# From Trial to Commercial Value: A Customer-Value Architecture for AI-Enabled Retail and Service Technologies

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## Abstract

Retailers and service firms use scan-and-go systems, autonomous stores, conversational agents, voice assistants, service robots and AI-supported recommendations at different points in the customer journey. Research explains many drivers of technology acceptance, but commercial value also depends on what happens after the first trial. This conceptual paper integrates seminal work on technology acceptance, innovation diffusion, expectation-confirmation, perceived value, habit, customer satisfaction and willingness to pay with recent retail and service research published from 2023 to 2025. The synthesis develops a five-stage customer-value architecture covering adoption readiness, assisted trial, value confirmation, routine formation and commercial conversion. Recent evidence strengthens four parts of the architecture. Familiarity can shape acceptance and disclosure in AI-mediated product search; automation, personalisation, efficiency and precision can improve engagement with service robots; empathy can support social presence and satisfaction but may weaken the experience under time pressure; and customer responses differ according to the level and location of in-store automation. The framework also identifies feedback through service recovery, social proof and cumulative satisfaction. Its main contribution is the separation of technology acceptance, usage value and payment value. A customer may accept and repeatedly use an AI-enabled service without choosing a paid option when familiar alternatives remain available or the value difference is unclear. The paper provides a source-based structure for commerce and service managers to assess AI-enabled customer journeys without treating intention as a commercial outcome.

***Keywords: artificial intelligence; retail technology; customer experience; technology adoption; perceived value; willingness to pay***

## 1. Introduction

Customer-facing artificial intelligence (AI) now appears in in-store technologies, autonomous retail formats, digital product search, chatbots, voice assistants and service robots (Grewal et al., 2023; Benoit et al., 2024; Arce-Urriza et al., 2025). These technologies can support customer efficiency, employee efficiency or experience enhancement, but the effect depends on where the technology is used in the customer and employee journeys (Grewal et al., 2023). Research on autonomous stores likewise shows that customer response should be examined according to the level of automation rather than by treating every technology-enabled store as the same format (Benoit et al., 2024).

Acceptance is the first commercial requirement, not the final commercial result. The technology acceptance model explains acceptance through perceived usefulness and perceived ease of use (Davis, 1989). The unified theory of acceptance and use of technology (UTAUT) adds performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003). UTAUT2 extends this logic to consumer settings through hedonic motivation, price value and habit (Venkatesh et al., 2012). Diffusion of innovations explains why customers differ in their readiness to try an innovation and in the evidence they require before adoption (Rogers, 2003).

The commercial problem continues after trial. Expectation-confirmation theory links confirmation with satisfaction and continuance intention (Bhattacherjee, 2001), following the satisfaction process described by Oliver (1980). Perceived value reflects the customer's comparison of benefits with monetary and non-monetary sacrifices (Zeithaml, 1988), while consumption value can contain functional, emotional and social components (Sweeney & Soutar, 2001). Customer satisfaction can raise willingness to pay, but the relationship can be nonlinear and cumulative satisfaction can matter more than satisfaction with one transaction (Homburg et al., 2005).

Recent evidence makes the gap between use and commercial value clearer. Consumers evaluating products may prefer familiar search engines to generative AI chatbots and may be more willing to disclose information to the familiar tool, although chatbot results can be perceived as less biased (Kim & Priluck, 2025). Familiarity also influences consumer acceptance of generative AI retail chatbots (Arce-Urriza et al., 2025). In paid mobile applications, perceived value, value for money, ratings and free alternatives affect purchase intention, while satisfaction does not necessarily create paid conversion for every user (Hsu & Lin, 2015). These findings show that trial, continued use and payment are related but distinct customer decisions (Hsu & Lin, 2015; Kim & Priluck, 2025).

This paper asks: How can a retailer or service firm convert customer acceptance of AI-enabled technology into confirmed value, repeated use and commercial return? The paper develops a customer-value architecture by connecting established theories with recent evidence from retailing, electronic commerce and frontline service. The framework is a conceptual synthesis; it does not report invented observations, pooled effects or empirical testing.

## 2. Conceptual Method and Evidence Base

The paper follows a theory-synthesis approach in which established concepts are connected to explain a broader managerial problem that no single theory covers fully (Jaakkola, 2020). The starting theories explain adoption, diffusion, confirmation, value, habit, satisfaction and willingness to pay (Davis, 1989; Oliver, 1980; Zeithaml, 1988; Ouellette & Wood, 1998; Bhattacherjee, 2001; Rogers, 2003; Venkatesh et al., 2003, 2012; Homburg et al., 2005). Recent studies were included only when they directly examined retail technology, AI-enabled customer experience, chatbot use, autonomous stores, service robots, digital product search or AI-enabled customer care (Grewal et al., 2023; Kamoonpuri & Sengar, 2023; Shah et al., 2023; Benoit et al., 2024; Ferraro et al., 2024; Huang & Rust, 2024; Arce-Urriza et al., 2025; Juquelier et al., 2025; Kim & Priluck, 2025).

The studies are interpreted within their actual designs. Kašparová (2024) surveyed 420 Czech consumers and validated the scan-and-go model with 235 active users. Gursoy et al. (2019) tested acceptance of AI devices with 439 potential customers in the United States. Hsu and Lin (2015) studied 507 Taiwanese mobile-application users, including users of free and paid applications. Homburg et al. (2005) used two experiments to examine satisfaction and willingness to pay. Shah et al. (2023) used a three-wave design with 416 restaurant customers, while Kim and Priluck (2025) experimentally compared product search through AI chatbots and search engines. Because the contexts and outcomes differ, the evidence is synthesised as connected stages rather than combined as a common statistical effect.

The synthesis follows three rules. First, empirical findings are attributed to the study that reported them. Second, managerial implications are linked to evidence instead of being presented as tested facts. Third, the proposed stages and feedback loops are identified as the authors' conceptual organisation of the literature.

## 3. Why Acceptance Does Not Equal Commercial Value

### 3.1 Functional performance and customer effort

Usefulness and expected performance remain central to initial acceptance in the technology acceptance model and UTAUT (Davis, 1989; Venkatesh et al., 2003). In scan-and-go retailing, performance expectancy, hedonic motivation and habit were important influences on behavioural intention, while intention and habit explained actual use among active users (Kašparová, 2024). In AI-enabled service delivery, performance expectancy supported positive emotional appraisal, which in turn supported willingness to accept the device (Gursoy et al., 2019).

Recent retail research places these customer effects beside operational effects. In-store technology can improve efficiency or experience for customers and employees, but a gain for one party does not automatically create a gain for the other (Grewal et al., 2023). The evidence therefore supports evaluating the technology at the exact journey point where it changes waiting, information, payment, fulfilment or employee assistance (Grewal et al., 2023).

Expected effort can weaken customers' positive response to AI device use (Gursoy et al., 2019). Customer-related barriers are also prominent in the implementation and use of AI-enabled retail virtual assistants (Kamoonpuri & Sengar, 2023). Facilitating conditions, visible guidance and system compatibility remain part of acceptance in UTAUT and UTAUT2 (Venkatesh et al., 2003, 2012). These findings support treating first-use difficulty as a service-design and operations issue rather than only as an interface issue.

### 3.2 Familiarity, transparency and trust

Familiarity can influence trust in electronic commerce (Gefen, 2000). It can also change the comparative evaluation of newer AI tools. Kim and Priluck (2025) found that consumers preferred search engines and showed greater willingness to disclose information to them than to AI chatbots because of perceived familiarity; they also found that AI-chatbot results were evaluated as less biased. Arce-Urriza et al. (2025) similarly positioned familiarity as an important antecedent of consumer acceptance of generative AI retail chatbots.

These results show why ease of use alone is incomplete. A customer can understand how to use an AI tool and still avoid it because the alternative is more familiar or because data use is unclear (Kim & Priluck, 2025). Explainable AI research further shows that post hoc explanations can affect consumer responses to AI recommendations, making the design of explanations part of the recommendation experience (Chen et al., 2024). The evidence supports separate assessment of usability, familiarity, explanation and disclosure comfort instead of combining them under one general acceptance score.

### 3.3 Social presence, empathy and human support

Automated interfaces can be interpreted as social actors at the organisational frontline (van Doorn et al., 2017). AI-chatbot design therefore includes not only functionality but also anthropomorphic role, appearance and interactivity (Chong et al., 2021). Retail research on AI digital humans likewise shows that AI changes the social practice of the service encounter, not only its speed or information content (Moore et al., 2022).

Shah et al. (2023) found that perceived automation, personalisation, efficiency and precision in robot service quality supported customer engagement, which then supported acceptance of service robots. Their study also found that anthropomorphism changed the relationships between robot service-quality dimensions and engagement (Shah et al., 2023). Gursoy et al. (2019), however, found that anthropomorphism increased effort expectancy rather than performance expectancy. Read together, these studies show that human-like design is a contextual feature whose effect depends on the service and the customer appraisal being examined (Gursoy et al., 2019; Shah et al., 2023).

Empathy is similarly conditional. Empathic chatbots can increase perceived social presence and information quality and thereby improve satisfaction, but the same design can damage the experience when customers feel time pressure (Juquelier et al., 2025). Feeling AI may support customer care, yet current AI capabilities and marketing requirements do not remove the need to recognise technical and relational limits (Huang & Rust, 2024). Service-robot research also identifies tasks involving judgement, empathy or recovery as important boundaries for complete automation (Wirtz et al., 2018). The evidence supports retaining a clear human hand-off where the customer needs discretion, reassurance or complaint resolution.

## 4. Customer-Value Architecture

The proposed architecture contains five stages. Each stage represents a different customer decision and therefore requires different evidence and measures.

| Stage | Customer decision | Evidence-based management focus | Evidence anchor |
|---|---|---|---|
| Adoption readiness | Is this relevant and credible enough to try? | Demonstrate usefulness, relative advantage, familiarity and social reassurance | Davis (1989); Rogers (2003); Arce-Urriza et al. (2025) |
| Assisted trial | Can I complete the task with acceptable effort and risk? | Provide guidance, compatible processes, disclosure clarity and human help | Venkatesh et al. (2003, 2012); Kamoonpuri and Sengar (2023) |
| Value confirmation | Did the service deliver the promised functional and experiential value? | Compare actual speed, accuracy, care and convenience with prior expectations | Oliver (1980); Bhattacherjee (2001); Juquelier et al. (2025) |

| Stage | Customer decision | Evidence-based management focus | Evidence anchor |
|---|---|---|---|
| Routine formation | Is repeated use becoming stable and convenient? | Preserve continuity, access, saved preferences and reliable recovery | Ouellette and Wood (1998); Limayem et al. (2007); Kašparová (2024) |
| Commercial conversion | Is the paid or higher-value option worth choosing? | Show value for money, credible differentiation, trustworthy ratings and advantages over alternatives | Homburg et al. (2005); Hsu and Lin (2015); Kim and Priluck (2025) |

Figure 1 brings the five stages together and shows how service recovery, social proof and cumulative satisfaction feed later experience back into earlier customer judgements.

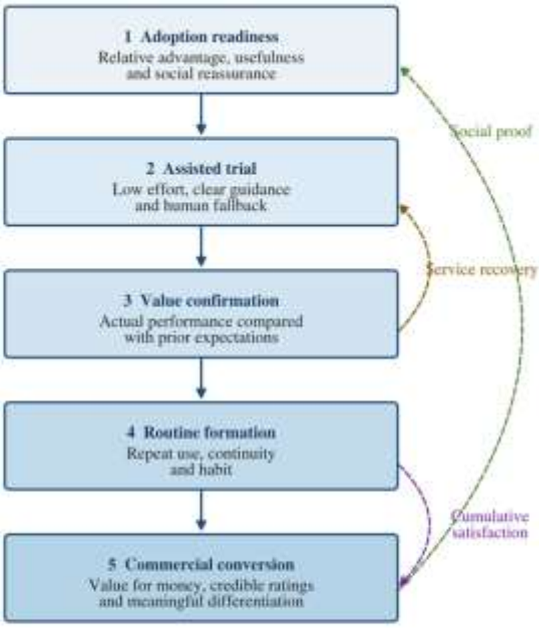


**Figure 1. Customer-value architecture for AI-enabled retail and service technologies**

*Source: Authors' conceptualisation based on Davis (1989), Venkatesh et al. (2003, 2012), Homburg et al. (2005), Hsu and Lin (2015), Grewal et al. (2023), Shah et al. (2023), Kašparová (2024), Arce-Urriza et al. (2025), and Juquelier et al. (2025).*

### 4.1 Adoption readiness

The adoption-readiness stage combines relative advantage, usefulness, innovation readiness, familiarity and social evidence. Relative advantage and the timing of adoption are central to diffusion of innovations (Rogers, 2003), while usefulness and performance expectancy are central to TAM and UTAUT (Davis, 1989; Venkatesh et al., 2003). Kašparová (2024) connected diffusion categories with UTAUT2 in the scan-and-go context, showing the value of distinguishing customers by their approach to innovation.

Familiarity adds a recent retail-specific condition. Consumers can favour an established search engine over a generative AI chatbot even when they see less bias in the chatbot output (Kim & Priluck, 2025). Retail-chatbot acceptance also rises through familiarity with generative AI (Arce-Urriza et al., 2025). Adoption communication should therefore provide evidence that makes the task and data exchange understandable, not merely describe the technology as innovative.

Social proof supports readiness through observations, ratings and recommendations. Online reputation systems transmit word-of-mouth information at scale (Dellarocas, 2003), blogger recommendations can influence online shopping intentions (Hsu et al., 2013), and application ratings can affect paid-app purchase intention (Hsu & Lin, 2015). These findings justify including credible ratings and visible successful use in the readiness stage.

### 4.2 Assisted trial

The assisted-trial stage converts promised usefulness into an actual first experience. Effort expectancy and facilitating conditions explain why a customer may intend to use a technology but fail to complete the task when support, compatibility or knowledge is insufficient (Venkatesh et al., 2003, 2012). Retail virtual-assistant research identifies customer-related barriers as a major implementation problem, confirming that technical deployment alone does not secure customer use (Kamoonpuri & Sengar, 2023).

The level of automation also matters during trial. Autonomous-store research examines patronage across different levels of in-store automation, supporting the view that automation should be designed as degrees and locations of customer participation rather than as a single all-or-nothing choice (Benoit et al., 2024). The assisted-trial stage therefore retains a visible route to employee support where an error, payment problem or information gap interrupts completion.

### 4.3 Value confirmation

Value confirmation occurs when the customer compares the delivered experience with the prior promise. Confirmation contributes to satisfaction and continuance in expectation-confirmation theory (Bhattacherjee, 2001), which extends the expectation and satisfaction process established by Oliver (1980). In paid mobile applications, confirmation improved perceived value and satisfaction (Hsu & Lin, 2015).

The value judgement includes what is received and what is sacrificed. Perceived value combines quality or benefits with monetary and non-monetary sacrifice (Zeithaml, 1988), while functional, emotional and social value can be distinguished in consumer evaluation (Sweeney & Soutar, 2001). In AI-enabled services, sacrifice can include time, effort, data disclosure and loss of desired human contact; benefit can include speed, availability, personalisation, precision and convenience (Ameen et al., 2021; Shah et al., 2023).

Recent chatbot research adds a situational boundary. Empathy can improve satisfaction through social presence and information quality, yet it can reduce the customer experience under time pressure (Juquelier et al., 2025). Value confirmation must therefore be assessed against the customer's immediate service goal. A caring conversational style and a rapid transactional style are not interchangeable in every encounter (Huang & Rust, 2024; Juquelier et al., 2025).

### 4.4 Routine formation

Routine formation is separate from first acceptance because repeated behaviour can become less dependent on deliberate intention (Ouellette & Wood, 1998). Information-systems research shows that habit can limit the predictive power of intention after a behaviour becomes established (Limayem et al., 2007). UTAUT2 accordingly includes habit as a consumer-use determinant (Venkatesh et al., 2012), and habit was important in the use of scan-and-go systems among active users (Kašparová, 2024).

Continuity supports routine by reducing the need to relearn the process. Stable access, saved preferences, predictable error handling and consistent employee support follow from the role of facilitating conditions and habit in use behaviour (Venkatesh et al., 2003, 2012; Limayem et al., 2007). Routine use should still be separated from loyalty because repeated use can arise from convenience without a strong relational commitment; customer-journey research treats experience as a sequence of touchpoints rather than a single isolated transaction (Lemon & Verhoef, 2016).

### 4.5 Commercial conversion

Commercial conversion asks whether confirmed usage value becomes payment, a higher-value purchase, retention or another measurable commercial outcome. Hsu and Lin (2015) found that value for money, ratings and free alternatives directly influenced paid-app purchase intention. Satisfaction did not directly predict purchase intention in the full sample, although it was relevant among actual purchasers (Hsu & Lin, 2015). The evidence establishes that a satisfied free user cannot be assumed to become a paying customer.

Price value in UTAUT2 compares perceived benefits with monetary cost (Venkatesh et al., 2012). Perceived-value research adds functional, emotional and social value to this comparison (Sweeney & Soutar, 2001). Recent product-search research shows that a familiar alternative can remain preferred even when AI-generated results are evaluated favourably on bias (Kim & Priluck, 2025). Commercial conversion therefore depends on a clear, credible difference between the focal offer and the available alternative.

## 5. Feedback Mechanisms

The first feedback mechanism is service recovery. A failed encounter changes the customer's later assessment of effort, risk and expected performance, while a reliable hand-off can protect the customer journey (Wirtz et al., 2018; Ferraro et al., 2024). Generative AI-enabled customer service contains managerial paradoxes because greater conversational capability can improve connection while also creating concerns about consistency, transparency and responsible use (Ferraro et al., 2024). Recovery design should therefore specify when the AI continues, when it explains and when an employee takes control.

The second mechanism is social proof. Individual experiences become ratings, recommendations and observations that influence later customers (Dellarocas, 2003; Hsu et al., 2013). Ratings also enter the commercial evaluation of paid applications rather than operating only as awareness signals (Hsu & Lin, 2015). This feedback connects value confirmation by one customer with adoption readiness and commercial conversion for another.

The third mechanism is cumulative satisfaction. Homburg et al. (2005) found a positive nonlinear relationship between customer satisfaction and willingness to pay and found cumulative satisfaction to be more influential than transaction-specific satisfaction. This evidence connects repeated confirmed experiences with later payment evaluation, while also showing why one satisfactory transaction is insufficient evidence of a price premium.

## 6. Managerial Application

The architecture can be used as a stage-based audit. Adoption readiness can be assessed through usefulness, relevance, familiarity and credible social evidence (Davis, 1989; Rogers, 2003; Arce-Urriza et al., 2025). Assisted trial can be assessed through completion, effort, support use and customer barriers (Venkatesh et al., 2003; Kamoonpuri & Sengar, 2023). Value confirmation can be assessed through confirmation, perceived value and satisfaction (Bhattacherjee, 2001; Hsu & Lin, 2015). Routine formation can be assessed through repeat use and habit (Limayem et al., 2007; Kašparová, 2024). Commercial conversion can be assessed through paid choice, retention, value for money and willingness to pay (Homburg et al., 2005; Hsu & Lin, 2015).

The architecture also separates customer metrics from operating metrics. In-store AI may affect customer efficiency, customer experience, employee efficiency and employee experience differently (Grewal et al., 2023). Robot-service quality may support engagement through automation, personalisation, efficiency and precision, but anthropomorphism can change these relationships (Shah et al., 2023). Managers therefore need measures tied to the particular customer task and service configuration instead of one general AI-adoption indicator.

Human support remains part of the service design. AI can take different roles at the frontline, and anthropomorphic role, appearance and interactivity shape the agency presented to customers (Chong et al., 2021). Feeling AI can contribute to customer care, but the technology has capability limits and must be aligned with marketing requirements (Huang & Rust, 2024). Empathic responses can raise satisfaction in some conditions and weaken experience under time pressure in others (Juquelier et al., 2025). A defined employee hand-off is therefore supported where speed, judgement, empathy or recovery requirements exceed the appropriate AI role.

## 7. Research Implications

The evidence supports longitudinal testing because confirmation, habit and cumulative satisfaction develop across repeated use rather than at one observation point (Bhattacherjee, 2001; Limayem et al., 2007; Homburg et al., 2005). It also supports field comparison of assisted and unassisted trial because customer barriers and facilitating conditions occur during actual task completion (Venkatesh et al., 2003; Kamoonpuri & Sengar, 2023). These designs would test the proposed stage transitions without assuming that every relationship is linear.

Context should be retained in future testing. Scan-and-go, autonomous stores, product-search chatbots, service robots and complaint-handling systems differ in task complexity, social presence, disclosure and consequence (Moore et al., 2022; Grewal et al., 2023; Benoit et al., 2024; Kim & Priluck, 2025). Customer segments should also distinguish free users, paid users and users with different levels of AI familiarity because these groups have shown different purchase and adoption responses (Hsu & Lin, 2015; Arce-Urriza et al., 2025).

## 8. Conclusion

AI-enabled retail and service technology creates commercial value through a sequence of customer decisions rather than through acceptance alone. Seminal research establishes the roles of usefulness, effort, facilitating conditions, diffusion, confirmation, value, habit, satisfaction and willingness to pay (Davis, 1989; Oliver, 1980; Zeithaml, 1988; Ouellette & Wood, 1998; Bhattacherjee, 2001; Rogers, 2003; Venkatesh et al., 2003, 2012; Homburg et al., 2005). Recent evidence adds familiarity, level of automation, robot-service quality, explainability, conditional empathy and human-AI service boundaries (Grewal et al., 2023; Shah et al., 2023; Benoit et al., 2024; Chen et al., 2024; Huang & Rust, 2024; Arce-Urriza et al., 2025; Juquelier et al., 2025; Kim & Priluck, 2025).

The resulting architecture separates adoption readiness, assisted trial, value confirmation, routine formation and commercial conversion. Service recovery, social proof and cumulative satisfaction connect later experience with earlier judgement. The central management conclusion is evidence-based: intention, use, satisfaction and payment must be measured separately because favourable results at one stage do not establish success at the next stage (Homburg et al., 2005; Hsu & Lin, 2015; Limayem et al., 2007).

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