658. https://doi.org/10.1007/s11747-020-00762-y

Brynjolfsson, E., Li, D., & Raymond, L. (2023). *Generative AI at work* (NBER Working Paper No. 31161). National Bureau of Economic Research. https://doi.org/10.3386/w31161

Cai, N., Gao, S., & Yan, J.-Z. (2024). How the communication style of chatbots influences consumers' satisfaction, trust, and engagement in the context of service failure. *Humanities and Social Sciences Communications, 11*, 1–11. https://doi.org/10.1057/s41599-024-03212-0

Candrian, C., & Scherer, A. (2023). How terminology affects users' responses to system failures. *Human Factors, 66*, 2082–2103. https://doi.org/10.1177/00187208231202572

Cardamone, P., & Trivieri, F. (2024). Out of sight, out of mind! Bank branch closures and new firm creation in Italy. *Regional Studies, Regional Science, 11*, 122–152. https://doi.org/10.1080/21681376.2024.2315187

Castelo, N., Boegershausen, J., Hildebrand, C., & Henkel, A. P. (2023). Understanding and improving consumer reactions to service bots. *Journal of Consumer Research*. https://doi.org/10.1093/jcr/ucad023

Chatzi, S., Peitzika, E., & Konsolaki, G. (2024). Enhancing brand loyalty: A relationship marketing perspective within the context of contractual services. *Journal of Relationship Marketing, 23*, 272–304. https://doi.org/10.1080/15332667.2024.2306019

Chen, S., & Atento, R. G. (2026). Big data as a strategic asset: Competitive advantage, business model transformation, and managerial intelligence in Chinese enterprises. *Journal of Enterprise Strategy and Management Innovation, 1*(2). https://doi.org/10.65166/mnn2n380

Chen, X., Guo, S., Xiong, J., & Ye, Z.-X. (2023). Customer engagement, dependence and loyalty: An empirical study of Chinese customers in multitouch service encounters. *Technological Forecasting and Social Change*. https://doi.org/10.1016/j.techfore.2023.122920

Cheung, C., Liu, J., Chen, L., Chen, Q., Li, L., Hui, P., Lee, L.-H., & Fan, M.-M. (2026). Who gets left out of digital banking in later life? Barriers and opportunities in Hong Kong's silver population. In *Proceedings of the 2026 Designing Interactive Systems Conference*. ACM. https://doi.org/10.1145/3800645.3812886

Cho, S., Lee, Z., Hwang, S., & Kim, J. (2023). Determinants of bank closures: What ensures sustainable profitability in mobile banking? *Electronics*. https://doi.org/10.3390/electronics12051196

Choi, H.-S., & Loh, R. (2023). Physical frictions and digital banking adoption. *Management Science, 70*, 6597–6621. https://doi.org/10.1287/mnsc.2023.4972

Clark, S., Newing, A., Hood, N., & Birkin, M. (2023). Retail banking closures in the United Kingdom: Are neighbourhood characteristics associated with retail bank branch closures? *Transactions of the Institute of British Geographers*. https://doi.org/10.1111/tran.12656

Costa, C., & Ghosh, S. (2025). Empowering customer service with generative AI: Enhancing agent performance while navigating challenges. *Information Research, 30*, 150–158. https://doi.org/10.47989/ir30iconf47566

De Oliveira Santini, F., Lim, W. M., Sampaio, C., Rasul, T., Ladeira, W., Thaichon, P., & Choudhury, D. (2025). The robot–human paradox: A meta-analysis of customer service by robots versus humans on customer experience. *Journal of Consumer Behaviour*. https://doi.org/10.1002/cb.2470

Ding, Z., Zhang, Y., Sun, J., Goh, M., & Yang, Z. (2025). Harmonizing human touch and AI precision in customer service. *Journal of Service Research, 29*, 377–390. https://doi.org/10.1177/10946705251384692

Dizon, G., & Ebardo, R. A. (2025). Barriers and motivations of older adults in digital banking adoption: Recent findings, gaps, and future directions. *International Journal of Innovative Research and Scientific Studies*. https://doi.org/10.53894/ijirss.v8i3.6929

El-Meouch, N. M., Banai, Á., & Alpek, B. L. (2023). Can online banking replace personal banking? A survey of Hungarian banking habits. *Acta Oeconomica*. https://doi.org/10.1556/032.2023.00027

Eskiler, E., & Safak, F. (2022). Effect of customer experience quality on loyalty in fitness services. *Physical Culture and Sport. Studies and Research, 94*, 21–34. https://doi.org/10.2478/pcssr-2022-0003

Fam, K.-S., Cham, T., & Ting, H. (2021). The role of cultural differences in customer retention: Evidence from the high-contact service industry. *Journal of Hospitality & Tourism Research, 47*, 257–288. https://doi.org/10.1177/10963480211014944

Filiz, I., Judek, J. R., Lorenz, M., & Spiwoks, M. (2023). The extent of algorithm aversion in decision-making situations with varying gravity. *PLOS ONE, 18*. https://doi.org/10.1371/journal.pone.0278751

Garvey, A. M., Kim, T., & Duhachek, A. (2021). Bad news? Send an AI. Good news? Send a human. *Journal of Marketing, 87*, 10–25. https://doi.org/10.1177/00222429211066972

Geca, M., Atento, A. G., Espelita, C. A. M. H., & Atento, R. G. O. (2026). Closing the backdoor: Fintech license strategies, regulatory reclassification, and the architecture of digital bank supervision in the Philippines. *Asian Financial Economics and Policy, 1*(1). https://doi.org/10.65166/d0m0k596

Gelbrich, K., Roschk, H., Miederer, S., & Kerath, A. (2025). Automated versus human agents: A meta-analysis of customer responses to robots, chatbots, and algorithms and their contingencies. *Journal of Marketing, 90*, 1–26. https://doi.org/10.1177/00222429251344139

George, S., C., M., & Edward, M. (2025). Artificial intelligence in frontline service encounters: A systematic review and research agenda. *International Journal of Consumer Studies*. https://doi.org/10.1111/ijcs.70048

Gnewuch, U., Morana, S., Hinz, O., Kellner, R., & Maedche, A. (2023). More than a bot? The impact of disclosing human involvement on customer interactions with hybrid service agents. *Information Systems Research, 35*, 936–955. https://doi.org/10.1287/isre.2022.0152

Gray News. (2026, October 7). *Chick-fil-A has no plans to add AI to its drive-thru ordering service despite other rivals doing so*. Hawaii News Now. https://www.hawaiinewsnow.com/2026/10/07/chick-fil-a-has-no-plans-add-ai-its-drive-thru-ordering-service-despite-other-rivals-doing-so/

Grewal, D., Ludwig, S., Herhausen, D., Grewal, L. S., Ordenes, F. V., Kopalle, P., & Bohling, T. (2026). How frontline employees' relational communication in online service interactions drives customer satisfaction. *Production and Operations Management, 35*, 2963–2980. https://doi.org/10.1177/10591478261420001

Han, J., & Ko, D. (2025). Trust formation, error impact, and repair in human–AI financial advisory: A dynamic behavioral analysis. *Behavioral Sciences, 15*. https://doi.org/10.3390/bs15101370

Hasan, N. B. (2025). AI efficiency versus human empathy: A paradox of AI and human agents in service support interactions. *Sociology Lens*. https://doi.org/10.1111/johs.70027

Hemo, O., Ingram, K., & Seniut, I. (2026). Employee loyalty as a driver of service quality and retention in culturally embedded food retail: Evidence from an Afro-Caribbean supermarket in Sweden. *Applied Business: Issues & Solutions*. https://doi.org/10.57005/ab.2025.4.4

Higgs, G., Price, A., & Langford, M. (2022). Investigating the impact of bank branch closures on access to financial services in the early stages of the COVID-19 pandemic. *Journal of Rural Studies, 95*, 1–14. https://doi.org/10.1016/j.jrurstud.2022.07.012

Hlembytskyi, O. (2025). Intellectual capital in customer service: How AI is changing the requirements for employee competences. *Business Navigator*. https://doi.org/10.32782/business-navigator.80-59

Hu, W., Wang, L., Ren, J., Bai, G., Cui, S., & Xu, Y. (2026). How and when organizational AI adoption improves employee innovation performance. *The Service Industries Journal, 46*, 926–964. https://doi.org/10.1080/02642069.2026.2632108

Jiménez-Jiménez, P., Pedragosa, V., Alguacil-Jiménez, M., & Calabuig-Moreno, F. (2025). Analyzing the value of social interaction for fitness center management: The influence of service encounter in consumer trust and loyalty. *Physical Culture and Sport. Studies and Research, 110*, 33–47. https://doi.org/10.2478/pcssr-2025-0022

Jin, X., & Li, J.-Y. (2025). The influence of 'algorithm aversion' and 'algorithm appreciation' among consumers in unstructured tasks. *International Journal of Consumer Studies*. https://doi.org/10.1111/ijcs.70133

Jin, X.-F., & Fan, M.-M. (2022). "I used to carry a wallet, now I just need to carry my phone": Understanding current banking practices and challenges among older adults in China. In *Proceedings of the 24th International ACM SIGACCESS Conference on Computers and Accessibility*. ACM. https://doi.org/10.1145/3517428.3544820

Kaye, T. (2026). Older generation disenfranchising: A health and business perspective on digital portals, login friction, and exclusion. *Journal of Community Medicine and Health Solutions*. https://doi.org/10.29328/journal.jcmhs.1001068

Kazakova, A., Kim, Y., Choi, S., & Kim, I. (2025). Human–robot collaboration in restaurant kitchens: How collaborative chefs foster consumers' willingness to pay a premium. *Journal of Travel & Tourism Marketing, 42*, 439–460. https://doi.org/10.1080/10548408.2025.2468465

Kim, A., Yang, M., & Zhang, J. (2022). When algorithms err: Differential impact of early vs. late errors on users' reliance on algorithms. *ACM Transactions on Computer-Human Interaction, 30*, 1–36. https://doi.org/10.1145/3557889

Kotze, T., & Mostert, P. (2025). A store-level analysis of frontline employees as enhancers of store loyalty. *Service Business, 19*. https://doi.org/10.1007/s11628-025-00589-z

Langford, M., Price, A., & Higgs, G. (2022). Combining temporal and multi-modal approaches to better measure accessibility to banking services. *ISPRS International Journal of Geo-Information, 11*, 350. https://doi.org/10.3390/ijgi11060350

Le, K. B., Sajtos, L., Kunz, W. H., & Fernandez, K. V. (2024). The future of work: Understanding the effectiveness of collaboration between human and digital employees in service. *Journal of Service Research, 28*, 186–205. https://doi.org/10.1177/10946705241229419

Lin, X., Wang, X.-Q., Shao, B., & Taylor, J. (2024). How chatbots augment human intelligence in customer services: A mixed-methods study. *Journal of Management Information Systems, 41*, 1016–1041. https://doi.org/10.1080/07421222.2024.2415773

Liu, N., Kirshner, S., & Lim, E. T. K. (2023). Is algorithm aversion WEIRD? A cross-country comparison of individual-differences and algorithm aversion. *Journal of Retailing and Consumer Services*. https://doi.org/10.1016/j.jretconser.2023.103259

Longoni, C., Cian, L., & Kyung, E. J. (2022). Algorithmic transference: People overgeneralize failures of AI in the government. *Journal of Marketing Research, 60*, 170–188. https://doi.org/10.1177/00222437221110139

Maasland, C., & Weißmüller, K. S. (2022). Blame the machine? Insights from an experiment on algorithm aversion and blame avoidance in computer-aided human resource management. *Frontiers in Psychology, 13*. https://doi.org/10.3389/fpsyg.2022.779028

Makki, M., Jafari, M., & Parsanejad, M. (2026). The effect of internal marketing on customer attraction and retention in service industries: Employee-centric strategies. *Sage Open*. https://doi.org/10.1177/21582440261426462

Mendoza, E., Magnaye, R., Mendoza, F., Atento, R. G., Atento, A. G., Quinto, L. F., Malolos, L. C., Sumague, L. S., & Espelita, C. A. M. (2026). Operational latency as a strategic liability: Service delivery failures, customer attrition, and the case for process innovation in full-service dining establishments. *Journal of Enterprise Strategy and Management Innovation, 1*(2). https://doi.org/10.65166/as485767

Money, A., Hall, A., Harris, D., Eost-Telling, C., Mcdermott, J., & Todd, C. (2023). Barriers to and facilitators of older people's engagement with web-based services: Qualitative study of adults aged >75 years. *JMIR Aging, 7*. https://doi.org/10.2196/46522

Morrison, B., Nicholson, J., Wood, B., & Briggs, P. (2023). Life after lockdown: The experiences of older adults in a contactless digital world. *Frontiers in Psychology, 13*. https://doi.org/10.3389/fpsyg.2022.1100521

Nafisah, I., Susanti, E., & Sumayyah, S. (2025). Customer orientation of service employees in retaining customers: The mediating role of satisfaction and commitment. *International Journal of Digital Entrepreneurship and Business*. https://doi.org/10.52238/ideb.v6i1.278

Naidoo, V. (2026). The dark side of AI-enabled industrial service recovery: The erosion of trust and customer engagement. *Industrial Marketing Management*. https://doi.org/10.1016/j.indmarman.2026.05.004

Nation's Restaurant News. (2024, June 17). *McDonald's is ending its AI drive-thru test with IBM*. https://www.nrn.com/technology/mcdonald-s-ending-its-ai-drive-thru-test-ibm

Nicolescu, L., & Tudorache, M. T. (2022). Human–computer interaction in customer service: The experience with AI chatbots—A systematic literature review. *Electronics*. https://doi.org/10.3390/electronics11101579

Odekerken-Schröder, G., Mennens, K., Steins, M., & Mahr, D. (2021). The service triad: An empirical study of service robots, customers and frontline employees. *Journal of Service Management*. https://doi.org/10.1108/josm-10-2020-0372

Papasin, J. (2026). Compassionate care skills among healthcare workers during emerging and re-emerging diseases. *International Journal of Health & Business Analytics, 2*(1). https://doi.org/10.65166/bt5ppj56

Pavone, G., Meyer-Waarden, L., & Munzel, A. (2022). Rage against the machine: Experimental insights into customers' negative emotional responses, attributions of responsibility, and coping strategies in artificial intelligence–based service failures. *Journal of Interactive Marketing, 58*, 52–71. https://doi.org/10.1177/10949968221134492

Quan, J., Li, Y., Zhang, M., & Wu, Z. (2025). Gain or pain: The double-edged sword effect of artificial intelligence adoption on employee service performance. *Journal of Organizational Behavior*. https://doi.org/10.1002/job.70023

Quinto, L. F., Bermido, C. M., & Atento, R. G. (2026). Psychosocial dimensions of caregiver support in geriatric care: A thematic review. *International Journal of Behavioral and Social Analytics, 1*(2). https://doi.org/10.65166/z2dnbk24

Reich, T., Kaju, A., & Maglio, S. J. (2022). How to overcome algorithm aversion: Learning from mistakes. *Journal of Consumer Psychology*. https://doi.org/10.1002/jcpy.1313

Renier, L., Mast, M. S., & Bekbergenova, A. (2021). To err is human, not algorithmic: Robust reactions to erring algorithms. *Computers in Human Behavior, 124*, 106879. https://doi.org/10.1016/j.chb.2021.106879

Röding, T., Wagner, G., Steinmann, S., Mennekes, T., & Schramm-Klein, H. (2023). How to infuse mobile technologies in frontline service encounters? An experimental analysis of customer perceptions of service competence. *The International Review of Retail, Distribution and Consumer Research, 34*, 183–200. https://doi.org/10.1080/09593969.2023.2290069

Roederer, C., Valentini, T., Bouqlila, F., & Dahab, D. (2026). AI-driven phygitalization: Enhancing customer and employee experience for improved well-being in financial services. *Journal of Macromarketing, 46*, 387–407. https://doi.org/10.1177/02761467251415501

S, A., & Sengupta, A. (2025). FinTech and older adults: A global synthesis of enablers, barriers, and research trends for inclusive digital finance. *Humanities and Social Sciences Communications, 12*. https://doi.org/10.1057/s41599-025-06077-z

Sachdev, H. J., & Sauber, M. (2023). Employee–customer identification: Effect on Chinese online shopping experience, trust, and loyalty. *Cogent Business & Management, 10*. https://doi.org/10.1080/23311975.2023.2275369

Shah, N. K. (2026, October 9). *How companies are using AI to lock out customers* [Video]. YouTube. https://www.youtube.com/watch?v=v5u_N4Xo-NM

Srinivasan, R., & Sarial-Abi, G. (2021). When algorithms fail: Consumers' responses to brand harm crises caused by algorithm errors. *Journal of Marketing, 85*, 74–91. https://doi.org/10.1177/0022242921997082

Tan, K., Liu, Y., & Litvin, S. (2024). ChatGPT and online service recovery: How potential customers react to managerial responses of negative reviews. *Tourism Management*. https://doi.org/10.1016/j.tourman.2024.105057

Tolentino, G., Quinto, L. F., Espelita, C. A. M. H., Atento, A. G., & Teodosio, G. M. (2026). Artificial intelligence and the strategic reconfiguration of work: A conceptual analysis of substitution, augmentation, and organizational redesign in manufacturing and marketing. *Journal of Enterprise Strategy and Management Innovation, 1*(3). https://doi.org/10.65166/bt13jr83

Tuomi, A., & Ascenção, M. (2021). Intelligent automation in hospitality: Exploring the relative automatability of frontline food service tasks. *Journal of Hospitality and Tourism Insights*. https://doi.org/10.1108/jhti-07-2021-0175

Wang, L., Huang, N., Hong, Y., Liu, L., Guo, X., & Chen, G.-Q. (2023). Voice-based AI in call center customer service: A natural field experiment. *Production and Operations Management, 32*, 1002–1018. https://doi.org/10.1111/poms.13953

Wang, Y.-W., Zhu, C.-Q., Feng, T., Lu, L., & Jia, B. (2026). *Agentic AI and human-in-the-loop interventions: Field experimental evidence from Alibaba's customer service operations* [Preprint]. arXiv. https://doi.org/10.48550/arxiv.2605.14830

Wirtz, J., Hofmeister, J., Chew, P. Y. P., & Ding, X. (2023). Digital service technologies, service robots, AI, and the strategic pathways to cost-effective service excellence. *The Service Industries Journal, 43*, 1173–1196. https://doi.org/10.1080/02642069.2023.2226596

Wirtz, J., & Stock-Homburg, R. (2025). Generative AI meets service robots. *Journal of Service Research, 28*, 527–543. https://doi.org/10.1177/10946705251340487

Wu, L., Fan, A., He, Z.-Y., & Her, E. (2021). To partner with human or robot? Designing service coproduction processes for willingness to pay more. *Journal of Hospitality & Tourism Research, 47*, 455–481. https://doi.org/10.1177/10963480211025594

Xu, M., & Wang, Y. (2024). Explainability increases trust resilience in intelligent agents. *British Journal of Psychology*. https://doi.org/10.1111/bjop.12740

Yang, Z., Zhou, J.-L., & Yang, H. (2023). The impact of AI's response method on service recovery satisfaction in the context of service failure. *Sustainability*. https://doi.org/10.3390/su15043294

Yi, H., Lee, M., & Park, K. (2022). Service orientation and customer performance: Triad perspectives of sales managers, sales employees, and customers. *Behavioral Sciences, 12*. https://doi.org/10.3390/bs12100373

Ying, S., & Encio, H. (2026). Influence of artificial intelligence application on the operational efficiency of commercial banks. *Journal of Enterprise Strategy and Management Innovation, 1*(2). https://doi.org/10.65166/tzazy288