

Artificial Intelligence-Driven Commerce: Consumer Trust, Adoption Behaviour and Firm Performance a Mixed-Methods Investigation Across Emerging and Developed Markets

¹Dr. Suby Baby, ²Dr Priya Mariyat

¹Assistant Professor, Head, Post Graduate and Research Department of Commerce, Nirmala College Muvattupuzha (Autonomous)

²Associate Professor, Post Graduate and Research Department of Commerce, Maharaja's College Ernakulam

DOI: <https://doi.org/10.51584/IJRIAS.2026.11060039>

Received: 22 May 2026; Accepted: 27 May 2026; Published: 20 June 2026

ABSTRACT

This study examines how AI-driven commerce shapes consumer trust, technology adoption and firm performance across six countries spanning emerging economies (India, Nigeria, Brazil) and developed economies (the United States, the United Kingdom, Germany). Three theoretical frameworks the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT2) and Trust-Risk Theory were combined within a single hierarchical structural equation model (SEM), with each framework contributing distinct constructs: TAM provided the adoption antecedents; UTAUT2 introduced contextual moderators; and Trust-Risk Theory supplied the mediating constructs of consumer trust and perceived risk. Survey data from 847 consumers and 214 firm managers, stratified by gender, age, income quartile and urban-rural status, were analysed alongside 32 semi-structured interviews with industry practitioners and regulators. Perceived usefulness, algorithmic transparency and data privacy assurance emerged as the strongest trust-building predictors across all markets, though their relative weight varied by context. Consumers in emerging markets placed comparatively greater emphasis on performance expectancy and peer endorsement, while those in developed markets prioritised algorithmic explainability and privacy controls differences traceable to cultural profiles and divergent regulatory regimes including the EU's GDPR, Brazil's LGPD and Nigeria's NDPR. At the organisational level, AI adoption improved efficiency, customer retention and revenue, but only where implementation was sufficiently mature and complementary capabilities were in place.

Keywords: AI-driven commerce; consumer trust; technology adoption; TAM; UTAUT2; firm performance; emerging markets

INTRODUCTION

Artificial intelligence has moved from experimental technology to operational backbone across retail, financial services and logistics within a remarkably short span. Recommendation systems, automated customer service, dynamic pricing and predictive inventory management now sit at the centre of competitive strategy for firms operating globally (Huang & Rust, 2021). Yet the commercial promise of AI does not translate uniformly. Consumer willingness to engage with AI-mediated transactions varies considerably across socioeconomic settings and the performance gains firms expect from AI investment depend on capabilities and conditions that differ markedly between developed and emerging market contexts (Rana et al., 2020).

Trust lies at the heart of this variation. Before a consumer accepts an AI-driven recommendation, places an order through a chatbot, or shares data for personalisation, a judgment about the reliability and good intentions of the system must occur. That judgment is shaped by the individual's prior experience, cultural outlook and regulatory environment in ways that aggregate statistics routinely obscure (McKnight et al., 2002).

Understanding those shaping forces and how they interact with technology design and firm strategy is the central motivation of this study.

Three gaps in the existing literature justify the present inquiry. First, the majority of empirical AI adoption research draws on single-country or single-region samples, which constrains the applicability of findings beyond Western consumer contexts (Dwivedi et al., 2021). Second, comparative studies rarely examine how structural differences in regulation and digital infrastructure moderate the trust-adoption relationship; cultural factors are acknowledged but seldom operationalised with adequate specificity. Third, studies typically apply TAM, UTAUT2 and trust constructs in parallel rather than within an integrated model, which limits the precision with which their interactions can be tested and interpreted.

This study addresses those gaps through a mixed-methods design spanning six countries. Three research questions guide the inquiry: (1) Which factors most strongly predict consumer trust in AI commerce and how do their effects vary between emerging and developed markets? (2) How do trust perceptions translate into adoption intentions and what cultural and regulatory conditions moderate that translation? (3) Under what conditions does AI adoption generate measurable performance gains at the firm level?

LITERATURE REVIEW

Ai-Driven Commerce

AI-driven commerce refers to the use of machine learning, natural language processing and computer vision to automate and personalise commercial interactions between firms and consumers (Davenport et al., 2020). It spans front-end functions such as product recommendation and conversational commerce as well as back-end functions such as demand forecasting and fraud detection. McKinsey Global Institute projects that AI could generate between \$1.4 and \$2.6 trillion in value for marketing and sales functions alone (Bughin et al., 2018), with personalisation improving conversion rates by 10–30% in certain retail environments (Grewal et al., 2020). These aggregate projections, however, mask substantial variance across firm types, market conditions and implementation approaches variance that this study is designed to explain.

Consumer Trust in AI Systems

Trust in AI-mediated commerce draws on established models of interpersonal and institutional trust. Mayer et al. (1995) identify three dimensions that transfer directly to algorithmic contexts: ability-based trust (confidence in the system's technical competence), benevolence-based trust (belief that the system acts in the consumer's interest) and integrity-based trust (assurance that the system operates by acceptable ethical principles). In AI contexts, a fourth dimension has gained prominence: algorithmic transparency, or the degree to which the reasoning behind automated decisions can be understood by users (Adadi & Berrada, 2018). Consumers are more willing to follow recommendations and share data when they can make sense of why a system behaves as it does.

Data privacy represents the primary trust-eroding force. The use of personal data to generate personalised experiences is also the mechanism through which consumers feel most exposed to exploitation (Acquisti et al., 2016). Privacy concern consistently predicts lower adoption intent, though the strength of this effect varies by national context. European consumers, shaped by GDPR expectations and extensive media coverage of data breaches, tend to express higher privacy sensitivity than consumers in markets where data protection frameworks are newer or less enforced (Bauer et al., 2019).

Theoretical Framework: TAM, UTAUT2 and Trust-Risk Theory

Three complementary frameworks underpin the analytical model. Each contributes constructs that address a distinct dimension of AI adoption behaviour; together they provide more complete explanatory coverage than any single model alone.

TAM (Davis, 1989) proposes that technology adoption is driven primarily by two user perceptions: perceived

usefulness whether the technology improves task performance and perceived ease of use whether it requires minimal effort. In this study, these constructs serve as the distal antecedents of adoption intention. They are foundational because they capture the cognitive cost-benefit assessment that precedes any adoption decision, regardless of market context.

UTAUT2 (Venkatesh et al., 2012) extends the TAM baseline by incorporating four additional determinants tailored to consumer technology contexts: performance expectancy (the expected functional benefit of using the technology), social influence (the degree to which peers and reference groups endorse use), hedonic motivation (the intrinsic enjoyment derived from use) and facilitating conditions (the availability of supporting infrastructure). In this model, UTAUT2 constructs function as contextual moderators. Their relative importance varies across the six study markets and helps account for the cultural and infrastructural differences between emerging and developed economies that TAM alone cannot capture.

Trust-Risk Theory (Mayer et al., 1995; McKnight et al., 2002) positions trust and perceived risk as the primary mediators between antecedent perceptions and behavioural intention. In AI commerce settings, trust aggregates the consumer's cumulative assessments of competence, benevolence and integrity into an affective disposition to engage with the system. Perceived risk captures the potential negative consequences of doing so financial loss, data misuse, or unwanted algorithmic manipulation. Both constructs mediate the path from TAM and UTAUT2 antecedents to adoption intention: trust amplifies the effect of positive antecedents, while perceived risk attenuates it.

Two constructs not present in the original frameworks were added to reflect the AI-specific literature: algorithmic transparency (Adadi & Berrada, 2018) and data privacy assurance (Acquisti et al., 2016). Both were hypothesised to influence trust directly and were operationalised using validated items from these sources. The integrated model was estimated as a single SEM rather than a series of sequential regressions, enabling simultaneous identification of direct, mediated and moderated pathways and avoiding the inflated error associated with piecemeal estimation.

Cultural and Regulatory Context

Cultural differences across the six markets were assessed through Hofstede's (1980) uncertainty avoidance and individualism-collectivism dimensions, which prior research has linked to differential adoption patterns (Srite & Karahanna, 2006). Germany's high uncertainty avoidance score (UAI = 65) predisposes its consumers to demand formal procedural assurances before engaging with unfamiliar AI systems. The United Kingdom (UAI = 35) and the United States (UAI = 46) sit at intermediate levels; in these markets trust tends to form through demonstrated system performance rather than procedural transparency. Brazil (UAI = 76) presents the highest uncertainty avoidance among the emerging markets in the sample, compounded by a strongly collectivist social orientation that amplifies the role of peer endorsement in adoption decisions. India (UAI = 40) is more ambiguity-tolerant and similarly collectivist, making it receptive to AI adoption when social networks signal approval. Nigeria (UAI = 55) combines moderate uncertainty avoidance with elevated scepticism rooted in widespread experience with digital fraud, an environment in which negative word-of-mouth travels quickly through close community networks.

Regulatory differences are equally relevant. GDPR, in force for Germany and the United Kingdom, imposes explicit consent requirements, data minimisation obligations and provisions for algorithmic explainability that collectively raise both the legal bar for AI systems and consumer expectations of transparency. The United States has no equivalent federal law, though California's CCPA approximates some GDPR provisions at state level. Brazil's LGPD and Nigeria's NDPR are more recent and operate within enforcement environments that are still maturing. India's personal data protection framework was pending formal implementation during the study period. These regulatory asymmetries shape both what firms are permitted to do with consumer data and what consumers in each country have learned to expect from digital services.

AI Adoption and Firm Performance

Firm-level evidence links AI adoption to gains in operational efficiency, customer retention, revenue growth

and innovation output (Brynjolfsson & McAfee, 2017; Davenport et al., 2020). These gains are not automatic. Fountaine et al. (2019) show that returns depend on complementary investments in data infrastructure, analytical talent and process redesign. Firms that deploy AI without building these capabilities often fail to move beyond pilot programmes and rarely capture the productivity improvements that drove the original investment decision a pattern Brynjolfsson and McAfee (2017) call the AI productivity paradox. This study tests whether market context, specifically the gap in digital infrastructure maturity between emerging and developed economies, moderates whether and how quickly firms move through the implementation stages at which returns become meaningful.

METHODOLOGY

Research Design

This study uses an explanatory sequential mixed-methods design (Creswell & Plano Clark, 2018). In the first phase, quantitative survey data were collected and analysed to identify patterns and test the structural model. In the second phase, semi-structured interviews were conducted to explain and contextualise those patterns. This sequence was chosen because the statistical findings raised questions about mechanism and context that survey data alone cannot resolve. The underlying philosophical orientation is pragmatism: the research design is justified by its fitness for the investigative purpose rather than by allegiance to a single epistemological position (Morgan, 2014).

Sampling Strategy and Participant Recruitment

Consumer survey participants were recruited across all six countries using stratified random sampling, with strata defined by gender (male, female, non-binary or other), age group (18–35, 36–55, 56 and above), household income quartile derived from country-specific distributions and urban-rural residence. Quotas were established using national census data and IMF household survey estimates, with a tolerance of ± 5 percentage points on each stratum to ensure that each national sample reflected the population distribution on all four dimensions. This approach was adopted because convenience or panel-only samples in cross-national studies tend to over-represent urban, higher-income and younger respondents, which would undermine comparability across markets with very different population profiles.

Recruitment methods differed by market to address unequal digital access. In developed markets, participants were recruited through established online panel providers with verified demographic quotas. In India, panel recruitment was supplemented by SMS-linked mobile surveys to reach rural respondents with limited broadband access. In Nigeria, fieldwork was conducted in partnership with a local research organisation to ensure coverage of states beyond Lagos and Abuja, which disproportionately dominate standard online panels. In Brazil, deliberate oversampling outside São Paulo corrected for regional concentration in commercial panels. These adjustments were necessary for the emerging market samples to be representative of national rather than metropolitan populations.

The final consumer sample comprised 847 respondents: 423 from developed markets and 424 from emerging markets. Sample sizes per country were determined by power analysis targeting 80% power ($1-\beta = 0.80$) for multi-group SEM at $\alpha = 0.05$, given the number of free parameters in the structural model. The firm-level sample comprised 214 managers who held direct responsibility for AI procurement, deployment, or performance evaluation within their organisations, with a minimum eligibility criterion of 12 months in that role. This sample was recruited through professional networks and snowball referral from interview participants, with 108 managers from developed markets and 106 from emerging markets. Demographic distributions for the consumer sample are shown in Tables 1 and 2.

Table 1. Sample Composition by Country and Method

Country	Market Type	Consumer Survey (n)	Firm Survey (n)	Interviews (n)	Female Respondents (%)
United States	Developed	142	38	6	51

United Kingdom	Developed	140	36	5	49
Germany	Developed	141	34	5	48
India	Emerging	143	36	6	44
Nigeria	Emerging	141	36	5	46
Brazil	Emerging	140	34	5	50
Total		847	214	32	48

Table 2. Consumer Sample Demographic Profile by Country (%)

Variable	USA	UK	GER	IND	NGA	BRA	n
Age 18–35	42	40	38	52	55	48	376
Age 36–55	38	39	40	33	31	36	307
Age 56+	20	21	22	15	14	16	164
Urban residence	84	83	76	62	55	87	631
Income Q1 (lowest)	22	24	23	26	28	27	211
Income Q4 (highest)	27	25	26	24	22	23	210

Survey Instrument Development

Survey items were drawn from validated scales and adapted for the AI commerce context. Perceived usefulness and ease of use items were sourced from Davis (1989); performance expectancy, social influence and hedonic motivation from Venkatesh et al. (2012); trust dimensions from McKnight et al. (2002); and perceived risk from Luo et al. (2020). Items for algorithmic transparency and data privacy assurance were developed from the conceptual definitions in Adadi and Berrada (2018) and Acquisti et al. (2016) respectively and reviewed by three subject-matter experts before inclusion.

Prior to full administration, the instrument was pre-tested through cognitive interviews with 24 participants, four per country, conducted in the local language. Participants were asked to verbalise their understanding of each item while completing it. Items generating consistent confusion or ambiguity were revised. All materials were professionally translated into German, Hindi and Portuguese, with independent back-translation and adjudication by a bilingual academic reviewer for any items where forward and back translations diverged materially. The instrument was administered in English in the United States, United Kingdom and Nigeria.

Qualitative Data Collection

Thirty-two semi-structured interviews were conducted with AI commerce practitioners (n = 20) and technology regulators or policymakers (n = 12). Practitioners were selected to represent diversity across firm size (from growth-stage businesses to established multinationals), commercial sector (retail, financial services, logistics and digital platforms) and market context, with at least three practitioners per country. Policymakers were recruited through regulatory authorities and technology ministries, with a minimum of one per country. Purposive maximum-variation sampling guided selection throughout to ensure that the interview data captured a wide range of organisational experiences and regulatory perspectives rather than a single dominant viewpoint.

Interviews lasted an average of 58 minutes and were conducted by video call. A structured topic guide covered AI adoption journeys, consumer trust management practices, data governance approaches and experience navigating cross-border regulatory requirements. All interviews were audio-recorded with participant consent, transcribed verbatim and returned to participants for member-checking before analysis.

Analytical Approach

Quantitative analysis was conducted in AMOS 26.0. A confirmatory factor analysis (CFA) was run first to assess the measurement model, evaluating composite reliability (threshold $CR > 0.70$), average variance extracted ($AVE > 0.50$) and discriminant validity via the HTMT criterion (Henseler et al., 2015). The structural model was then estimated as a single integrated SEM, with trust and perceived risk as mediators between antecedent constructs and adoption intention. Multi-group SEM compared path coefficients between emerging and developed market sub-samples to test for contextual moderation. Common method variance was examined using Harman’s single-factor test and the marker-variable technique.

Qualitative data were analysed through reflexive thematic analysis (Braun & Clarke, 2006), with initial codes generated inductively from interview transcripts and subsequently organised into themes guided by the theoretical framework. NVivo 14 supported data management and query. Quantitative and qualitative findings were integrated at the interpretation stage: qualitative themes were used to explain and contextualise statistically significant patterns identified in the SEM output. Ethical approval was granted by the university institutional review board; all participants provided written informed consent.

RESULTS

Measurement Model

All factor loadings fell within the range of 0.71 to 0.94, exceeding the 0.70 threshold. Composite reliability values ranged from 0.81 to 0.93 and AVE values from 0.52 to 0.74, satisfying convergent validity requirements (Hair et al., 2019). All HTMT values were below 0.85, confirming discriminant validity. Importantly, the two AI-specific extensions algorithmic transparency and data privacy assurance each loaded onto factors distinct from the nearest related constructs (algorithmic transparency was clearly separated from perceived ease of use; perceived risk from general negative affect), confirming that the integrated model does not conflate constructs across its constituent theories. Harman’s single-factor test and marker-variable analysis indicated that common method bias did not materially threaten the validity of findings.

Structural Model: Consumer Trust and Adoption

The structural model accounted for 62% of variance in consumer trust ($R^2 = 0.62$) and 54% of variance in adoption intention ($R^2 = 0.54$). Across the pooled sample, perceived usefulness ($\beta = 0.41, p < 0.001$), algorithmic transparency ($\beta = 0.33, p < 0.001$) and data privacy assurance ($\beta = 0.29, p < 0.001$) were the strongest positive predictors of trust. Perceived risk exerted a negative effect ($\beta = -0.24, p < 0.001$) and social influence a modest positive one ($\beta = 0.18, p < 0.01$). Trust, in turn, was the strongest single predictor of adoption intention ($\beta = 0.47, p < 0.001$).

Multi-group comparisons revealed three significant between-context differences. Algorithmic transparency had a meaningfully stronger effect on trust in developed markets ($\beta = 0.39$) than in emerging markets ($\beta = 0.25$; $\Delta\beta = 0.14, p < 0.05$). Social influence showed the reverse pattern, exerting a stronger effect in emerging markets ($\beta = 0.28$ vs. $\beta = 0.11$; $\Delta\beta = 0.17, p < 0.01$). Performance expectancy was also more influential in emerging markets ($\beta = 0.35$ vs. $\beta = 0.22$; $\Delta\beta = 0.13, p < 0.05$). Full path coefficients are reported in Table 3.

Table 3. SEM Path Coefficients: Trust and Adoption Intention

Path	Pooled β	Developed β	Emerging β	Sig. Diff.	Framework Source
Perceived Usefulness → Trust	0.41***	0.40***	0.43***	No	TAM
Algorithmic Transparency → Trust	0.33***	0.39***	0.25***	Yes*	Extension
Data Privacy Assurance → Trust	0.29***	0.31***	0.27***	No	Extension
Perceived Risk → Trust	-0.24***	-0.25***	-0.22***	No	Trust-Risk Theory

Social Influence → Trust	0.18**	0.11*	0.28***	Yes**	UTAUT2
Performance Expectancy → Adoption	0.29***	0.22***	0.35***	Yes*	UTAUT2
Trust → Adoption Intention	0.47***	0.49***	0.45***	No	Trust-Risk Theory

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Framework Source indicates which theoretical model contributed each construct to the integrated SEM.

Qualitative Findings: Four Themes

Analysis of the 32 interviews produced four themes that explain and add texture to the quantitative results.

The first theme, transparency as a commercial imperative, captured the view among practitioners in the United Kingdom and Germany that consumer trust could not be taken for granted and required deliberate investment in explainable AI features. A UK e-commerce director described a 14% increase in click-through rates following the introduction of visible recommendation rationale in the firm’s personalisation engine, attributing the gain directly to reduced consumer uncertainty about why certain products were shown. Policymakers in both countries noted that GDPR’s Article 22 provisions had, in effect, forced firms to develop explanation capabilities that many had previously deprioritised and that consumer expectations had risen correspondingly since 2018.

The second theme, trust by performance rather than procedure, captured a different dynamic in emerging markets. Practitioners in India, Nigeria and Brazil consistently described consumers as primarily interested in whether a system delivered reliable value rather than how it arrived at its outputs. An implementation manager in Mumbai framed this directly: the typical question is not whether the algorithm is fair but whether it gives a good deal. In Brazil, interviewees attributed this orientation to a broader consumer scepticism towards institutional assurances rooted in the country’s history of public service unreliability, which has conditioned consumers to weigh observable outcomes over procedural claims. Nigerian practitioners described trust formation as substantially social: where community members vouched for a platform through personal experience, adoption followed; where they reported poor outcomes or suspected fraud, networks amplified those concerns rapidly.

The third theme, the compliance floor effect, described a pattern observed among multinationals operating across both market types. Rather than maintaining jurisdiction-specific data standards, several firms had adopted GDPR-equivalent practices globally, citing the operational simplicity of a single standard and the reputational risk of being seen to apply weaker protections in markets with less regulatory oversight. While this had the practical effect of raising consumer data protection in markets where local law required less, policymakers in India and Nigeria expressed concern that it reduced incentives for local regulators to develop domestically relevant frameworks and gave multinational firms a compliance advantage over local competitors who lacked the resources to implement GDPR-calibre systems voluntarily.

The fourth theme, scepticism contagion, documented the speed with which negative experiences with AI-driven systems spread through social networks in Nigeria and Brazil. Practitioners described cases where a single instance of erroneous product recommendations or unexplained account restrictions had generated visible drops in platform engagement within the affected consumer community over the following days. The mechanism was primarily peer messaging and group conversations rather than formal review platforms, which made it difficult for firms to identify and respond to emerging trust damage quickly. This finding reinforces the quantitative result showing elevated social influence effects in collectivist markets and suggests that risk management in these contexts must account for the social amplification of individual failure events.

AI Adoption and Firm Performance

AI adoption intensity measured as a composite of investment depth, integration breadth and operational maturity was positively associated with operational efficiency ($\beta = 0.44$, $p < 0.001$), customer retention ($\beta = 0.37$, $p < 0.001$) and revenue growth ($\beta = 0.31$, $p < 0.001$) across the firm sample. Implementation

maturity moderated all three relationships. Firms at the institutionalised stage where AI was embedded in core operational processes reported performance returns approximately 2.3 times larger than firms still in the experimental stage. This pattern held across both market groups and is consistent with the complementary assets argument advanced by Fountaine et al. (2019).

Market context moderated the direction of the maturity effect differently across outcomes. Developed market firms reported higher absolute returns on operational efficiency, reflecting more mature data infrastructure and cleaner historical data pipelines. Emerging market firms, by contrast, reported steeper retention gains at equivalent maturity levels, plausibly because AI-driven personalisation represents a more significant departure from service baselines in those contexts. Table 4 presents the full set of performance coefficients by maturity stage and market group.

Table 4. AI Adoption and Firm Performance by Market Context and Maturity Stage

Outcome	Implementation Stage	Developed β	Emerging β	Pooled β	n firms
Operational Efficiency	Institutionalised	0.61***	0.49***	0.55***	89
Operational Efficiency	Experimental	0.24**	0.20*	0.22**	62
Customer Retention	Institutionalised	0.44***	0.57***	0.51***	89
Customer Retention	Experimental	0.18*	0.26**	0.22**	62
Revenue Growth	Institutionalised	0.38***	0.41***	0.40***	89
Revenue Growth	Experimental	0.14	0.17*	0.16*	62

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

DISCUSSION

The results support the core proposition that trust is both the dominant mediator of AI adoption intention and the construct most sensitive to contextual variation. The integrated model performed well across all six markets, explaining over half the variance in both trust and adoption intention, but the multi-group analysis makes clear that the same variables do not operate with equal force in every setting.

The elevated importance of algorithmic transparency in developed markets reflects two reinforcing factors: regulatory exposure through GDPR and cultural predisposition toward formal procedural assurance, most pronounced in Germany. Consumers in these markets have been educated, partly by regulation and partly by media coverage of high-profile AI controversies, to scrutinise the reasoning behind algorithmic decisions. Firms operating in these markets cannot rely on outcome quality alone; they need to make the decision logic legible. The GDPR’s Article 22 provisions have served as a forcing mechanism in this regard, compelling investment in explainability features that have subsequently become commercially differentiating.

The stronger social influence effect in emerging markets follows from collectivist cultural orientations and the relative novelty of AI commerce in those settings. When institutional signals are weak because regulatory frameworks are new, enforcement is limited, or consumer experience with AI systems is shallow individuals rely more heavily on peer networks for guidance. This is not a deficit of sophistication; it is a rational response to uncertainty. The practical implication is that trust-building in these markets requires investment in social proof mechanisms, active community engagement and rapid, visible responses to reported failures, rather than the transparency documentation and consent architecture that works in European markets.

The regulatory asymmetry theme from the qualitative analysis adds a dimension that quantitative modelling cannot capture. The tendency of multinationals to implement GDPR-equivalent standards globally is partly a risk management strategy and partly a product of the difficulty of maintaining separate compliance architectures. Its effects on local regulatory development in emerging markets are genuinely ambiguous and deserve further attention from both researchers and policymakers. Raising the de facto data protection floor

may benefit consumers in under-regulated markets, but it may also reduce the incentive for domestic regulatory institutions to develop frameworks calibrated to local conditions and enforcement realities.

At the firm level, the implementation maturity finding is the most actionable. The gap in performance returns between experimental and institutionalised firms a factor of 2.3 times across outcomes suggests that the common practice of treating AI as a series of discrete project deployments is likely to produce disappointing results. The performance case for AI is made, but it requires the kind of sustained capability building and process integration that most firms are not set up to manage as technology projects.

CONCLUSION

This study set out to examine how AI-driven commerce shapes consumer trust, adoption behaviour and firm performance across markets that differ meaningfully in culture, digital infrastructure and regulatory regime. The six-country mixed-methods design has produced several findings with clear implications for theory and practice.

For technology adoption theory, the study demonstrates that integrating TAM, UTAUT2 and Trust-Risk Theory within a single hierarchical SEM yields more differentiated and precise findings than applying any of the three frameworks independently. The frameworks are not redundant; they explain distinct aspects of the adoption process at different stages of the decision pathway. TAM's distal antecedents, UTAUT2's contextual moderators and Trust-Risk Theory's mediating constructs each contribute independently to the model's explanatory power.

For practitioners, three conclusions warrant particular attention. First, trust-building strategies need to be calibrated to market context. Algorithmic transparency investments pay off more in regulatory environments like the EU; social proof and community engagement matter more in collectivist emerging markets. A uniform global approach will underperform in at least some markets. Second, data privacy remains a universal concern but its weight in the adoption calculus varies: firms should not assume that the privacy management strategies effective in Europe will be equally valued in markets where the regulatory context and consumer experience are different. Third, the maturity-performance relationship should recalibrate how firms plan AI investments. Returns are concentrated at the institutionalised stage; the path to that stage requires capability and process investment that should be budgeted as part of the AI programme from the outset.

Several limitations constrain the conclusions. The cross-sectional design does not permit causal inference and the six-country sample, though more diverse than most prior research, cannot represent the full range of global variation. Future research should employ longitudinal methods to track how trust and performance evolve as AI commerce matures in each market and extend the comparative framework to contexts in Southeast Asia and the Middle East that are absent here. Experimental designs isolating specific transparency and privacy interventions would strengthen causal claims that this study can only infer from structural associations.

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