EPH-International Journal of Business & Management Science

SMART RETAILING IN INTERNET COMMERCE: AN AI-ENABLED CUSTOMER-CENTRIC SERVICE FRAMEWORK

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Article History
Received : *2026-05-16*
Revised : *2026-09-26*
Accepted : *2026-10-20*
Published : *2026-11-17*

Abstract

This conceptual paper examines AI-enabled smart retailing as a customer-facing service transformation in Internet commerce rather than as a narrow technological or operational innovation. Drawing on a selective, theory-driven synthesis of services marketing, smart retailing, AI-enabled marketing, customer experience, service-dominant logic, human–AI interaction, and responsible-AI research, it develops a three-layer framework linking AI-enabled service capabilities, customer-experience mechanisms, and Internet-commerce outcomes. The framework identifies three capability groups—algorithmic personalisation and decision support, AI-mediated service interaction, and predictive service intelligence—and four evaluative mechanisms: decision value, interaction quality, transaction confidence, and algorithmic legitimacy. These mechanisms shape customer satisfaction, engagement, service-recovery effectiveness, platform trust, relationship quality, continuance intention, value co-creation, and inclusive service value. Human–AI governance, including privacy protection, transparency, fairness, customer control, human review, and digital accessibility, is treated as a boundary condition that determines whether AI-enabled services are perceived as trustworthy and customer-centred or as intrusive, opaque, unfair, and exclusionary. The paper contributes to Internet-commerce research by repositioning AI as a service-enabling capability and by explaining how customer evaluations translate AI applications into commercial and relational outcomes. It also proposes a focused research agenda for empirical testing across e-commerce websites, mobile applications, online marketplaces, social-commerce platforms, and omnichannel systems.

Keywords: *Artificial Intelligence, Internet Commerce, Smart Retailing*

Vol. 12 Issue 11 (November, 2026)
ISSN: 2208-2190 Pages- 01-16
DOI: https://doi.org/10.69980/jns7m743

1. Introduction

India is now one of the most meaningful test beds for enterprise generative AI in the world, not mainly as a builder of foundation models but as the home of the largest number of multinational Global Capability CentrInternet commerce has become a service environment that is integrated with e-commerce websites, mobile apps, online marketplaces, social commerce apps and omnichannel systems that facilitate customer interactions from search to purchase to fulfilment to after-sales. These activities are influenced by artificial intelligence (AI) in various ways, such as through personalised recommendations, intelligent search, conversational agents, predictive analytics, sentiment analysis, payment security, fraud detection, and fulfilment coordination, as noted by Davenport et al. (2019), Anica-Popa et al. (2021), and Huang and Rust (2021). Thus, AI becomes a service capability which are perceived by customers and can therefore have an impact on the way the customer considers alternatives, finalizes purchases and works out solutions for service issues.

In terms of services marketing, AI-driven smart retailing is a service system that creates value through the service interactions between customers, retailers, digital systems and data systems. Service-dominant logic puts the focus on value creation beyond technology, emphasizing the importance of the integration of resources (Vargo and Lusch 2004), and the service-ecosystem perspective places these relations in actor networks (Akaka and Vargo 2015). AI is therefore an operant resource to aid personalisation, prediction, coordination and decision support. It is dependent on the experiences customers have during the pre-purchase, transaction, fulfilment and post-purchase interaction with AI (Lemon and Verhoef 2016; Voorhees et al. 2017).

AI can enhance Internet commerce experiences in a variety of ways, including the ability to eliminate information overload, provide more relevant recommendations, speed up the support process, ensure more reliable fulfilment, and bolster the security of transactions. These benefits can improve decision confidence and satisfaction, engagement, platform trust, and continuance intention. Yet, AI can create negative responses when the personalisation is too in your face, the chatbot is limited, the decisions are not transparent, the recommendations seem biased, or a legitimate transaction is flagged as suspect (Kaplan 2020; Mahmoud, Tehseen and Fuxman 2020; Nguyen et al. 2024). New studies show there are differences in the responses to AI use. Anthropomorphic chatbots can elicit various responses based on context (Jia et al. 2024), biased recommendations can cause resistance (Nguyen et al. 2024), and implementing the chatbots in services requires certain conditions (Zhang, Følstad, and Bjørkli 2023). Kumar, Jain and Sharma (2025) additionally emphasize the behavioural ramifications of anthropomorphic AI in digital commerce.

While this growing body of literature has emerged, there are significant conceptual gaps that could be filled. While there are studies on individual AI applications or organizational capabilities, the studies generally lack an understanding of the way customer-facing AI technologies function together as a system in the Internet-commerce context (Davenport et al. 2019; Mikalef and Gupta 2021; Chatterjee, Chaudhuri, and Mikalef 2022). There has also been limited attention to mechanisms at the customer level where AI will lead to commercial and relational outcomes. The term privacy is often considered alongside but not as related to the other terms, transparency, explainability, fairness, customer control, human oversight, and accessibility; the latter are more likely to be seen as governance aspects that inform customer evaluations. The same gaps in the Internet-commerce experience exist with regard to interactions with AI. However, the literature provides scant insight into how AI capabilities generate value for customers, why similar technologies yield varying results, and which governance regimes have a positive or negative impact on that.

This study introduces a novel perspective on the concept of smart retailing enabled by AI under the form of an integrated service transformation of Internet-commerce, to overcome the aforementioned limitations. It builds a three-layer structure of higher-order service capabilities that are AI-enabled – algorithmic personalisation and decision support, AI-mediated service interaction and predictive service intelligence – and customer-experience mechanisms – decision value, interaction quality, transaction confidence, and algorithmic legitimacy. These mechanisms underpin the impact of the AI capabilities on the customer and commercial outcomes. The governance of human-AI interaction, including privacy protection, transparency and explainability, fairness, control by the customer, human review and redress, and digital accessibility, will make the difference between trustworthy, customer-oriented AI-enabled services, and intrusive, opaque, unfair, and exclusionary ones. The study thus investigates three questions that are interwoven along the Internet-commerce journey: How do AI service capabilities affect customers' decision-making and service interactions along the journey (RQ1)? How does the relationship between customers and AI service capabilities affect commercial

Vol. 12 Issue 11 (November, 2026)
ISSN: 2208-2190 Pages- 01-16
DOI: https://doi.org/10.69980/jns7m743

and relational outcomes (RQ2)? and How do transparency, protection of privacy, fairness, human oversight, customer control, and digital inclusion influence these relationships (RQ3)?

The study makes a unique and valuable contribution to the body of knowledge on Internet-commerce in three ways. It is not technology-centric, it groups the customer facing AI applications under 3 overarching service capabilities:1. It isn't technology-centric, it categorises the customer facing AI applications under 3 higher-order service capabilities: Second, it elucidates the ways in which these capabilities drive outcomes via different customer-evaluation pathways, not just directly through the use of AI, which allows for a more detailed understanding of how the technology influences customer evaluation and value. Third, it separates out the mechanisms of governance between humans and AI from algorithmic "legitimacy" as perceived by the customer, enabling readers to understand how the use of technically effective AI can either foster or detract from trust and relationship quality in this context. The study's approach of weaving capabilities, mechanisms, outcomes, and governance conditions into a customer-centred approach offers a unified platform to consider the use of AI in the context of smart retailing both in e-commerce websites, mobile apps, online marketplaces, social-commerce platforms, and omnichannel systems.

2. Literature Background

Artificial intelligence in retailing has matured beyond its role as an automation and operational efficiency tool to an AI that is customer-facing and service-enabling on the Website, mobile applications, marketplaces, social commerce and omnichannel platforms. Recommendation systems, conversational agents, intelligent search, predictive analytics, and visual search are used to improve customer interactions, decision-making, and service delivery (Davenport et al. 2019; Kumar, Ashraf, and Nadeem 2024). With a service-dominant view, the value of the retail is created by customers, the firms, the technologies, the platforms, and the data infrastructure (Vargo and Lusch 2004). For now, though, research is still scattered in various study areas related to different applications of AI and governance issues. A systematic view is thus required to understand the combined effects of the AI capabilities on the Internet-commerce outcomes from a customer-centred and responsible service system perspective on customer experience, trust, and fairness.

2.1 Conceptual review approach

This paper is a conceptual review selective rather than systematic or bibliometric. It is designed to integrate existing theories and representative findings that account for the smart retailing phenomenon with the use of artificial intelligence as an Internet-commerce and services-marketing phenomenon. The review is based on literature related to services marketing, Internet commerce, smart retailing, customer experience, service-dominant logic, AI-driven marketing, human–AI communication, service innovation, algorithmic fairness, platform governance and digital inclusion. The synthesis process was conducted in three phases: (1) identifying AI-based customer-impacting applications and governance issues; (2) comparing the customer-experience mechanisms and outcomes of the identified applications; and (3) categorising commonalities in applications to converge into higher-order capabilities, mechanisms, outcomes, and governance processes. This process yielded the three AI-enabled service capabilities, four mechanisms for customer experience and governance conditions integrated in the framework and propositions. The review is selective and theory-building, which means that this framework is not a complete map of the literature and that it needs to be tested in practice.

2.2 AI-Enabled Smart Retailing as a Service System

The shift in the early days of AI in retailing from the mechanics of automation and efficiencies to the ability for AI to be used with customers and services. AI has made its way into e-commerce websites, mobile apps, online marketplaces, social-commerce platforms, and omnichannel systems in Internet commerce. However, in practice, the use of personalised recommendations, conversational agents, intelligent search, predictive analytics and visual search allows customers to interact, make decisions, provide services and make commercial transactions with the company (Davenport et al. 2019; Kumar, Ashraf, and Nadeem 2024) as illustrated in Table 1, the literature supports viewing AI-enabled smart retailing as an integrated service system. Retailing is viewed under the service-marketing prism, as a value co-creating service system (Vargo and Lusch 2004) that involves customers, companies, people, platforms, technologies and infrastructures of data. But current literature is divided by application of AI in a single context, and lacks common understandings about the impacts of AI that brings them together in Internet-commerce contexts regarding customer experience, trust, fairness, and responsible governance.

Vol. 12 Issue 11 (November, 2026)
ISSN: 2208-2190 Pages- 01-16
DOI: https://doi.org/10.69980/jns7m743

Table 1. Selected literature informing AI-enabled smart retailing

Author(s)	Research focus	Key finding	Relevance to present paper
Shah et al. (2006)	Customer centricity	Customer-centric firms align offerings and processes with valuable customer needs.	Frames smart retailing as customer-centred service transformation.
Kumar et al. (2024)	AI-powered marketing	AI enables proactive, data-driven customer interaction.	Supports personalised engagement and proactive service delivery.
Davenport et al. (2019)	AI in marketing	AI applications include recommendations, chatbots, customised search and analytics.	Positions AI as a customer-facing service capability.
Jarek and Mazurek (2019)	AI in marketing	Machine learning improves through repeated customer interaction.	Supports data-enabled personalisation and co-creation.
Chatterjee et al. (2022)	NLP and analytics	NLP supports chatbots, virtual assistants and automated customer interaction.	Supports AI-mediated service encounters.
Huang and Rust (2021)	AI strategy	AI performs mechanical, thinking and feeling tasks.	Provides theoretical grounding for AI-enabled service experience.
Ghosh et al. (2020)	Predictive analytics	Predictive models improve forecasting and decision-making.	Supports service reliability and product availability.
Cambria et al. (2020)	Sentiment analysis	Sentiment analysis identifies satisfaction and dissatisfaction signals.	Supports complaint detection and service recovery.
Mikalef and Gupta (2021)	AI capability	AI capability supports decision-making and firm performance.	Treats AI as an organisational service capability.
Obermeyer et al. (2019)	Algorithmic bias	Biased data can produce unequal algorithmic outcomes.	Supports responsible AI, fairness and accountability.

2.3 Customer experience and AI-enabled service encounters

There are four evaluative mechanisms to consider when understanding the experience of the customer in the context of AI-powered Internet commerce: decision value, interaction quality, transaction confidence, and algorithmic legitimacy. Decision value refers to how AI enhances relevance, saves search time and aids in product evaluation through personalised recommendations and intelligent search (Huang and Rust 2021). The quality of interaction shows responsiveness, clarity, assurance, perceived control and access to human support during AI-mediated interactions (Voorhees et al. 2017; Jia et al. 2024). Transaction confidence relates to

Vol. 12 Issue 11 (November, 2026)
ISSN: 2208-2190 Pages- 01-16
DOI: https://doi.org/10.69980/jns7m743

reliability, security, and uncertainty reduction when completing a transaction or fulfilling a purchase. Algorithmic legitimacy is the extent to which AI-driven decision making is considered transparent, fair, accountable, controllable and reviewable. These mechanisms work together to form customer reactions to AI-powered commerce and are greatly driven by responsible human-AI governance (Kaplan 2020; Nguyen et al. 2024).

2.4 Human–AI Governance and Algorithmic Legitimacy

Human–AI governance involves practices at the organisational and platform level to design, monitor, explain, review, and correct AI-enabled services, while algorithmic legitimacy refers to the evaluations of customers about whether the decisions made by AI are fair, transparent, accountable, and controllable. The role of effective governance in Internet commerce is becoming more significant because of the value of AI for personalisation, pricing, recommendations, payments, fraud detection and access to services. The key governance dimensions are: privacy protection, meaningful consent, transparency, explainability, fairness, human review, redress and customer control (Kaplan 2020; Martin et al. 2019). Lack of good governance can lead to concerns of surveillance, decision-making bias, transparency in pricing, and false-positive fraud detection, which affect trust (Obermeyer et al. 2019; Sarna et al. 2025). Clear data practices, understandable explanations, fair procedures, and accessible review mechanisms, can increase the legitimacy of algorithms and platform trust and relationship quality, in contrast.

2.5 AI-Enabled Online Service Recovery and Human Escalation

In an AI-powered Internet commerce, service recovery becomes essential as it is possible for intelligent systems to create and cause service failures. Through AI, retailers can identify negative sentiment, repeated complaints, cart abandonment, and decreased engagement rates before they turn into customer dissatisfaction, switching, or even negative electronic word of mouth, which can be prevented (Cambria et al. 2020; Zhang et al. 2023). The conversational agents, recommendation systems and automated decision tools, on the other hand, can also lead to failures because of wrong answers, irrelevant recommendations, declined payments or seemingly unfair decisions. Technical justice and justice based on outcome, procedural and interactional justice are, therefore, essential for effective recovery (Tax, Brown, and Chandrashekaran 1998).

Human-AI complementarity becomes more critical as the level of failure and complexity rises. AI is fast, consistent, and available around the clock, while employees are empathetic, have context awareness, explain, and repair relationships (Wirtz et al. 2018; Huang and Rust 2022). Some common issues can be addressed automatically, but if they are high consequence, emotionally sensitive, repeated or unfair failures, they need to be escalated quickly to a human for resolution to maintain trust, satisfaction, and quality of relationship.

2.6 Digital Inclusion as a Boundary Condition

Transformative service research (Anderson et al. 2013) not only impacts efficiency and customer experience with the Internet commerce service, but customer well-being and involvement. When it comes to the world of retail, digital inclusion is essential because AI-powered retailing isn't an equal opportunity.

Although AI can make things more convenient and personalised for digitally proficient persons, it could marginalise customers who lack digital literacy, connectivity, disabilities, language, or access to devices, or who don't have the trust in digital payments. When humans and other support options are not available, reliance on apps, chatbots, biometric authentication and self-service systems can further limit access. Therefore, technology use is not enough to ensure meaningful participation.

Accessible interfaces, multilingual support, compatibility with assistive technology, alternative payment and communication options and ongoing availability of human service are all aspects of inclusive service design (Fisk et al. 2018). It also needs protection from algorithmic discrimination which can restrict access to a product, service, or service or support.

Digital inclusion can be viewed as a boundary condition which influences the ability of customer participation with or without AI capabilities. While AI systems that are inclusive and accessible can enhance engagement and value of services, AI systems that are poorly designed or overly digital can serve to create barriers for vulnerable groups and limit participation. Therefore, AI-powered retailing needs to be evaluated beyond its efficiency and profitability, but also on accessibility, fairness, and equitable customer engagement.

In the context of sustainability, AI can also contribute by providing better predictions, minimizing returns, optimizing inventory, and minimizing waste (Dhama et al. 2024) all of which are crucial in high impact

Vol. 12 Issue 11 (November, 2026)
ISSN: 2208-2190 Pages- 01-16
DOI: https://doi.org/10.69980/jns7m743

industries like fashion. Sustainability is however not in the center of a conceptual framework, but is rather a secondary, complementary result.

3. Proposed Conceptual Framework: AI-Enabled Service Transformation in Internet Commerce

The proposed framework regards the use of AI to smarten retailing as a service transformation that focuses on the customer instead of just as a technological or operational improvement. The service dominant logic (SDL) perspective of AI can be achieved through the use of an operant resource that is not simply a technical asset, but becomes valuable when it interacts with other resources and integrates with other services. (Vargo and Lusch 2004) This is amplified by the service-ecosystem perspective which puts AI-driven retailing into interdependent ecosystems of customers, retailers, platforms, service providers and digital infrastructure (Akaka and Vargo 2015).

The framework has three higher-order capabilities: algorithmic personalisation and decision support, AI-mediated service interaction and predictive service intelligence. These capabilities affect four mechanisms of the customer experience: decision value, quality of interactions, trust in transactions and algorithmic legit. The research of customer experience and service encounter makes it evident that responsiveness, quality of interaction, and evaluation of the journey are important at all digital touchpoints (Voorhees et al. 2017). Secondly, human–AI service governance as a boundary condition is expressed through privacy, transparency, fairness, customer control, human oversight, redress and digital inclusion. In the context of automated service that needs contextual judgement or human intervention, human–AI complementarity is especially crucial (Huang and Rust 2022). As illustrated in Figure 1, these relationships determine whether AI-enabled retailing fosters trust and engagement or creates opacity, unfairness, and exclusion.

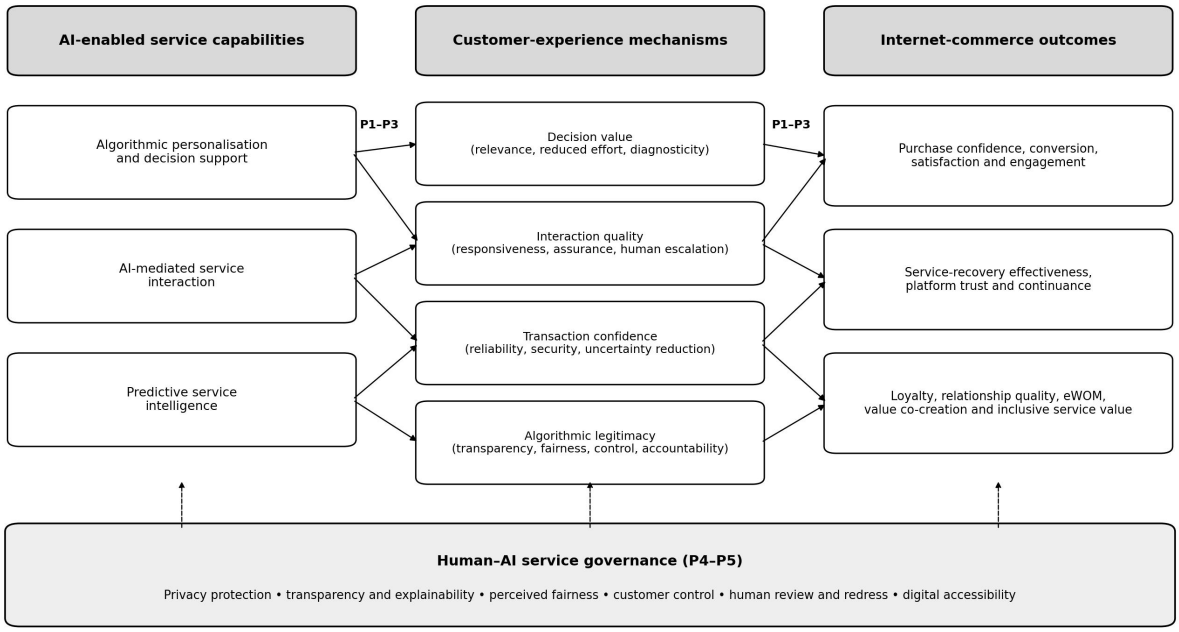


Figure 1. Integrated conceptual framework of AI-enabled smart retailing in Internet commerce

3.1 Algorithmic Personalisation and Decision Support

Algorithmic personalisation and decision support are two significant customer-facing AI-powered features in the Internet commerce industry. AI systems can deliver more precise search results, product recommendations, tailored offers, and alternative options that filter out the noise and facilitate better product evaluation by examining browsing patterns, purchase records, loyalty trends, preferences, and context (Davenport et al. 2019). In the context of services marketing, personalisation is more than just targeted selling; it is about enhancing the relevance, convenience, and responsiveness of the customer journey.

Recommendations can lower search effort when they are timely and appropriate, enhance customers' perceived diagnosticity and boost customers' confidence in evaluating and selecting products when they are appropriate and timely (Huang and Rust 2021). AI-powered visual search, computer-vision-based virtual try-on, and intelligent immersive interfaces can also provide customers with valuable support when deciding on the look,

Vol. 12 Issue 11 (November, 2026)
ISSN: 2208-2190 Pages- 01-16
DOI: https://doi.org/10.69980/jns7m743

fit, and suitability of products, especially in high-uncertainty categories. These tools can help build customer's sense of control by allowing them to explore options and make informed decisions.

The success of personalisation relies on customers' awareness of and attitude towards the gathering and processing of their information, however. Inappropriate targeting, mismatched product recommendations, data profiling, data discrimination, or lack of control can cause privacy concerns and loss of trust (Kaplan 2020). Given this, customer impact is likely to stem from the relevance, effort saving, diagnosticity, and decision value of AI-driven personalisation, with potentially negative impacts from privacy concerns.

P1: Algorithmic personalisation and AI-enabled decision support increase customer satisfaction and engagement by improving decision value; privacy concerns weaken this relationship.

3.2 AI-Mediated Service Interaction

The three types of service interaction that can be achieved by AI are conceptualized as: conversational service interaction, automated service interaction, sentiment-based service interaction, and hybrid human-AI service interaction. Conversational technologies like chatbots, virtual assistants, voice agents, platform messaging systems facilitate product enquiries, information search, product recommendations and routine service procedures. By incorporating NLP, companies can automate and expand them across digital channels (Chatterjee, Chaudhuri, and Mikalef 2022). Automated transactional support also helps customers place orders, pay, receive status notifications on fulfilled orders, return goods, file complaints and post-sales service requests for greater responsiveness and less waiting times. Thus, for an Internet-commerce interaction, the quality of interaction is related to clarity, responsiveness, perceived control, assurance, and access to human support that is appropriate (Voorhees et al. 2017).

Sentiment-based intervention extends these functions by capturing the dissatisfaction signals in reviews, surveys, social-media and chatbot messages, and enabling retailers to take proactive steps to address emerging service issues (Cambria et al. 2020; Ligthart et al. 2021). Automated systems, however, are less effective when the failure has a high level of complexity, significant monetary impact, emotional sensitivity, privacy issues or perceived unfairness. Hybrid human–AI service is important in such cases, where employees can bring empathy, contextual judgement, explanation, and accountability, while AI can bring analytical and informational support (Huang and Rust 2022). Thus, AI-based service interaction can help to improve the effectiveness of service recovery by improving the quality of the interaction, and the timely escalation to human intervention becomes more critical as the severity of the failure and complexity of the interaction increases.

P2: AI-mediated service interaction increases service-recovery effectiveness by improving interaction quality; timely human escalation strengthens this effect in complex, high-risk, or emotionally sensitive service failures.

3.3 Predictive Service Intelligence

Predictive service intelligence is when AI-driven analytics helps predict customer needs, service risks, product availability, conditions for fulfilment and possible transactions that could fail. It has two complementary roles in Internet commerce: predictive fulfilment intelligence and predictive transaction-risk intelligence. Predictive fulfilment intelligence can aid the demand forecasting, inventory planning, delivery-time prediction, product substitution, return prediction, replenishment and proactive delay management. These features can minimize stock out, ensure accurate orders and boost fulfilment reliability reducing the uncertainty of customers during the transaction, delivery process (Ghosh et al. 2020). While customers are not directly seeing the underlying analytics, they feel it in the products available, the consistency of the delivery, how quickly the service responds, how accurate the delivery expectations, etc.

Predictive transaction-risk intelligence is all about fraud detection, payment authentication and account protection, return-abuse detection and suspicious-transaction monitoring. These systems can help enhance the sense of security and trust on platforms, recognize suspicious actions and safeguard legitimate transactions (Sarna et al. 2025). But the risk of false-positive decisions can cause unnecessary verification, delay orders, or even prevent payments. However, if they are not explained or there are no clear review and appeal procedures, they can lower the sense of fairness and result in a loss of trust. Predictive service intelligence therefore adds customer value through increased fulfilment reliability and transaction security that enhances transaction confidence, whilst adverse automated decision making decisions are transparent, explainable and open to proper human review.

Vol. 12 Issue 11 (November, 2026)
ISSN: 2208-2190 Pages- 01-16
DOI: https://doi.org/10.69980/jns7m743

P3: Predictive service intelligence positively influences customer satisfaction and platform trust by strengthening transaction confidence through improved fulfilment reliability and transaction security; however, unexplained false-positive risk decisions weaken these positive effects.

3.4 Human–AI Service Governance and Algorithmic Legitimacy

Human–AI service governance acts as a boundary condition that influences and guides the design, monitoring, review, and correction of AI-enabled retail capabilities in Internet-commerce situations. AI embedded interactions are not a capability in the realm of parallel technologies, but rather they are a precondition for how the interactions are perceived as trusted, fair, controllable and inclusive in the organisation and in the design of the service. These five governance dimensions are of particular importance: privacy and consent, transparency and explainability, procedural and outcome fairness, human review and redress and accessibility and digital inclusion.

The focus on privacy and consent is crucial, as AI-powered retail systems rely on various types of data, such as behavioural, transactional, location, payment, and loyalty data. The acceptance of the data by the customer is enhanced when clear information about how it is collected, used, and shared is provided, and is diminished when the information is less clear about how the data is collected and shared (Kaplan 2020; Martin et al. 2019).

When AI makes a recommendation, a personalised pricing, a fraud detection, a promotional eligibility or access to a service, transparency and explainability are also crucial. When customers know why a decision was reached, and understand that it is human-reviewable, they are likely to accept the automated decision (Adanyin 2024).

Fairness issues are about how decisions are made and the decisions that are made for customers. The platform's trust and relationship quality may be jeopardized if the platform is poorly trusted, pricing policies are discriminatory, recommendations are biased, or there are hidden profiling or fraud controls that are not clearly explained (Mahmoud et al. 2020). When an automated decision has financial, emotional or relational implications, it is particularly important that it is monitored by human beings. The impact of bad decisions can be mitigated and accountability increased by having access to review, appeal, and redress processes.

Digital accessibility is a way of bringing governance beyond trust to participation. Customer choice should be maintained by making services accessible to customers via simple interfaces, providing multiple languages, alternative payment and communication methods and ensuring that human support continues to be readily available. These practices are especially critical for customers who do not have a high level of digital literacy, aren't getting the service they need on their phone or devices, are disabled, or don't have access to a device.

Thus, the governance of human–AI interactions influences algorithmic legitimacy, which is based on customers' perceptions of whether algorithmic decisions are transparent, fair, accountable and controllable.

P4: Stronger human–AI service governance enhances algorithmic legitimacy, which in turn strengthens platform trust and relationship quality.

P5: Digital accessibility acts as a boundary condition that strengthens the positive effect of AI-enabled service capabilities on participation and continuance in Internet commerce.

3.5 Integrated Framework Summary

The proposed framework regards "smart retailing" based on AI as an integrated service system of the Internet-commerce that connects the three capabilities of "algorithmic personalisation and decision support", "AI-mediated service interaction" and "predictive service intelligence", and visualises the three capabilities as having different experience mechanisms that influence customer reactions. These capabilities, in turn, positively affect the decision value, quality of interaction and confidence in transactions for customers and subsequently affect their satisfaction, engagement, service-recovery effectiveness, platform trust, relationship quality and continuance intention. This process-oriented view builds on service-dominant logic by shifting the focus away from the technological power or complexity of the technology and towards how consumers encounter and interpret them in the service. This process-oriented view is an extension of service-dominant logic because it attempts to see AI as an operant resource, meaning its value lies not in the sophistication of its technology but in the process through which the consumer interacts with and gives meaning to the AI-enabled service.

These relationships are also shaped by human–AI service governance, which impacts algorithmic legitimacy and customer engagement. The safeguards of privacy protection, transparency, fairness, customer control, human review and redress can build trust and quality of the relationship; lack of governance can lead to feelings

Vol. 12 Issue 11 (November, 2026)
ISSN: 2208-2190 Pages- 01-16
DOI: https://doi.org/10.69980/jns7m743

of intrusion, opacity and unfairness. Digital accessibility also influences the extent to which the use of AI technologies expands or limits participation, especially for people with technological, literacy, connectivity and accessibility barriers (Fisk et al. 2018).

3.6 Theoretical and Managerial Implications

Theoretical implications. The framework proposed focuses on processes instead of specific AI technologies, moving from the technological to the value creation aspect for customers in Internet commerce. It binds various applications into service capabilities and provides explanations of the impacts of those services using decision value, interaction quality, transaction confidence, and algorithmic legitimacy. This machine perspective can be helpful to understand how similar applications of AI can produce different responses from customers for different types of services. The framework also builds upon service-dominant logic by understanding that the value of AI is derived from interaction and customer interpretation as well as the use of this resource, not just its technological capabilities (Vargo and Lusch 2004). Furthermore, separating human–AI governance from customer perceived algorithmic legitimacy also helps to explain the relationship between the policies of AI governance in organisations and the resulting trust and relationship.

Managerial implications. Customer-journey stage and the consequence of the decision should be used to set up AI for retailers and platforms. Personalisation should be used to be more relevant to the individual, without losing the control of the data held, and conversational services should be utilised so that human escalation is provided when the data cannot be resolved by the bot (Huang and Rust 2022). Uncertainty should be communicated, adverse decisions explained, and there must be accessible review/reduction processes. There should be a mechanism to communicate uncertainty, explain adverse decisions, and have access to review/reduction processes. Digital services must also maintain accessible interfaces and alternative customer assistance to meet accessibility needs (Fisk et al. 2018). So, the assessment on the performance should be the mixture of the efficiency indicators and indicators that reflect customers' perspective, including decision confidence, the customer's satisfaction in the recovery, platform trust, perceived fairness, the intention of continued use by customers, and accessibility. Low impact, low consequence interactions can be automated more so than high impact, high consequence interactions, which must be explained more, overseen more, and have more human interaction.

4. Research Agenda

The research agenda is directly linked to the unresolved relationships and boundary conditions noticed in the proposed framework. Future research should investigate the role of AI-driven service capabilities on the various Internet-commerce platforms and phases of the customer journey, their impact in relation to the customer experience mechanisms and governance contexts. Special focus is needed on algorithmic personalisation, AI-as-mediated service interactions, predictive service intelligence, platform security, fairness and transparency, human escalation and digital inclusion. While the studies on trust, service quality, service recovery and vulnerability focus on their individual aspects, the relationships between them in the context of AI-based Internet-commerce service systems have not been fully understood. Future studies should thus examine the relationship between the AI capabilities and the outcomes (satisfaction, engagement, platform trust, relationship quality, continuance intention) as well as how decision value, interaction quality, transaction confidence and algorithmic legitimacy relate to these outcomes. The agenda should also explore the potential impact of privacy protection, explainability, fairness, customer control, human oversight and accessibility on these relationships in different contexts and moments of the digital customer journey.

4.1 AI Personalisation and Privacy Calculus

Further studies are needed on customers' assessment of benefits and risks of AI personalisation in Internet-commerce service interactions. In the era of customer-centricity, companies must be able to understand the customer needs and react to them, increasingly relying on the analysis of behavioral, transactional and preference data (Kohli, Jaworski, and Shabshab 2019). These data can then be used by AI-powered business intelligence to deliver tailored recommendations, offers, segmentation and live service modifications (Mirza et al. 2025). Consumers might perceive differently, however, about first-party data gathered directly from them as a result of their interactions with the retailer, compared to third party data collected from external platforms or tracking systems, especially under the transparency and control aspect.

Vol. 12 Issue 11 (November, 2026)
ISSN: 2208-2190 Pages- 01-16
DOI: https://doi.org/10.69980/jns7m743

The technology acceptance and readiness frameworks indicate that the perceived usefulness, ease of use, compatibility, and security of the AI-driven services positively influence adoption. The technology acceptance and readiness theories suggest that AI-service adoption is more likely to occur when the service is perceived as useful, easy to use, compatible, and safe (Davis 1989; Parasuraman 2000). These benefits span from speeding up search, to recommending relevant products, to lowering the effort consumers have to put in to make a choice, but they come at a cost of privacy issues like behavioural profiling and tracking, unauthorised data sharing and loss of autonomy.

The impact of consent, transparency, preference controls and data-management options on consent to share data should thus be explored in future studies. There is also a need for longitudinal studies to explore the issues of privacy fatigue, resistance, decreased engagement, or switching platforms when targeted by algorithms. Such assessments can be made via online experiments, conjoint analysis, longitudinal surveys, and cross-country comparisons, among other methods. Issues of interest include the attitudes of customers towards the use of their first-party and third-party data, the point at which personalisation becomes overbearing, and if privacy fatigue leads to reduced trust and platform loyalty in the medium to long-term.

4.2 Human–AI Service Recovery

The research and development of human-AI service recovery are crucial in the era of growing adoption of chatbots and virtual assistants in customer enquiries, complaints, delivery issues, product-related problems, and post-purchase assistance. The technologies can enhance the responsiveness, offer continuous assistance and mitigate waiting times, thus enhancing customer experience in Internet commerce (Nwabekee, Okpeke, and Onalaja 2025). But a service recovery that is effective also requires empathy, contextual judgement, explanation, taking responsibility and emotional sensitivity, in addition to speed and efficiency.

Future studies could compare chatbot based, human and hybrid recovery in various categories of service failure and failure severity. Escalation by human may be especially relevant where the failures result in financial loss, repeated failures in service, customer vulnerability, emotional sensitivity, and/or perceived unfairness. Escalation effectiveness also might rely on chatbot anthropomorphism, the waiting time, and perceived accountability (Kumar, Jain, and Sharma 2025). AI can handle routine issues effectively, but it is more likely to be a human intervention that is necessary to restore trust and perceived justice for more complex or high consequence failures.

Additional emotion- and sentiment-recognition technologies could also help with service recovery by detecting customer dissatisfaction and prompt action, but there are concerns about privacy, surveillance, and customer consent that need to be addressed and overcome to justify the benefit of such technology (Pantano 2020). Future studies should thus focus on post-recovery satisfaction as well as trust reconstruction, repurchase intention, platform switching, eWOM and perceived justice. Some of the most critical research questions involve the conditions under which customers accept recovery based on AI, the circumstances of when human agency is necessary to facilitate recovery, the impact of recovery failure severity, vulnerability, anthropomorphism, waiting time, accountability, and emotional cues in restorative processes in AI-mediated retail situations, and the conditions under which people are willing to trust the recovery process in AI-mediated interactions with customers.

4.3 Algorithmic Fairness in Pricing and Recommendations

Internet-commerce applications like personalised pricing, sponsored product ranking, personalised discounting, visibility, promotional targeting, fraud prevention, loyalty segmentation and eligibility for purchase through credit are becoming increasingly dependent on AI, making algorithmic fairness a key research goal. When such price or promotion disparities are clearly related to demand, inventory or existing promotions, customers may consider them to be fair. The same practices can, however, be seen as discriminatory if they are based on personal data or hidden profiling or inferred willingness to pay, and can decrease satisfaction, platform trust, and relationship quality.

Evidence from algorithmic bias studies suggest that automated systems can perpetuate or exacerbate inequitable outcomes when the data used by the systems is incomplete, biased or inappropriate (Obermeyer et al. 2019). This evidence comes from health & healthcare, but it is an example of the need for auditing automated decision systems for systematic disadvantage. Related risks in Internet commerce are recommendation bias, product visibility, discrimination amongst marketplace sellers, personalized pricing, loyalty incentives, credit based purchasing decisions, and fraud controls. While AI's help with fraud detection

Vol. 12 Issue 11 (November, 2026)
ISSN: 2208-2190 Pages- 01-16
DOI: https://doi.org/10.69980/jns7m743

can bolster transaction security, it can also cause a nuisance to legitimate users if it makes false-positive decisions and impedes transactions or access to services (Sarna et al. 2025).

Future research is needed to differentiate distributive fairness (referring to perceived fairness of outcomes, e.g., prices, discounts, rankings, service access, etc.), procedural fairness (referring to perceived fairness of decision processes, e.g., fairness of the decision, transparency and openness of decision processes, etc.), and explanatory fairness (referring to perceived understandability of explanations provided to customers about automated decisions, e.g., transparency of explanations, clarity of explanations, etc.). Further research is needed to determine if algorithmic disclosure, human review, and explanations attributing price differences to demand and not to profiling techniques enhances fairness perceptions. Research should also examine the responsibility that customers attribute to the platform, their expectations regarding compensation by the platform and third party sellers, and its impact on complaints, recovery, platform switching, and platform loyalty. The questions that are important, then, are how customers assess distributive, procedural and explanatory fairness, what explanations mitigate perceptions of discrimination, who customers blame when their automated experiences are perceived as unfair, and so on.

4.4 Trust, Transparency and Explainability

A key factor in AI-powered smart retailing is trust—after all, not all customers are aware of how AI systems affect the recommendations they receive, personalised pricing, service prioritisation, fraud detection, prediction of customer needs, payment, access to services and complaint handling. Studies and research in the future should therefore differentiate between the various transparency aspects, such as the disclosure of the use of AI, the way data is collected, the logic behind the recommendations, personalised pricing, decisions regarding fraud, and the possibility of reviewing by humans and investigate their respective effects on customer confidence.

Other characteristics of the explanations that should be compared in the research are simple vs technical, pre-decision vs post-decision, and the format (textual, layered, visual, or interactive). However, in some cases, the increase in transparency will only worsen the customer's reaction as too much or too much complicated information can cause confusion and information overload. Explanations should therefore be judged using the dimensions of clarity, credibility, relevance and timeliness and not on the quantity of information alone.

Explanations can be interpreted differently based on customer AI literacy, and managerial AI literacy is relevant for comprehending system outputs, making decisions and communicating them appropriately (Mogaji and Nguyen 2022). Further studies should therefore investigate the relationship between managerial AI literacy and disclosure quality, accountability, and transparency in the design of the Internet-commerce. The key research questions focus on which disclosures are most effective in establishing trust, the impact of explanation design on the acceptance of AI decisions, when transparency gives rise to information overload, and how the AI literacy of customers and managers influence transparency, accountability and trust of AI-powered retailing.

4.5 AR, Visual Search and Perceived Risk

Online pre-purchase evaluation is also becoming a game-changer with AI-powered visual and immersive decision support features, such as computer-vision-based virtual try-on, AI-powered visual search, personalised 3D visualisation, augmented reality, and product demonstration generated by AI. They enable customers to visualize, compare, and evaluate products better, especially in product types that fall into the 'high uncertainty' category, like fashion, cosmetics, furniture, eyewear, and home décor, for which traditional product pages are not necessarily effective in communicating fit, scale, or appearance.

These technologies can improve the product diagnosticity, fit perception, sensory engagement, and control of the product, which, in turn, can lower perceived product risk, increase purchase confidence and intention. The findings of virtual-reality retailing further suggest that VR can not only influence product evaluation but also extend its impact to consumer decision making, affecting both purchase and non-purchase behavioural intentions (Fan et al. 2025; Mishra et al. 2024).

Their impacts on conversion, return intention, and actual returns of the product should be further investigated, and functional benefits (e.g., better fit assessment and uncertainty reduction) should be distinguished from experiential benefits (e.g., enjoy, novelty, engagement). Barriers like device access, digital literacy, and confidence in technology use should also be taken into account in comparative studies across product sectors, online, offline and omnichannel settings. Questions of interest include: How does immersive AI enhance the

Vol. 12 Issue 11 (November, 2026)
ISSN: 2208-2190 Pages- 01-16
DOI: https://doi.org/10.69980/jns7m743

perceived risk reduction, fit perception, diagnosticity, decision confidence and conversion? Do the effects vary by sector and by customer group?

4.6 Digital Inclusion and Customer Vulnerability

Digital inclusion is an essential boundary condition of Internet commerce with the incorporation of artificial intelligence, as not all customers can benefit from the services provided by the AI. At the customer level, vulnerabilities can include low digital literacy, low connectivity, limited access to appropriate devices and/or applications, language barriers, disability, low trust of digital payments, age, rural residence, or low income. The evidence also reveals that customers' experience of AI adoption varies by technological maturity, as seen in Indian retail (Seranmadevi and Kumar 2019). If access relies heavily on applications, chatbots, biometric systems or other automated interfaces, this can limit access without compromising the functions of the service. If reliance is high on applications, chatbots, biometric systems or any other automated interface, this can hinder access, even though the service may be efficient and convenient when using AI. Future work should therefore focus on inclusive service designs that keep autonomy, accessibility, dignity and choice of customers in mind, such as user-friendly interfaces, the ability to choose languages, payment methods, and human support.

Platforms and retailers also need to be able to put digital inclusion in place. Large companies may have more access to data, technical expertise, governance systems, and investment resources, while SMEs have less access to investment resources, evidence of return on investment (ROI), technical expertise and governance systems (Adanyin 2024; Korenyuk 2024). The disparities could result in a disparity in service quality in Internet-commerce environments. Future research should, therefore, explore the applicability of scalable platforms, cloud-based AI, workforce upskilling, shared data resources for the SMEs. Questions focus on the people who are most at risk of being excluded; the relationship between payment trust, literacy and use of platforms; and the need to reduce the disparity in capability between large retailers and SMEs, and the balance between automation and human support.

4.7 AI-Enabled Sustainability and Transformative Service

AI-driven Internet retailing can help to facilitate sustainable and transformative service via demand forecasting, optimisation of inventory, more efficient fulfilment, minimisation of online returns, and less overstocking and waste. Predictive analytics can enable retailers to match inventory with customer demand, boost product availability, manage fulfilment activities more effectively and minimize the use of unneeded resources. While Nguyen et al. (2022) discuss data analytics in pharmaceutical value chains, their focus on forecasting, coordination, and data-driven supply chain management offers a more comprehensive analytical framework for exploring the potential applications of data analytics in digitally enabled retail environments.

Future research should focus on the potential for AI to minimize unnecessary returns, on platforms for circular-commerce, on a more robust repair and recycling service and on more responsible product recommendations. The two outcomes of the operational efficiency and less waste reduction should be assessed, along with customer perceptions of trust, authenticity, and readiness to participate in sustainable consumption. It is important to consider sustainability as a supporting part of the proposed framework and not as a customer experience mechanism per se. Key research questions include the impact of AI-driven forecasting on service reliability and waste minimisation, as well as how inventory can be optimised without ramping up stock-outs or compromising customer satisfaction, whether AI recommendations drive down return rates, and how customers' perceptions and trust of sustainability claims relate to AI-powered retail channels.

4.8 Summary of Future Research Priorities

Table 2 summarises the principal research priorities emerging from the conceptual framework and identifies the unresolved issues, focal variables, recommended methods, and relevant Internet-commerce contexts.

Table 2. Future research priorities for AI-enabled smart retailing

Vol. 12 Issue 11 (November, 2026)
ISSN: 2208-2190 Pages- 01-16
DOI: https://doi.org/10.69980/jns7m743

Research priority	Unresolved issue	Main variables	Recommended method	Internet-commerce context
Personalisation and privacy	Determining when AI-enabled personalisation is perceived as useful rather than intrusive	Perceived relevance, privacy concern, consent, customer control, willingness to share data, platform trust	Online experiments, longitudinal surveys, conjoint analysis	E-commerce websites, mobile applications, online marketplaces
Human–AI service recovery	Identifying when chatbot-based recovery is sufficient and when human escalation is required	Failure severity, responsiveness, empathy, perceived justice, trust restoration, repurchase intention	Scenario experiments, field studies, mixed-method research	Chatbot support, online complaints, delivery and payment failures
Pricing and recommendation fairness	Explaining how customers evaluate personalised prices, rankings, promotions, and recommendation outcomes	Distributive fairness, procedural fairness, explanatory fairness, trust, loyalty	Experiments, vignette studies, cross-platform comparisons	Dynamic pricing, sponsored ranking, personalised recommendations
Transaction security	Balancing fraud prevention with procedural fairness and customer access	Perceived security, false positives, explainability, appeal availability, platform trust	Field experiments, customer surveys, complaint-data analysis	Digital payments, fraud detection, return-abuse systems
Immersive commerce	Determining whether immersive tools improve product evaluation and reduce returns	Diagnosticity, perceived fit, decision confidence, conversion, return intention	Controlled experiments, longitudinal tracking, sector comparisons	Virtual try-on, AR, visual search, 3D product visualisation
Digital inclusion	Identifying customers and retailers at risk of exclusion from AI-enabled commerce	Digital literacy, accessibility, connectivity, human-support availability, SME adoption capability	Cross-country surveys, qualitative studies, comparative case research	Mobile commerce, emerging markets, SME platforms

Vol. 12 Issue 11 (November, 2026)
ISSN: 2208-2190 Pages- 01-16
DOI: https://doi.org/10.69980/jns7m743

Research priority	Unresolved issue	Main variables	Recommended method	Internet-commerce context
Sustainability	Assessing whether AI-enabled retailing produces credible environmental and customer benefits	Waste reduction, return reduction, service reliability, customer trust, sustainable consumption	Longitudinal studies, field research, platform-data analysis	Circular commerce, inventory optimisation, responsible recommendations

5. Conclusion

AI-powered smart retailing is changing the Internet commerce world by moving Artificial Intelligence from an operational technology to a service capability, directly accessible by customers. The paper presents an integrated framework that links, through the intermediary of customer value, quality of interaction, trust in the transaction, and perceived algorithmic legitimacy, algorithmic personalisation, decision support, AI-mediated service interaction, and predictive service intelligence to customer outcomes. With service-dominant logic (SDL), value is not obtained from technology itself but through interactions and integration of resources. So, its effectiveness is reliant on how customers feel relevant, responsive, reliable, fair and in control at each digital touchpoint.

It also reveals that there is a need for human-AI governance to transform the capabilities of AI into trusted Internet-commerce outcomes. Clear and transparent data practices, safeguarding privacy, explainability, fairness, human review, and accessible service options can enhance trust and relationship quality with platforms, while opaque or exclusionary service practices can erode trust in the platform and its relationship with the customer. Human support is especially critical in the case of complex, vulnerable, and negative consequences automated encounters. In essence, the key to achieving successful AI-driven smart retailing lies in achieving a balance between automation, customer-centred service design, and responsible governance. The envisaged relationships serve as a basis to conduct empirical testing in e-commerce, marketplace, social e-commerce and omnichannel e-commerce systems, in various customer and regulatory settings around the world.

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Vol. 12 Issue 11 (November, 2026)

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