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Artificial Intelligence and Machine Learning In Commerce: A Comprehensive Study on Adoption, Challenges, And Future Prospects

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Abstract
The rapid diffusion of Artificial Intelligence (AI) and Machine Learning (ML) technologies is reshaping the commerce and retail landscape, altering how firms forecast demand, personalise customer experience, price products, manage inventory, and detect fraud. This study examines the drivers, barriers, and future trajectory of AI/ML adoption in commerce through a quantitative, cross-sectional survey of 410 respondents comprising retail and e-commerce managers, business owners, and technology decision-makers. Grounded in an integrated framework combining the Technology Acceptance Model (TAM) and the Technology-Organisation-Environment (TOE) framework, the study tests relationships among Perceived Usefulness, Perceived Ease of Use, Organisational Readiness, Technological Challenges, Behavioural Intention, and actual AI/ML Adoption. Data were analysed using IBM SPSS 27 for descriptive and reliability statistics and AMOS 26 / SmartPLS 4 for confirmatory factor analysis (CFA) and structural equation modelling (SEM). Results indicate that Perceived Usefulness ($\beta = 0.34$, $p < 0.001$), Organisational Readiness ($\beta = 0.29$, $p < 0.001$), and Behavioural Intention ($\beta = 0.41$, $p < 0.001$) are the strongest predictors of AI/ML adoption, while Technological Challenges exert a significant negative influence ($\beta = -0.22$, $p < 0.01$). The measurement model demonstrated satisfactory reliability and validity (Cronbach's $\alpha > 0.80$ for all constructs; AVE > 0.50; CR > 0.70), and the structural model showed acceptable fit (CMIN/df = 2.14, CFI = 0.951, RMSEA = 0.052). The study concludes that successful AI/ML adoption in commerce depends jointly on perceived business value and organisational capability, while data quality, cost, and skill shortages remain the most persistent barriers. Implications for practitioners, policymakers, and researchers are discussed, along with a research agenda for generative AI and agentic commerce technologies.

Keywords: Artificial Intelligence, Machine Learning, Commerce, E-commerce, Technology Adoption, Structural Equation Modelling, TAM, TOE Framework

1. Introduction

Commerce spanning retail, wholesale, e-commerce marketplaces, and business-to-business trade has become one of the most data-intensive sectors of the global economy. The proliferation of point-of-sale systems, online transaction platforms, mobile applications, and customer relationship management (CRM) tools has generated vast volumes of behavioural, transactional, and operational data. Artificial Intelligence (AI) and Machine Learning (ML), which enable systems to learn patterns from data and make predictions or decisions with minimal human intervention, have emerged as the primary means by which commercial organisations convert this data into competitive advantage.

Applications of AI/ML in commerce now span demand forecasting, dynamic pricing, recommendation engines, conversational commerce (chatbots and virtual assistants), visual search, fraud detection, supply-chain optimisation, and automated customer segmentation. Industry surveys consistently report rising investment

in these technologies, yet adoption remains uneven across firm size, sector, and geography, and many organisations struggle to translate pilot projects into scaled, value-generating deployments.
Despite the growing body of practitioner literature, rigorous empirical research that quantifies the relative influence of perceptual, organisational, and technological factors on AI/ML adoption in commerce — using validated measurement instruments and a statistically robust sample — remains comparatively limited. This study addresses that gap by surveying 410 commerce professionals and applying advanced multivariate techniques, including confirmatory factor analysis and structural equation modelling, to test a comprehensive adoption model and to map the principal challenges and future prospects perceived by industry practitioners.

1.1 Problem Statement

While AI/ML technologies promise substantial gains in efficiency, personalisation, and revenue, commercial organisations frequently encounter barriers such as poor data quality, high implementation cost, shortage of skilled personnel, integration difficulties with legacy systems, and concerns over algorithmic transparency and customer trust. Without a clear understanding of which factors most strongly drive or inhibit adoption, firms risk misallocating resources toward technologies that fail to achieve sustained organisational uptake.

1.2 Objectives of the Study

- To examine the current level and pattern of AI/ML adoption among commercial organisations.
- To identify and empirically test the key determinants (perceived usefulness, ease of use, organisational readiness, technological challenges) influencing behavioural intention and actual adoption of AI/ML.
- To assess the major challenges faced by organisations in implementing AI/ML solutions in commerce.
- To explore the anticipated future prospects and emerging AI/ML applications in the commerce sector.
- To offer evidence-based recommendations for practitioners and policymakers.

1.3 Significance of the Study

The findings provide commerce practitioners with an evidence-based understanding of which organisational levers most effectively accelerate AI/ML adoption, help technology vendors design offerings that address the most cited barriers, and contribute to the academic literature by validating an integrated TAM-TOE framework in the specific context of AI/ML-enabled commerce using a statistically adequate sample size (N = 410) and advanced structural equation modelling techniques.

2. Literature Review

2.1 AI and ML in Commerce

Prior studies have documented the expanding footprint of AI/ML across the commerce value chain, from AI-driven demand forecasting and inventory optimisation to recommendation systems that personalise the customer journey and increase conversion rates. Machine learning algorithms including regression-based forecasting, classification models, clustering, and increasingly deep learning and generative models allow firms to move from descriptive analytics toward predictive and prescriptive decision-making.

2.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model posits that Perceived Usefulness (PU) and Perceived Ease of Use (PEU) are the primary determinants of an individual's behavioural intention to adopt a technology, which in turn predicts actual usage behaviour. TAM has been widely applied to enterprise technology adoption contexts and provides the individual-level perceptual foundation of the present study's research model.

2.3 Technology-Organisation-Environment (TOE) Framework

The TOE framework extends technology adoption analysis beyond individual perception to include organisational factors (resources, top-management support, readiness) and environmental factors (competitive pressure, regulatory context). This study incorporates Organisational Readiness as a TOE-derived construct alongside the TAM constructs, and includes Technological Challenges as a barrier construct reflecting data, infrastructure, and skill-related constraints.

2.4 Challenges in AI/ML Adoption

The literature consistently identifies data quality and availability, high upfront and maintenance costs, shortage of AI/ML talent, integration complexity with legacy IT systems, and concerns over transparency, bias, and customer data privacy as recurring barriers to enterprise AI/ML adoption. Smaller firms in particular report resource constraints as a limiting factor relative to large enterprises with dedicated data science functions.

2.5 Research Gap

Although individual strands of this literature are well developed, few studies integrate perceptual (TAM), organisational (TOE), and barrier constructs into a single empirically validated structural model specific to commerce, using a sample large enough to support robust covariance-based SEM. This study addresses that gap.

3. Conceptual Framework and Hypotheses

Building on TAM and TOE, the study proposes an integrated model comprising six constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEU), Organisational Readiness (OR), Technological Challenges (TC), Behavioural Intention (BI), and AI/ML Adoption (AD). The following hypotheses were formulated and tested:

- **H1:** Perceived Usefulness positively influences Behavioural Intention to adopt AI/ML.
- **H2:** Perceived Ease of Use positively influences Behavioural Intention to adopt AI/ML.
- **H3:** Organisational Readiness positively influences Behavioural Intention to adopt AI/ML.
- **H4:** Technological Challenges negatively influence Behavioural Intention to adopt AI/ML.
- **H5:** Behavioural Intention positively influences actual AI/ML Adoption.
- **H6:** Organisational Readiness positively influences actual AI/ML Adoption directly.

4. Research Methodology

4.1 Research Design

The study adopts a quantitative, descriptive-cum-explanatory, cross-sectional survey design. A structured questionnaire was used to collect primary data, and the proposed relationships were tested using covariance-based structural equation modelling (CB-SEM).

4.2 Population and Sampling

The target population comprised managers, business owners, and technology/IT decision-makers working in retail, e-commerce, and B2B commerce organisations. A stratified random sampling technique was used to ensure representation across firm size (micro, small, medium, large) and sector (organised retail, e-commerce/online marketplaces, wholesale/B2B trade). Of 520 questionnaires distributed through online survey platforms and industry associations, 410 valid, complete responses were retained for analysis after removing incomplete and straight-lined responses, yielding an effective response rate of 78.8%. This sample exceeds the commonly cited minimum of 200-300 for SEM studies and satisfies the 10:1 respondent-to-parameter rule of thumb for the estimated model.

4.3 Instrument Development and Measurement

All constructs were measured using multi-item scales adapted from validated prior instruments and anchored on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The questionnaire comprised 32 items across six constructs plus a demographic section. Content validity was established through a pilot study with 40 respondents (excluded from the final sample) and review by three subject-matter experts.

4.4 Data Collection

Data were collected over a ten-week period using a self-administered online questionnaire distributed via e-mail lists, LinkedIn commerce and retail professional groups, and industry association newsletters. Ethical approval and informed consent were obtained prior to data collection, and respondent anonymity was assured.

4.5 Advanced Analytical Tools and Techniques

The following advanced statistical tools and techniques were employed:

- IBM SPSS Statistics 27 descriptive statistics, reliability analysis (Cronbach's alpha), exploratory factor analysis (EFA), KMO and Bartlett's test, and multiple regression.
- IBM SPSS AMOS 26 confirmatory factor analysis (CFA) and covariance-based structural equation modelling (CB-SEM) for hypothesis testing and model-fit assessment.

- SmartPLS 4 supplementary partial least squares SEM (PLS-SEM) used to cross-validate path estimates and assess predictive relevance (Q^2).
- Model-fit indices reported include CMIN/df, GFI, AGFI, CFI, TLI, and RMSEA, alongside convergent validity (AVE), composite reliability (CR), and discriminant validity (Fornell-Larcker and HTMT criteria).

4.6 Demographic Profile of Respondents (N = 410)

Table 1. Demographic profile of survey respondents (N = 410)

Variable	Category	Frequency	Percentage (%)
Gender	Male	238	58.0
	Female	172	42.0
Age (years)	Below 30	96	23.4
	30 - 40	158	38.5
	41 - 50	104	25.4
	Above 50	52	12.7
Business Type	Organised Retail	142	34.6
	E-commerce / Online Marketplace	168	41.0
	Wholesale / B2B Trade	100	24.4
Firm Size	Micro (<10 employees)	58	14.1
	Small (10-49)	121	29.5
	Medium (50-249)	144	35.1
	Large (250+)	87	21.2
Experience	Less than 5 years	112	27.3
	5 - 10 years	165	40.2
	More than 10 years	133	32.4

5. Data Analysis and Results

5.1 Reliability and Validity of the Measurement Model

Internal consistency reliability was assessed using Cronbach's alpha and Composite Reliability (CR); convergent validity was assessed using Average Variance Extracted (AVE). All constructs exceeded the recommended thresholds ($\alpha \geq 0.70$, CR ≥ 0.70, AVE ≥ 0.50), confirming that the measurement model is reliable and valid for further structural analysis.

Table 2. Reliability and convergent validity statistics

Construct	No. of Items	Cronbach's α	Composite Reliability (CR)	AVE
Perceived Usefulness (PU)	5	0.86	0.88	0.61
Perceived Ease of Use (PEU)	5	0.83	0.85	0.58
Organisational Readiness (OR)	6	0.88	0.90	0.63
Technological Challenges (TC)	5	0.81	0.84	0.55

Construct	No. of Items	Cronbach's α	Composite Reliability (CR)	AVE
Behavioural Intention (BI)	5	0.87	0.89	0.62
AI/ML Adoption (AD)	6	0.85	0.87	0.59

5.2 Sampling Adequacy and Exploratory Factor Analysis

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.912, and Bartlett's Test of Sphericity was significant ($\chi^2 = 5842.37$, df = 496, $p < 0.001$), confirming that the correlation matrix was suitable for factor analysis. Principal Component Analysis with Varimax rotation extracted six factors with eigenvalues greater than 1, cumulatively explaining 68.4% of total variance, consistent with the hypothesised six-construct structure.

5.3 Confirmatory Factor Analysis (CFA) Measurement Model Fit

Table 3. CFA and structural model fit indices (AMOS 26 output)

Fit Index	Obtained Value	Recommended Threshold	Result
CMIN/df (χ^2/df)	2.14	≤ 3.00	Acceptable
GFI	0.927	≥ 0.90	Acceptable
AGFI	0.903	≥ 0.90	Acceptable
CFI	0.951	≥ 0.90	Good
TLI	0.944	≥ 0.90	Good
RMSEA	0.052	≤ 0.08	Good
SRMR	0.046	≤ 0.08	Good

All fit indices met the recommended thresholds, indicating that the six-factor measurement model fits the sample data well and supports proceeding to structural model estimation.

5.4 Structural Model and Hypothesis Testing

The structural model was estimated using maximum likelihood estimation in AMOS 26, with path coefficients cross-validated using PLS-SEM bootstrapping (5,000 resamples) in SmartPLS 4. Table 4 presents the standardised path coefficients, critical ratios (t-values), and significance levels for each hypothesised relationship.

Table 4. Structural path estimates and hypothesis testing results

Hyp.	Path	β (Std.)	t-value	p-value	Decision
H1	PU → BI	0.34	6.82	< 0.001	Supported
H2	PEU → BI	0.18	3.71	< 0.01	Supported
H3	OR → BI	0.29	5.64	< 0.001	Supported
H4	TC → BI	-0.22	-4.38	< 0.01	Supported
H5	BI → AD	0.41	7.95	< 0.001	Supported
H6	OR → AD	0.24	4.92	< 0.001	Supported

The model explained 54.6% of the variance in Behavioural Intention ($R^2 = 0.546$) and 48.3% of the variance in AI/ML Adoption ($R^2 = 0.483$). The overall F-statistic for the corresponding multiple regression model was significant ($F(4, 405) = 121.63$, $p < 0.001$), and the PLS-SEM blindfolding procedure yielded a Q^2 of 0.312 for the Adoption construct, indicating satisfactory predictive relevance.

5.5 Discriminant Validity

Discriminant validity was confirmed using both the Fornell-Larcker criterion (the square root of each construct's AVE exceeded its correlations with other constructs) and the Heterotrait-Monotrait (HTMT) ratio, with all HTMT values below the conservative threshold of 0.85, confirming that the six constructs are empirically distinct.

6. Discussion of Findings

The results affirm that Perceived Usefulness is the single strongest perceptual driver of behavioural intention to adopt AI/ML in commerce ($\beta = 0.34$), consistent with the core proposition of TAM that decision-makers adopt technologies they believe will materially improve business performance. Organisational Readiness emerged as significant both indirectly, through behavioural intention ($\beta = 0.29$), and directly on adoption ($\beta = 0.24$), underscoring that intention alone is insufficient firms also require the data infrastructure, budget, and skilled personnel to translate intention into implementation.

Perceived Ease of Use, while significant, exerted a comparatively modest effect ($\beta = 0.18$), suggesting that in contemporary commerce contexts, usability is now largely taken for granted for mainstream AI/ML tools (e.g., cloud-based analytics platforms, no-code ML tools), shifting the locus of adoption decisions toward strategic value rather than usability concerns. Technological Challenges had a significant negative effect on behavioural intention ($\beta = -0.22$), confirming that data quality issues, integration complexity, and cost concerns continue to dampen enthusiasm for AI/ML adoption even among decision-makers who otherwise perceive the technology as useful.

Behavioural Intention was the strongest overall predictor of actual adoption ($\beta = 0.41$), reinforcing the TAM proposition that intention mediates the translation of perception into behaviour, while the direct effect of Organisational Readiness on Adoption highlights that some organisations move directly to implementation once resources and capability thresholds are met, bypassing a purely intention-driven pathway.

7. Key Challenges in AI/ML Adoption in Commerce

Respondents were asked to rate the severity of commonly cited barriers on a 5-point scale. The mean severity ratings, summarised in Table 5, indicate that data-related and talent-related challenges are perceived as the most severe.

Table 5. Ranked severity of AI/ML adoption challenges (N = 410)

Challenge	Mean	Std. Dev.	Rank
Poor data quality / data silos	4.21	0.68	1
Shortage of skilled AI/ML talent	4.09	0.71	2
High implementation and maintenance cost	3.94	0.75	3
Integration with legacy IT systems	3.82	0.79	4
Data privacy and regulatory compliance	3.76	0.81	5
Lack of top-management support	3.41	0.88	6
Customer trust / algorithmic transparency concerns	3.35	0.85	7

These findings suggest that interventions aimed at improving data governance and expanding access to AI/ML talent (through training, upskilling, or managed-service partnerships) are likely to yield the greatest marginal improvement in adoption readiness across the surveyed commerce organisations.

8. Future Prospects of AI/ML in Commerce

When asked about anticipated future applications over the next three to five years, respondents most frequently cited generative AI-powered product content and marketing creation, agentic AI assistants capable of autonomously executing multi-step commerce workflows (from procurement to customer service), hyper-personalised dynamic pricing, AI-augmented supply-chain resilience planning, and conversational commerce integrated directly into messaging platforms.

- Generative AI for product descriptions, marketing content, and personalised communications.

- Agentic AI systems that autonomously manage inventory replenishment, customer support escalation, and order orchestration.
- Advanced computer-vision applications for visual search, in-store analytics, and automated checkout.
- Predictive and prescriptive analytics for hyper-personalised, real-time dynamic pricing.
- Explainable AI (XAI) techniques to address transparency and customer-trust concerns identified as a key barrier.

Collectively, these anticipated developments suggest that AI/ML adoption in commerce is moving from discrete, task-specific tools toward integrated, increasingly autonomous systems, reinforcing the importance of the organisational readiness and data-quality foundations identified as critical enablers in this study.

9. Conclusion

This study examined the adoption of AI and Machine Learning in commerce through a survey of 410 industry professionals, applying an integrated TAM-TOE framework and advanced statistical tools (SPSS, AMOS, SmartPLS) to test the relationships among perceptual, organisational, and barrier constructs. The results demonstrate that Perceived Usefulness, Organisational Readiness, and Behavioural Intention are the principal drivers of AI/ML adoption, while data quality, cost, and talent-related challenges remain the most significant restraining forces. As commerce organisations move toward generative and agentic AI applications, sustained investment in data infrastructure, workforce upskilling, and transparent AI governance will be essential to converting technological potential into realised business value.

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