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AI Adoption in Retail: Social Influences, Trust, and Technological Readiness Across Emerging and Developed Economies A Literature Review and the STAR-AI Framework

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Abstract

Artificial intelligence (AI) is fundamentally transforming the retail sector through personalised recommendations, conversational agents, and autonomous decision-making systems. Adoption patterns, however, differ markedly between emerging and developed economies due to variations in cultural values, trust dynamics, and technological infrastructure. This literature review synthesises empirical evidence from 31 peer-reviewed studies, selected from 630 records across five major databases in accordance with PRISMA guidelines (2020–2024), to examine how social influence, trust, and technological readiness shape consumer AI adoption. Through a comparative analysis of India, representing an emerging economy, and Australia, representing a developed economy, the study introduces the STAR-AI (Social, Trust, Adoption, and Readiness for AI) Framework as an integrative theoretical contribution. The findings indicate that social influence operates through informational, normative, and identification mechanisms, exerting a stronger impact on consumer attitudes in collectivist cultures, such as India, than in individualistic cultures, such as Australia. Trust emerges as a dynamic construct, ranging from initial transparency to performance-based calibration. Technological readiness, which includes digital infrastructure, AI literacy, and generational disposition, significantly moderates adoption intentions. High uncertainty avoidance is found to reduce the impact of performance and effort expectancies, while Generation Z exhibits distinct adoption behaviours driven by digital fluency and heightened personalisation expectations. The STAR-AI Framework integrates macro-level contexts, meso-level antecedents, individual-level constructs, and specific AI touchpoints to predict adoption outcomes. The study offers actionable managerial and policy implications, recommending culturally tailored strategies such as leveraging community endorsements in collectivist markets and prioritising algorithmic transparency in high-uncertainty-avoidance cultures, alongside robust data privacy and AI literacy initiatives

Keywords: artificial intelligence, retail adoption, social influence, trust calibration, technological readiness, UTAUT2, Technology Readiness Index, cultural dimensions, perceived risk, algorithmic transparency, omnichannel, Generation Z, emerging economies, developed economies, STAR-AI Framework

1. Introduction

Artificial intelligence (AI) is transforming the retail sector by fundamentally changing how consumers discover, evaluate, and purchase products. AI-powered recommendation engines analyse browsing patterns and purchase histories to provide highly personalised product suggestions. Conversational agents deliver continuous customer support through natural language interfaces, and autonomous decision-making systems can execute purchases for consumers based on learned preferences (Pillai et al., 2020; Roy et al., 2020; Sharma et al., 2024). These technologies yield significant benefits, such as enhanced operational efficiency, reduced labour costs, improved customer satisfaction, and increased revenue through precision targeting (Dwivedi et al., 2021; Huang & Rust, 2020; Moore et al., 2022). Nevertheless, AI adoption rates in retail differ substantially across geographic markets and consumer segments.

Emerging economies such as India are undergoing rapid integration of artificial intelligence (AI) in e-commerce platforms, driven by a mobile-first infrastructure and a large, digitally literate youth population. India currently has the third-largest internet community globally(Khan, 2022), with internet penetration reaching 52% in 20242. This digital expansion has propelled the Indian online grocery market to a valuation of INR 760.2 billion in 2024, with projections indicating growth to INR 1,864.33 billion by 2028 at a compound annual growth rate (CAGR) of 19.55% (Bhatt & Singh, 2025). AI adoption in this retail sector is accelerating over 50% of grocery stores in India are now accessible via online platforms(Bhatt & Singh, 2025), 51% of Indian retail customers utilise AI chatbots for product searches and shopping recommendations (Bhatt & Singh, 2025), and more than 28% of all online product search inquiries are conducted using AI-enabled voice search technology. Adoption patterns in these contexts are influenced by collectivist cultural values that emphasise community endorsements and social validation rather than individual experimentation (Aruna et al., 2024) These differences suggest that AI adoption in retail is influenced by a combination of technological factors, cultural context, social influences, trust dynamics, and technological readiness.

2. Research Gap and Motivation

Existing literature on technology adoption in retail predominantly focuses on discrete constructs, including perceived usefulness and ease of use [TAM -Technology Acceptance Model](Davis, 1989) performance expectancy and social influence [UTAUT- Unified Theory of Acceptance and Use of Technology](Venkatesh et al., 2003), and subjective norms and perceived behavioural control [TPB-Theory of Planned Behaviour](Ajzen, 1991). Research on chatbot adoption has similarly utilised the Technology Acceptance Model for conversational agents (Fu et al., 2024; Myin & Watchravesringkan, 2024; Silva et al., 2022), while studies on recommendation systems have extended UTAUT2 (Venkatesh et al., 2012) to personalisation contexts (Alalwan, 2020). While these frameworks provide important insights, they exhibit three notable limitations when applied to artificial intelligence in retail settings.

First, conceptual fragmentation remains prevalent among overlapping constructs. Terms such as 'social influence' (UTAUT), 'subjective norms' (TPB), and 'social norms' are often used interchangeably, despite their distinct theoretical bases and measurement methods (Sharma et al., 2024). This conflation obscures the specific mechanisms through which social factors affect AI adoption, such as informational influence (peers provide credible information), normative influence (desire for social approval), and identification (alignment with aspirational reference groups).

Second, trust in AI systems is frequently treated as a static, unidimensional construct in retail adoption studies. However, recent cross-disciplinary research distinguishes between initial trust, established through transparency and explainability cues, and calibrated trust, which evolves based on system performance and user experience (Gefen et al., 2003; Kumar & Bargavi, 2024; McKnight et al., 2002; Oyekunle et al., 2024). Furthermore, trust frameworks from organisational behaviour, such as the Mayer–Davis–Schoorman model emphasising ability, benevolence, and integrity (Mayer et al., 1995) are rarely integrated into retail AI adoption research. Pavlou's (Pavlou, 2014) foundational work on e-commerce trust and risk further illustrates how perceived risk mediates the relationship between trust and adoption.

Third, cultural and economic contexts are insufficiently theorised in existing research. Although Hofstede's cultural dimensions theory is frequently cited(Sharma et al., 2024), it is often applied superficially and without triangulation with other cross-cultural frameworks, such as Innovation Diffusion Theory (Aruna et al., 2024) or the Technology Readiness Index 2.0, or with objective digital readiness indicators, including the ITU ICT Development Index and World Bank income classifications(Sector, 2025). This over-reliance on Hofstede increases the risk of ecological fallacy and fails to capture the multidimensional nature of cultural influence on technology adoption (Aruna et al., 2024; Fan et al., 2022; Guerra-Tamez et al., 2024).

3. Research Objectives

- This study synthesises empirical evidence on the roles of social influence, trust, and technological readiness in shaping consumer adoption of artificial intelligence in retail, with explicit delineation of overlapping constructs and their theoretical foundations.
- A comparative analysis is conducted between an emerging economy (India) and a developed economy (Australia) to identify culturally contingent adoption mechanisms and infrastructure-related moderating factors.
- The STAR-AI Framework (Social, Trust, Adoption, and Readiness for AI) is proposed as an integrative theoretical model that maps macro-level context, meso-level antecedents, individual-level constructs, and AI retail touchpoints to adoption outcomes.

4. Theoretical Contribution

This review provides four principal contributions.

Theoretically, this review advances understanding by (1) differentiating social influence mechanisms (informational, normative, identification) from the Theory of Planned Behaviour's subjective norms construct; (2) integrating initial trust and calibrated trust frameworks into retail AI adoption models (Gefen et al., 2003; McKnight et al., 2002; Pavlou, 2014); and (3) triangulating Hofstede's cultural dimensions with Innovation Diffusion Theory (Rogers, 2003), Technology Readiness Index 2.0 (Parasuraman & Colby, 2014), and digital infrastructure indicators.

Empirically, this review presents the first systematic synthesis of AI adoption in retail across both emerging and developed economies, identifying culturally contingent effect sizes and moderation patterns.

Methodologically, this review demonstrates rigorous systematic review procedures, including PRISMA flow, quality appraisal, and inter-construct mapping.

Practically, this review provides actionable managerial implications segmented by consumer readiness profiles and cultural contexts, as well as policy recommendations for data privacy, algorithmic transparency, and AI literacy initiatives

5. Theoretical Foundations

This section provides the theoretical foundation for understanding AI adoption in retail by reviewing and integrating seven foundational frameworks. The accompanying table maps constructs across these frameworks to minimize conceptual overlap and clarify their unique contributions

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) (Davis, 1989) proposes that perceived usefulness (PU) and perceived ease of use (PEOU) are the primary determinants of technology acceptance. In retail artificial intelligence (AI) contexts, PU denotes the belief that recommendation engines help consumers efficiently identify relevant products, thereby saving time and improving purchase decisions (Arachchi & Samarasinghe, 2023; Nagy & Hajdu, 2021). PEOU refers to the intuitiveness of conversational agent interfaces and the cognitive effort required to interact with autonomous shopping systems (Fu et al., 2024; Lopes et al., 2024). While TAM has been validated across a range of technologies, typically explaining 30–40% of the variance, its simplicity omits social influences, facilitating conditions, and individual differences that can moderate technology acceptance (Gefen et al., 2003; Venkatesh et al., 2003).

UTAUT and UTAUT2

The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) synthesise eight prior adoption models into four core constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. These constructs predict behavioural intention and use behaviour, with their effects

moderated by gender, age, experience, and voluntariness. Empirical research in retail contexts demonstrates that UTAUT constructs explain 45–56% of the variance in AI adoption intentions (Roy et al., 2020; Sharma et al., 2024). UTAUT2 (Venkatesh et al., 2012) adapts the model for consumer contexts by adding hedonic motivation, price value, and habit. In AI retail, hedonic motivation captures the entertainment value of interacting with AI digital humans (Moore et al., 2022), while habit refers to routinised reliance on AI recommendations (Alalwan, 2020; Pillai et al., 2020).

Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (TPB)(Ajzen, 1991) asserts that behavioural intention is shaped by attitude toward the behaviour, subjective norms perceived social pressure, and perceived behavioural control. In AI retail contexts, subjective norms reflect the perceived expectations of friends, family, and colleagues regarding AI use. Importantly, TPB's subjective norms are conceptually distinct from UTAUT's social influence construct. Subjective norms measure the perceived expectations of significant others, while social influence includes broader mechanisms such as informational influence, normative conformity, and identification with aspirational groups (Sharma et al., 2024).

Hofstede's Cultural Dimensions Theory

Hofstede's cultural dimensions (Hofstede, 2010) provide a framework for understanding cross-national variation in AI adoption. Three dimensions are particularly relevant:

- **Individualism versus Collectivism (IDV):** Collectivist cultures, such as India (IDV = 48), prioritise group harmony and social validation, which amplifies the effects of social influence on AI adoption (Sharma et al., 2024). Conversely, individualistic cultures, such as Australia (IDV = 90), emphasize personal autonomy and self-reliance.
- **Uncertainty Avoidance (UA):** Cultures characterised by high uncertainty avoidance tend to experience discomfort with algorithmic opacity, which diminishes the effects of performance expectancy, effort expectancy, and social influence (Sharma et al., 2024) India (UA = 40) exhibits moderate avoidance, whereas Australia (UA = 51) exhibits moderate-to-high avoidance.
- **Power Distance (PD):** Cultures with high power distance, such as India (PD = 77), accept hierarchical authority, which leads to increased deference to AI recommendations from trusted brands (Lundgren & Walczuch, 2003).

Trust Frameworks: Mayer–Davis–Schoorman and Calibrated Trust

The Mayer–Davis–Schoorman (MDS) model (Mayer et al., 1995) defines trust as the willingness to accept vulnerability grounded in positive expectations of another party's behaviour. Within this model, trustworthiness comprises three dimensions: ability, defined as competence to perform; benevolence, or motivation to act in the trustor's interest; and integrity, which refers to adherence to accepted principles. In AI retail contexts, ability denotes recommendation accuracy, benevolence reflects the perceived alignment of AI objectives with consumer interests, and integrity concerns transparency about data usage and algorithmic logic.Recent research differentiates initial trust, established prior to direct experience through transparency cues, explainability, and interface design (Kumar & Bargavi, 2024), from calibrated trust, which is dynamically adjusted based on system performance, error recovery, and accumulated interaction experience(Oyekunle et al., 2024) .This distinction is essential for AI retail systems, as trust trajectories evolve across multiple consumer touchpoints. The emergence of Generative AI and Large Language Models (LLMs) has fundamentally transformed trust dynamics in digital systems. Recent advancements in LLM-enabled explainable recommender systems demonstrate that transparent, diffusion-based explanations enhance both recommendation accuracy and initial consumer trust. Responsible GenAI syntheses suggest that explainability is an essential requirement for regulatory compliance in contemporary retail environments. Additionally, lightweight transparency signals, such as accuracy badges or explicit disclosure of AI involvement, can address the "market for lemons" problem in AI adoption. These findings indicate that actionable transparency improves consumer decision efficiency more effectively than exhaustive technical detail.

Innovation Diffusion Theory

Rogers' (2003) Innovation Diffusion Theory (Rogers, 2003) explains how innovations spread within social systems. The theory identifies five adopter categories—innovators, early adopters, early majority, late majority, and laggards—as well as five perceived attributes of innovations: relative advantage, compatibility, complexity, trialability, and observability. Within the context of AI adoption in retail, the attribute of relative advantage corresponds to the performance expectancy construct in the Unified Theory of Acceptance and Use of Technology (UTAUT). Conversely, the complexity attribute is inversely related to the effort expectancy. Innovation Diffusion Theory (IDT) introduces observability, which refers to the degree to which the benefits of AI are apparent to potential adopters. Observability is particularly important in collectivist cultures, where peer observation exerts a strong influence on the spread of adoption cascades.

Technology Readiness Index 2.0 (TRI 2.0)

The Technology Readiness Index 2.0 (Parasuraman & Colby, 2014) measures consumers' propensity to adopt new technologies. This index evaluates four dimensions: optimism, defined as a positive view of technology; innovativeness, characterised by a pioneering tendency; discomfort, reflecting a perceived lack of control; and insecurity, indicating distrust of technology. In contrast to the Technology Acceptance Model (TAM), which examines perceptions of specific technologies, the Technology Readiness Index 2.0 captures dispositional readiness, a stable trait that predicts technology acceptance across diverse contexts. Within retail artificial intelligence (AI) adoption, elevated optimism and innovativeness facilitate initial adoption, while higher discomfort and insecurity contribute to resistance, especially in cultures characterized by high uncertainty avoidance (UA) (Kolar et al., 2024).

Table 1 -Construct and theoretical framework

Construct	TAM	UTAUT / UTAUT2	TPB	Other Frameworks
Perceived Usefulness	PU	Performance Expectancy	Attitude (partial)	Relative Advantage (IDT)
Ease of Use	PEOU	Effort Expectancy	Perceived Behavioural Control	Complexity (IDT, inverse)
Social Factors	—	Social Influence	Subjective Norms	Observability (IDT); Collectivism (Hofstede)
Infrastructure	—	Facilitating Conditions	—	Trialability (IDT); ICT Index
Trust	—	—	—	MDS Model; TRI 2.0 (Insecurity)
Cultural Context	—	Moderators (Gender, Age)	—	Hofstede; IDT Adoption Curves
Generational Disposition	—	Age Moderator	—	TRI 2.0; Gen Z TAM Extension

6. Methodology

Research Questions

This review investigates three primary research questions:

- RQ1. How do social influence and subjective norms shape consumer AI adoption in retail, and how do these effects differ between emerging and developed economies?
- RQ2. What role does trust, including initial trust formation and calibrated trust dynamics, play in consumer AI adoption in retail?
- RQ3. How does technological readiness, including infrastructure, AI literacy, and generational disposition, moderate AI adoption intentions across cultural contexts?

Search Strategy

We performed systematic searches across five databases: Scopus, Web of Science, IEEE Xplore, Google Scholar, and EBSCO. The searches were conducted in January 2024 and included publications from January 2020 to December 2024. The search strategy utilised terms from three concept clusters: The concept clusters were as follows:

- *Cluster 1 (Technology): "artificial intelligence" OR "AI" OR "machine learning" OR "recommendation system" OR "chatbot" OR "conversational agent" OR "autonomous decision-making"*
- *Cluster 2 (Retail/Consumer): "retail" OR "e-commerce" OR "online shopping" OR "consumer behaviour" OR "purchase intention" OR "omnichannel"*
- *Cluster 3 (Adoption/Trust): "technology adoption" OR "TAM" OR "UTAUT" OR "trust" OR "perceived risk" OR "privacy" OR "social influence" OR "social norms" OR "technological readiness" OR "TRI" OR "cultural dimensions"*

Screening and Selection Process

The inclusion criteria were: (1) peer-reviewed empirical studies (quantitative, qualitative, or mixed-methods); (2) focus on consumer AI adoption in retail or e-commerce contexts; (3) published in English between January 2020 and December 2024; (4) examining at least one of: social influence, trust, technological readiness, or cultural factors.

The exclusion criteria were: (1) non-empirical opinion pieces, editorials, or commentaries; (2) studies focused exclusively on B2B AI adoption without consumer-facing components; (3) grey literature, conference abstracts without full text, or non-peer-reviewed sources; (4) studies pub-published before 2020 (retained only for foundational theoretical frameworks).The screening process adhered to PRISMA 2020 guidelines (Page et al., 2021). Initial database searches retrieved 630 records (Scopus: 187, Web of Science: 143, IEEE Xplore: 89, Google Scholar:10 142, EBSCO: 69). After removing 124 duplicates, 506 records were screened at the title and abstract level, resulting in 68 full-text articles for eligibility assessment. Quality appraisal (see Section below) excluded 37 articles for insufficient methodological rigour, resulting in a final corpus of 31 peer-reviewed articles.

Table 2- Selection stages

Stage	Records
Initial database search results	630
Duplicates removed	124
Records after deduplication	506
Excluded at title/abstract screening	438
Full-text articles assessed	68

Excluded after quality appraisal	37
Final corpus (included studies)	31

Quality Appraisal

The appraisal criteria included: (1) clearly stated research objectives; (2) research design appropriate to the objectives; (3) valid and reliable measurement instruments; (4) adequate sample size and recruitment strategy; (5) appropriate statistical analysis; and (6) clear reporting of findings and limitations. Studies rated as 'low quality' on three or more criteria were excluded.

Data Extraction and Synthesis

Data extraction employed a standardised coding framework to capture study context (country, economy type, retail channel), theoretical frameworks, measured constructs, key findings (including effect directions and sizes where reported), and quality appraisal scores. Thematic synthesis (Page et al., 2021) was used to identify patterns across studies, while comparative analysis contrasted findings between emerging and developed economy contexts.

7. Methodology Social Influence and Normative Determinants in AI Adoption within Retail Contexts

- **Conceptual Clarification:** Distinguishing Social Influence from Subjective Norms. A recurring conceptual ambiguity in AI adoption research involves conflating social influence, as defined by the Unified Theory of Acceptance and Use of Technology (UTAUT)(Venkatesh et al., 2003), with subjective norms from the Theory of Planned Behaviour (TPB). This section explicitly differentiates between these constructs.
- **Social Influence: -** Within the UTAUT framework, social influence is defined as the degree to which individuals perceive that significant others believe they should use a particular technology (Venkatesh et al., 2003). This construct operates through three primary mechanisms: (a) informational influence, where peers provide credible information that reduces perceived uncertainty; (b) normative influence, in which the desire for social approval motivates conformity to group patterns of AI usage; and (c) identification, where consumers adopt AI behaviours to align with aspirational reference groups.
- **Subjective norms: -** as defined in the Theory of Planned Behaviour (TPB), refer specifically to the perceived expectations of significant others regarding whether an individual should perform a particular behaviour (Ajzen, 1991). This construct is narrower than social influence, as it emphasises injunctive pressure rather than encompassing broader social learning mechanisms.

Empirical evidence demonstrates that social influence significantly predicts attitudes toward autonomous AI systems (Sharma et al., 2024). These effects are more pronounced in collectivist cultures, such as India, where community endorsements are pivotal (Aruna et al., 2024), and are less pronounced in individualistic cultures, such as Australia, where personal experiences exert greater influence (Quintus et al., 2024).

Social Influence Effects Across Cultural Contexts

In collectivist cultures, social influence primarily operates through informational and normative mechanisms. Consumers in India demonstrate a strong reliance on peer recommendations and word-of-mouth endorsements when evaluating AI retail platforms (Bhatt & Singh, 2025; Manikandan & Bhuvaneswari, 2024). This behaviour aligns with Hofstede's collectivism dimension (India IDV = 48), where group identity and interdependence influence technology evaluations (Fan et al., 2022; Hofstede, 2010). Positive word-of-mouth from trusted community members, such as family, friends, and religious leaders, serves as a credibility signal that reduces perceived risk associated with delegating purchase decisions to AI systems (Guerra-Tamez et al., 2024).

In individualistic cultures, social influence effects are less pronounced but still present. Australian consumers (IDV = 90) primarily depend on personal experience and self-efficacy assessments (Quintus et al., 2024). In these contexts, social influence operates mainly through identification mechanisms, as consumers adopt AI tools used by aspirational peers, such as fitness influencers and lifestyle bloggers, rather than responding to direct normative pressure. This distinction has significant implications for marketing strategy: collectivist markets benefit from community-based testimonials, whereas individualistic markets respond more effectively to personalised demonstrations of AI value.

Social Significance of AI

The integration of AI digital humans into physical retail environments generates new forms of social dynamics. These dynamics extend beyond traditional constructs of social influence (Moore et al., 2022). Ethnographic research in Australasian technology retail stores identifies three distinct social phenomena:

- **Social tensions**: Consumers report stress and social anxiety when interacting incorrectly with AI digital humans, often perceiving negative judgment from other shoppers and staff (Moore et al., 2022). This performance-related pressure is particularly acute among older consumers and individuals with low AI literacy.
- **Life of the party effect**: AI digital assistants unexpectedly transform the social environment by creating opportunities for shared entertainment and strengthening social bonds among shopping companions (Moore et al., 2022). Groups of shoppers engage with AI for humorous interactions, thereby enhancing hedonic shopping experiences.
- **Paradox of human interaction**: AI digital humans simultaneously attract consumers who seek to avoid human service interactions and repel those who prefer human connection. A positive customer experience for one segment may correspond with a negative experience for another. These findings underscore that AI retail adoption is not solely a cognitive decision-making process but also a socially embedded practice shaped by contextual social norms, audience effects, and performance anxiety (Moore et al., 2022).

Generation Z and Social Influence

Generation Z consumers, defined as individuals born from the mid-1990s to the early 2010s, exhibit distinct patterns of social influence, particularly in the context of AI retail adoption. As digital natives, this cohort is marked by digital fluency, familiarity with algorithmic interfaces, and heightened expectations for personalized experiences (Bunea et al., 2024; Jeffrey, 2021; Saklani & Kala, 2024). Social influence among Generation Z primarily occurs through digital channels, including social media endorsements, influencer recommendations, and peer reviews on platforms such as TikTok and Instagram, which function as primary information sources for evaluating AI retail offerings (Guerra-Tamez et al., 2024; Vitezić & Perić, 2021). Bunea et al. demonstrate that exposure to AI (EAI), usage of AI (UOAI), and knowledge about AI (KAAI) directly influence perceived usefulness and purchase intention. Collectively, these factors account for 53.8% of the variance in purchase intentions. These findings indicate that, for Generation Z, familiarity developed through social exposure, rather than direct normative pressure, constitutes the primary mechanism by which social influence operates.

8. Trust in AI Retail Systems

Formation of Initial Trust

People often form initial trust in AI retail systems before using them, and this trust is shaped by three main factors primary antecedents (Kumar & Bargavi, 2024):

1. System transparency and explainability: Consumers tend to trust AI systems more at first when these systems clearly explain how their recommendations work (Adanyin, 2024; Kumar & Bargavi, 2024). Transparent sharing information about data sources, algorithms, and the reason behind recommendations helps reduce confusion and build trust in the system's abilities, as explained in the MDS model (Gefen et al., 2003; Mayer et al., 1995).

2. Interface design and user experience: Easy-to-use, intuitive interfaces show that the system is competent and make users feel less effort is needed (Lopes et al., 2024; Nagy & Hajdu, 2021). First impressions from using the interface create trust anchors that last through later interactions (Fogg, 2002; McKnight et al., 2002).
3. Perceived value alignment: Consumers are more likely to trust AI systems that seem to put their interests ahead of commercial goals (Canhoto et al., 2023; Oyekunle et al., 2024). People develop benevolence-based trust when AI recommendations match what they want, instead of just trying to maximize platform revenue (Lappeman et al., 2022; Wang et al., 2019).

Calibrated Trust and Dynamic Adjustment

Calibrated trust means that people adjust their trust in AI over time as they gain more experience. Consumers increase trust when AI recommendations prove accurate, when systems recover effectively from errors, and when personalisation improves over time. Conversely, trust decreases following recommendation failures, privacy violations, or perceived manipulation. Quantitative evidence from (Oyekunle et al., 2024) identifies perceived usefulness, domain expertise, and perceived transparency as significant positive predictors of consumer trust in AI. In contrast, perceived risk and prior negative experiences significantly decrease trust.

Perceived Risk, Privacy, and Trust Erosion Risk

Perceived risk is a major reason people hesitate to use AI in retail. It works through three main channels: privacy risk (worry about unauthorised data collection and use), performance risk (concern that AI recommendations might be wrong or not useful), and social risk (worry about being judged for using AI shopping tools) (Kim et al., 2008). When it comes to AI in online shopping, most consumer concerns are about privacy (45%), algorithmic bias (25%), and transparency (30%) (Akbar et al., 2024). These worries are even stronger in cultures with high uncertainty avoidance, where people are especially uncomfortable with ambiguity and uncertainty (Lundgren & Walczuch, 2003). Privacy risk stands out even more when AI systems make decisions on their own and access financial data, purchase histories, and behaviour patterns (Brooksbank et al., 2022; Kim et al., 2023; Sharma et al., 2024). The personalization–privacy paradox (Canhoto et al., 2023; Wang et al., 2019) makes things more complicated: people want personalized AI experiences but are also afraid of the data collection needed to make them possible.

Cultural Moderators of Trust

How people form trust in AI varies across cultures (Qin, 2017). In cultures with high power distance, like India (PD = 77), people are more likely to trust AI systems that are supported by big institutions such as banks, government, or major retailers (Lundgren & Walczuch, 2003). In cultures with low power distance, like Australia (PD = 38), support from institutions matters less. Instead, trust is built through personal experience and what peers say. Cultures with high uncertainty avoidance need more transparency and clear explanations to reach the same trust levels as cultures with low uncertainty avoidance, since ambiguity tolerance affects how people respond to unclear algorithms and how trust is formed (Quintus et al., 2024).

9. Technological Readiness

Infrastructure Readiness

Infrastructure readiness encompasses internet penetration, mobile connectivity, digital payment systems, and the availability of AI platforms. These factors represent necessary but not sufficient conditions for the adoption of AI in retail. India's digital infrastructure has undergone rapid transformation: Internet penetration reached 52% in 2024 (Sector, 2025), driven by affordable mobile data and government digital initiatives. Nevertheless, significant disparities between rural and urban regions persist, with AI retail adoption concentrated in metropolitan centres (Bhatt & Singh, 2025). Australia's advanced infrastructure (internet

penetration: 96%, (Sector, 2025) provides universal access but does not guarantee adoption, as consumer readiness and trust continue to serve as critical mediating factors.

AI Literacy and Knowledge

AI literacy, defined as the capacity to understand, evaluate, and use AI systems effectively, is an emerging construct that moderates the relationship between technological readiness and the intention to adopt AI intention (Bunea et al., 2024; Jeffrey, 2021). Individuals with higher AI literacy demonstrate a greater ability to evaluate the quality of recommendations, detect algorithmic bias, and make informed decisions regarding data sharing (Adanyin, 2024; Xing et al., 2023). The combined predictors, including EAI, UOAI, and KAAI, account for 17.7% of the variance in perceived usefulness of AI (PUAI) and 15.9% of the variance in perceived ease of use of AI (PEUAI) among Generation Z consumers (Bunea et al., 2024).

Generation Z: A Distinct Readiness Profile

Generation Z consumers exhibit a distinct technological readiness profile compared to prior generational cohorts (Bunea et al., 2024; Jeffrey, 2021; Saklani & Kala, 2024; Vitezić & Perić, 2021):

- High optimism and innovativeness (TRI 2.0): Generation Z consumers report above-average scores on the optimism and innovativeness dimensions of TRI 2.0, indicating positive dispositions toward AI technologies.
- Critical evaluation: Despite high familiarity, Generation Z consumers engage in critical assessment before adopting AI technologies. They assess AI recommendations in relation to personal values, social identity, and ethical considerations (data privacy, algorithmic fairness).
- Personalisation expectations: Generation Z expects AI systems to deliver highly personalised experiences that adapt to individual preferences in real time. Non-personalised recommendations are perceived as system failures rather than acceptable defaults.
- Seamless integration: Generation Z consumers expect AI to function seamlessly across channels such as mobile, web, and in-store platforms, ensuring consistent personalisation across all touchpoints.

Attitude as a Mediator

Attitude toward AI adoption serves as a mediator between individual-level constructs (performance expectancy, effort expectancy, AI literacy) and behavioural intention (Sharma et al., 2024). Sharma et al. demonstrate that attitude explains 56% of the variance in autonomous shopping adoption intention, with performance expectancy, effort expectancy, social influence, and facilitating conditions as significant antecedents. Collectivism strengthens the relationship between social influence and attitude. In contrast, uncertainty avoidance reduces the associations of performance expectancy, effort expectancy, and social influence with attitude (Sharma et al., 2024).

10. Comparative Analysis: - Emerging vs. Developed Economies

India as an Emerging Economy Exemplar

India's AI retail adoption landscape is characterised by five distinctive features: (1) collectivist cultural values amplifying social influence effects; (2) high power distance increasing deference to institutional endorsements of artificial intelligence, combined with the rapid development of mobile-first infrastructure, facilitates access to artificial intelligence. However, a significant rural-urban digital divide leads to varying levels of readiness among user groups. Pronounced price sensitivity further influences the perceived value of premium artificial intelligence services (Bhatt & Singh, 2025; Manikandan & Bhuvaneswari, 2024). Collectively, these factors create an adoption environment where social validation and community endorsement are primary drivers, while affordability and infrastructure access remain critical constraints (Pillai et al., 2020; Roy et al., 2020).

Australia as a Model Developed Economy

Australia's artificial intelligence retail adoption landscape is shaped by several factors, including individualistic cultural values that emphasize personal autonomy and self-reliance(Bunea et al., 2024), advanced digital infrastructure that ensures universal access, and strong data privacy regulations (Adanyin, 2024; Department, 1988; Lappeman et al., 2022), which enhance consumer awareness of data rights. Additionally, moderate-to-high uncertainty avoidance increases demand for algorithmic transparency. The technologically sophisticated consumer base exhibits high baseline artificial intelligence literacy (Brooksbank et al., 2022; Quintus et al., 2024). These factors collectively create an adoption environment in which transparency, privacy protection, and demonstrated personal value are the primary drivers of adoption (Canhoto et al., 2023; Lappeman et al., 2022).

Table 3: Summary of Included Studies and Key Findings

Author (Year)	Country	Method	Framework	Key Finding
(Adanyin, 2024)	Multi-country	Survey	AI Ethics Framework	Transparency, fairness, and data protection are critical for consumer trust.
(Akbar et al., 2024)	Multi-country	Review	Trust Framework	The influence of artificial intelligence on consumer trust poses ethical challenges.
(Alalwan, 2020)	Saudi Arabia	SEM	TAM Extension	Trust and perceived risk impact continued intention to reuse AI-based apps.
(Arachchi & Samarasinghe, 2023)	Sri Lanka	PLS-SEM	Extended TAM	Attitudes towards technology strongly drive impulse purchase intentions.
(Aruna et al., 2024)	Multi-country	Comparative	TAM + Hofstede + IDT	Cultural values moderate AI adoption: collectivist cultures show stronger social influence.
(Bhatt & Singh, 2025)	India	Survey	TAM + UTAUT	Social influence and perceived usefulness are key drivers in Indian e-grocery adoption.
(Brooksbank et al., 2022)	USA	Survey / t-tests	TAM Extension	Consumers reject covert tracking but accept transparent surveillance if rewarded.
(Bunea et al., 2024)	Romania	PLS-SEM	Adapted TAM	AI exposure, usage, and knowledge explain 53.8% of variance in purchase intention.
(Canhoto et al., 2023)	UK	Qualitative	Privacy Paradox	Consumers deploy active boundary management to mitigate AI privacy risks.

(Guerra-Tamez et al., 2024)	Mexico	PLS-SEM	Flow Theory	Brand trust drives flow experience: AI exposure builds brand trust.
(Jeffrey, 2021)	Multi-country	Survey	Gen Z Perception	Generation Z's perception of AI in marketing is heavily influenced by trust.
(Kanapathipillai et al., 2024)	Malaysia	Linear Regression	Trust & Quality Model	Trust and service quality strongly enhance personalised customer experiences.
(Kim et al., 2023)	US & Singapore	CFA / SEM	Privacy Calculus	Cultural context moderates the effect of privacy concerns on AI adoption.
(Kolar et al., 2024)	Slovenia	Survey	TRI 2.0	Gender moderates TRI dimensions: women report higher discomfort with in-store AI.
(Kumar & Bargavi, 2024)	India	Conceptual + Empirical	TAM + Fogg Model	Transparency and explainability are critical for initial trust formation.
(Lappeman et al., 2022)	South Africa	PLS-SEM	Trust & Privacy Model	Willingness to disclose personal information is heavily contingent on brand trust.
(Thi Kim Hoa, 2025)	Vietnam	PLS-SEM	TAM Extension	Attitude mediates the relationship between AI attributes and purchase decisions.
(Lopes et al., 2024)	Portugal	SEM	TAM + Psychosocial	Perceived ease of use mediates the relationship between social factors and purchase intention.
(Manikandan & Bhuvaneswari, 2024)	India	ANOVA / Regression	General Adoption	AI has a significant positive impact on online consumer buying behaviour.
(Moore et al., 2022)	Australasia	Ethnographic	Practice Theory	AI digital humans create social tensions and a “life of the party” effect.
(Myin & Watchravesringkan, 2024)	US	CFA / SEM	BRT + TAM	Complexity significantly hinders the perceived ease of use of AI chatbots.

(Nagy & Hajdu, 2021)	Hungary	SEM	Extended TAM	Trust is the strongest predictor of perceived usefulness in AI adoption.
(Oyekunle et al., 2024)	Multi-country	SEM + Interviews	TAM + TPB + MDS	Transparency and risk significantly influence trust.
(Pillai et al., 2020)	Multi-country	PLS-SEM	TRAM	Perceived usefulness, fairness, and customization predict shopping intentions at AI stores.
(Quintus et al., 2024)	Advanced vs. Emerging	Survey	Trust Model	Consumers in advanced markets show higher privacy concerns and demand greater transparency.
(Sharma et al., 2024)	Fiji	CB-SEM	UTAUT + Hofstede	Social influence significantly impacts attitude; collectivism strengthens this effect.
(Shi et al., 2020)	Unspecified (Lab)	PLS-SEM	Heuristic-Systematic	Performance efficacy builds cognitive trust in AI recommendation systems.
(Silva et al., 2022)	Portugal & Italy	PLS-SEM	Flow Theory	Trust positively relates to flow experience in e-retailing chatbot interactions.
(Tubadji et al., 2021)	11 Countries	OLS / Probit	Cultural Relativity	Country-level cultural effects account for 20% of deviation in AI adoption.
(Vitezić & Perić, 2021)	Croatia	PLS-SEM	AIDUA Framework	Emotions directly influence Generation Z's willingness to use AI devices.
(Xing et al., 2023)	Multi-country	Systematic Review	Value Co-destruction	Identifies ethical, privacy, and security risks causing negative AI impacts.

11. Overview of the STAR-AI Framework

Drawing upon synthesised evidence, the STAR-AI Framework (Social, Trust, Adoption, and Readiness for AI) is presented as an integrative theoretical model that maps macro-level context, meso-level antecedents, individual-level constructs, and AI retail touchpoints to adoption outcomes (see Figure 1). This framework addresses gaps in existing models by: (1) explicitly integrating cultural dimensions and digital infrastructure as macro-level moderators; (2) distinguishing initial trust from calibrated trust; (3) incorporating generational disposition and AI literacy as individual-level moderators; and (4) specifying AI retail touchpoints as distinct contexts with differential adoption dynamics

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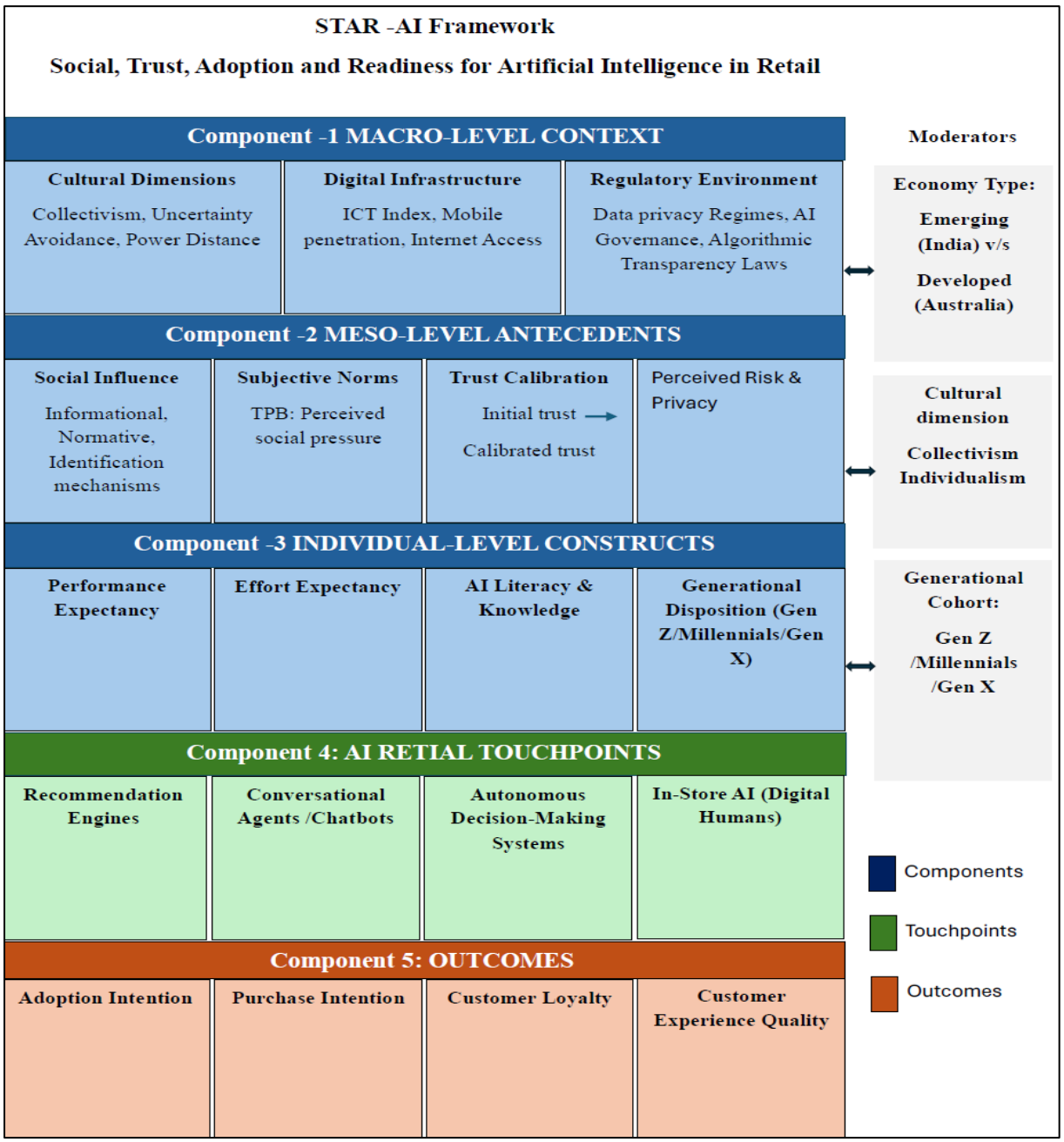

Figure 1:-The STAR-AI Framework: Social, Trust, Adoption, and Readiness for Artificial Intelligence in Retail .The framework delineates the progression from macro-level contexts, such as cultural dimensions, digital infrastructure, and regulatory environment, through meso-level antecedents, including social influence, trust calibration, and perceived risk, to individual-level constructs like performance expectancy, effort expectancy, AI literacy, and generational disposition. These factors collectively influence AI retail touchpoints and adoption outcomes. Moderators, including economy type, cultural dimensions, and generational cohort, operate across all layers (Hofstede, 2010; Mayer et al., 1995; Parasuraman & Colby, 2014; Venkatesh et al., 2003).

12. Key components of the framework

Component 1: Macro-Level Context. The macro-level context defines the environmental conditions that shape AI adoption decisions. Three sub-dimensions are identified within this context: cultural dimensions (collectivism versus individualism, uncertainty avoidance, power distance), (Hofstede, 2010); digital infrastructure (ICT

Development Index, mobile penetration, internet access, digital payment infrastructure); and regulatory environment (data privacy regimes, algorithmic transparency laws, AI governance frameworks).The macro-level context does not directly predict adoption but instead moderates the strength and direction of all lower-level relationships. Predict adoption but moderates the strength and direction of all lower-level relationships.

Component 2: Meso-Level Antecedents. Meso-level antecedents encompass social and relational factors that mediate between macro-level context and individual cognition. Four primary constructs are identified: social influence (informational, normative, and identification mechanisms)(Lopes et al., 2024; Venkatesh et al., 2003);subjective norms (Theory of Planned Behaviour-based perceived social pressure) (Ajzen, 1991); trust calibration (initial trust leading to a calibrated trust trajectory) (Gefen et al., 2003; Mayer et al., 1995; Oyekunle et al., 2024); and perceived risk and privacy (Canhoto et al., 2023; Kim et al., 2008; Wang et al., 2019).

Component 3: Individual-Level Constructs. Individual-level constructs capture consumer cognitive and dispositional factors. These include performance expectancy (Sharma et al., 2024; Venkatesh et al., 2003); effort expectancy (Lopes et al., 2024; Venkatesh et al., 2003); AI literacy and knowledge(Bunea et al., 2024; Jeffrey, 2021); and generational disposition (as measured by TRI 2.0: optimism, innovativeness, discomfort, and insecurity by cohort) (Kolar et al., 2024; Parasuraman & Colby, 2014; Vitezić & Perić, 2021); AI literacy and knowledge (Bunea et al., 2024; Jeffrey, 2021); and generational disposition (TRI 2.0 optimism/ innovativeness/discomfort/insecurity by cohort)(Kolar et al., 2024; Parasuraman & Colby, 2014; Vitezić & Perić, 2021). Advanced artificial intelligence introduces novel interaction-level risks, often conceptualised as "LLM dark patterns." These manipulative designs, including simulated human authority, brand favouritism, and conversational manipulation, can significantly undermine consumer autonomy(Canhoto et al., 2023). As AI develops into agentic systems capable of autonomously executing financial transactions on behalf of users, the perceived risks increase substantially. This evolution shifts the consumer relationship from viewing AI as a decision aid to relying on it as a fully delegated financial agent, thereby necessitating robust safeguards against data misuse.

Component 4: AI Retail Touchpoints. AI retail touchpoints refer to the specific contexts in which adoption decisions are enacted. These include recommendation engines (personalised product suggestions)(Alalwan, 2020); conversational agents and chatbots (customer service and product queries) (Fu et al., 2024; Myin & Watchravesringkan, 2024; Silva et al., 2022); autonomous decision-making systems (AI-executed purchases on behalf of consumers) (Pillai et al., 2020; Sharma et al., 2024); and in-store AI and digital humans (physical retail AI assistants)(Kolar et al., 2024; Moore et al., 2022); conversational agents and chatbots (customer service, product queries)(Fu et al., 2024; Myin & Watchravesringkan, 2024; Silva et al., 2022); autonomous decision-making systems (AI-executed purchases on behalf of consumers)(Pillai et al., 2020; Sharma et al., 2024); and in-store AI and digital humans (physical retail AI assistants) (Kolar et al., 2024; Moore et al., 2022).Each touchpoint is characterized by distinct trust requirements, social dynamics, and readiness thresholds(Huang & Rust, 2020; Roy et al., 2020).

Component 5: Outcomes. Adoption outcomes encompass adoption intention (behavioural intention to use AI retail systems), purchase intention (likelihood of completing AI-facilitated transactions), customer loyalty (repeat engagement and platform commitment), and customer experience quality (holistic evaluation of the AI-mediated shopping journey).

Operationalising the Framework: Empirical validation of the STAR-AI framework requires that researchers operationalise its constructs using established psychometric instruments. Trust Calibration can be assessed by adapting the Mayer–Davis–Schoorman (MDS)(Mayer et al., 1995) dimensions in conjunction with items measuring algorithmic explainability. Generational Disposition should be evaluated using the Technology Readiness Index (TRI 2.0) subscales, including Optimism, Innovativeness, Discomfort, and Insecurity (Parasuraman & Colby, 2014). Social Influence mechanisms should be measured with extended Unified Theory of Acceptance and Use of Technology (UTAUT) scales that distinguish between informational and normative pathways.

13. Framework Propositions

The STAR-AI Framework yields eleven testable propositions:

P1. Social influence positively predicts attitudes toward AI retail adoption, with stronger effects observed in collectivist cultures than in individualistic cultures.
P2. Subjective norms positively predict behavioural intention to adopt AI retail systems, with stronger effects in high power distance cultures.
P3. Initial trust, as determined by transparency, explainability, and interface quality, positively predicts AI retail adoption intention.
P4. Calibrated trust mediates the relationship between AI system performance and long-term customer loyalty.
P5. Perceived privacy risk negatively moderates the relationship between initial trust and adoption intention, with stronger effects in high uncertainty avoidance cultures.
P6. Performance expectancy positively predicts adoption intention, although this effect is reduced in contexts with high uncertainty avoidance (Sharma et al., 2024).
P7. AI literacy positively moderates the relationship between performance expectancy and adoption intention.
P8. Generational cohort moderates TRI 2.0 effects: Generation Z demonstrates higher optimism and innovativeness but exhibits similar privacy concerns compared to older cohorts.
P9. Digital infrastructure readiness moderates the relationship between individual-level constructs and adoption intention, with stronger effects observed in emerging economies.
P10. Touchpoint type moderates the trust-adoption relationship: autonomous decision-making systems require higher trust thresholds than recommendation engines.
P11. Regulatory environment moderates perceived privacy risk: robust data privacy regimes reduce privacy risk perceptions and increase adoption intentions.

14. Framework Applications: Comparative Analysis of India and Australia

1. India (Emerging, Collectivist, High Power Distance): The STAR-AI Framework identifies social influence (P1) and subjective norms (P2) as the primary drivers of AI adoption in India, an illustrative case of an emerging economy. Initial trust is predominantly established through institutional endorsements, which reflects the country's high-power-distance culture. Nevertheless, substantial within-country heterogeneity exists, particularly a pronounced digital divide between urban and rural populations. Metropolitan consumers tend to adopt AI rapidly due to mobile-first infrastructure, whereas rural consumers encounter significant access barriers (Bhatt & Singh, 2025). Retailers seeking to enter this market are advised to employ community-based marketing strategies and collaborate with trusted institutions to reduce perceived risks.
2. Australia (Developed, Individualistic, Moderate-High Uncertainty Avoidance): In contrast, Australia exemplifies a developed economy where performance expectancy and trust calibration serve as the primary drivers of adoption. High individualism leads social influence to operate through identification mechanisms rather than normative pressure. Additionally, moderate-to-high uncertainty avoidance reduces the impact of performance expectancy (P6), underscoring the need for robust algorithmic transparency. Supported by strict privacy regulations such as the Privacy Act 1988 (Adanyin, 2024; Department, 1988), Australian consumers require granular privacy controls. Retailers must therefore prioritise explainability and demonstrate the accuracy of personalisation to address initial consumer scepticism

15. Discussions

Theoretical Contributions

This review provides a comprehensive synthesis of artificial intelligence adoption in retail across both emerging and developed economies. By examining India and Australia as illustrative cases, the study quantifies culturally contingent effect sizes and moderation patterns, while acknowledging heterogeneity within these distinct economic contexts. The review identifies five key theoretical contributions to the literature on AI retail adoption.

First, it provides explicit conceptual differentiation between social influence (Unified Theory of Acceptance and Use of Technology, UTAUT), subjective norms (Theory of Planned Behaviour, TPB), and descriptive and injunctive norm types, thereby resolving a persistent ambiguity in the literature (Ajzen, 1991; Sharma et al., 2024; Venkatesh et al., 2003).

Second, it integrates the Mayer–Davis–Schoorman trust model (Mayer et al., 1995) with the initial and calibrated trust distinction(Kumar & Bargavi, 2024; Oyekunle et al., 2024), providing a dynamic, multi-stage trust framework for AI retail contexts and building upon foundational e-commerce trust research (Gefen et al., 2003; McKnight et al., 2002; Pavlou, 2014).

Third, it triangulates Hofstede's cultural dimensions with Innovation Diffusion Theory (Rogers, 2003), Technology Readiness Index (TRI) 2.0(Parasuraman & Colby, 2014), and objective digital infrastructure indicators, thereby addressing the ecological fallacy risk of single-framework cultural analysis (Aruna et al., 2024; Fan et al., 2022).

Fourth, it positions Generation Z as a theoretically distinct consumer segment with unique readiness profiles, social influence mechanisms, and personalisation expectations (Bunea et al., 2024; Jeffrey, 2021; Saklani & Kala, 2024; Vitezić & Perić, 2021).

Fifth, the STAR-AI Framework introduces the first integrative model that simultaneously accounts for macro-level context, meso-level social and trust antecedents, individual-level constructs, and touchpoint-specific dynamics in predicting AI retail adoption outcomes (Dwivedi et al., 2021; Huang & Rust, 2020).

Managerial Implications

Collectivist Markets (India and similar emerging economies): Retailers should leverage community-based AI endorsement strategies, such as testimonials from trusted community figures, social proof mechanisms (for example, '1,000 people in your area bought this') and group-oriented AI features (shared Wishlist's, family recommendation profiles) (Fan et al., 2022; Guerra-Tamez et al., 2024). Mobile-first AI design is essential given infrastructure constraints (Pillai et al., 2020). Autonomous decision-making features should be introduced gradually, with clear opt-in mechanisms that enable consumers to maintain perceived control (Sharma et al., 2024; Xing et al., 2023).

Individualistic Markets (Australia and similar developed economies): Retailers should prioritise algorithmic transparency through explainable AI features (for example, 'We recommended this because...'disclosures), granular privacy controls, and data minimisation practices (Adanyin, 2024; Canhoto et al., 2023; Lappeman et al., 2022). AI literacy programmes embedded within onboarding experiences can reduce discomfort and insecurity (TRI 2.0 inhibitors) (Kolar et al., 2024; Parasuraman & Colby, 2014). Performance-based trust calibration strategies (for example, recommendation accuracy dashboards, A/B testing of AI versus non-AI shopping outcomes) can accelerate trust development (Oyekunle et al., 2024; Wang et al., 2019).

Generation Z Segment: Retailers targeting Generation Z should invest in seamless omnichannel AI integration, hyper-personalisation capabilities, and social commerce features that embed AI recommendations within social media environments (Bunea et al., 2024; Jeffrey, 2021; Saklani & Kala, 2024). Generation Z's critical evaluation tendencies require genuine personalisation accuracy. Generic

AI recommendations are likely to be perceived as system failures and may erode trust (Guerra-Tamez et al., 2024; Vitezić & Perić, 2021).

Policy and Governance Recommendations

Data privacy regimes: Governments in emerging economies should accelerate the development of comprehensive data protection legislation analogous to the European Union's General Data Protection Regulation (GDPR) or Australia's Privacy Act to reduce consumer privacy risk perceptions and create a trust-enabling regulatory environment (P11) (Kim et al., 2023; Lappeman et al., 2022).

Algorithmic transparency standards: Industry bodies should develop minimum transparency standards for retail AI systems, including disclosure of data sources, recommendation logic, and personalisation mechanisms. Requirements for explainable AI (XAI) should be incorporated into AI governance frameworks (Adanyin, 2024; Dwivedi et al., 2021; Xing et al., 2023).

AI literacy initiatives: Educational programmes targeting digital literacy and AI understanding standing should be integrated into school curricula and adult education programmes, particularly in emerging economies where AI literacy gaps are most pronounced (Jeffrey, 2021; Saklani & Kala, 2024). Higher AI literacy reduces discomfort (TRI 2.0), increases performance expectancy, and enables more informed consent decisions (Parasuraman & Colby, 2014).

16. Limitation

This review has four primary limitations.

- First, the restriction to English-language publications cations may introduce language bias, potentially underrepresenting findings from non-English-speaking emerging economies.
- Second, the 2020–2024 timeframe, while appropriate given AI's recent retail deployment, excludes foundational empirical work that may provide important baseline comparisons.
- Third, the India–Australia comparative framing, while theoretically motivated, risks oversimplification of within-country heterogeneity, including urban and rural, socioeconomic, and generational variation.
- Fourth, as a literature review, this study cannot establish causal relationships. The STAR-AI Framework's propositions require empirical testing through primary data collection.

17. Conclusion

This systematic literature review synthesizes findings from 31 peer-reviewed empirical studies to advance understanding of AI adoption in retail across both emerging and developed economies. Three core findings emerge.

- First, social influence operates through distinct mechanisms (informational, normative, identification), and the relative importance of these mechanisms is moderated by cultural collectivism. Collectivist cultures, such as India, demonstrate stronger social influence effects (Aruna et al., 2024; Fan et al., 2022; Sharma et al., 2024), whereas individualistic cultures, such as Australia, prioritise personal experience and perceived value (Brooksbank et al., 2022; Quintus et al., 2024).
- Second, trust in AI retail systems is dynamic and multi-stage, necessitating differentiated strategies for initial trust formation, including transparency, explainability, and interface quality (Fogg, 2002; Gefen et al., 2003; Kumar & Bargavi, 2024), and calibrated trust maintenance, such as performance accuracy, error recovery, and privacy protection(McKnight et al., 2002; Oyekunle et al., 2024; Pavlou, 2014).
- Third, technological readiness encompasses infrastructure availability, AI literacy, and dispositional readiness (TRI 2.0). Generation Z exhibits a distinct profile characterised by high optimism and innovativeness, but also critical personalization expectations (Bunea et al., 2024; Jeffrey, 2021; Saklani & Kala, 2024).
- The STAR-AI Framework integrates these findings into a comprehensive theoretical model that maps macro-level contexts, including cultural dimensions, digital infrastructure, and regulatory environment,

meso-level antecedents, such as social influence, trust calibration, perceived risk, and transparency, and individual-level constructs, including performance and effort expectancy, AI literacy, TRI 2.0, generational disposition, and attitude, as well as AI retail touchpoints such as recommendation engines, chatbots, autonomous systems, and in-store AI, to predict adoption outcomes(Dwivedi et al., 2021; Huang & Rust, 2020; Pillai et al., 2020; Roy et al., 2020). The framework generates It provides eleven testable propositions and provides culturally contingent guidance for AI strategy (Hofstede, 2010; Parasuraman & Colby, 2014; Rogers, 2003).

- As AI continues to transform retail, understanding the social, trust, and readiness factors that shape adoption, and how these factors vary across cultural contexts, generational cohorts, and technological touchpoints, is essential for retailers, policymakers, and researchers. The STAR-AI Framework provides a roadmap for this understanding, guiding future empirical research and practical implementation. By adopting culturally sensitive, trust-centered, and readiness-aware strategies, retailers can harness the transformative potential of AI while respecting consumer values, protecting privacy, and promoting inclusive digital participation.

18. Future research directions

Five priority directions for future research emerge from this review:

1. **Empirical STAR-AI Framework testing**: Large-scale cross-cultural surveys testing framework's 11 propositions across diverse emerging and developed economies.
2. **Longitudinal trust calibration studies:** Tracking trust trajectories across AI retail interactions to understand how initial trust converts to, or fails to convert to, calibrated trust.
3. **Autonomous decision-making adoption:** Dedicated empirical investigation of consumer willingness to delegate purchase decisions to AI systems, examining the trust threshold required for autonomy delegation (Sharma et al., 2024).
4. **Regulatory impact assessment:** Quasi-experimental studies examining how the introduction of data privacy legislation affects AI retail adoption intentions.
5. **Generational cohort comparisons**: Systematic comparison of AI retail adoption patterns across Generation Z, Millennials, Generation X, and Baby Boomers, testing whether generational differences in TRI 2.0 profiles translate to differential adoption trajectories.

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