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Adoption of artificial intelligence in E-Business supply chain operations

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Abstract
Background: The integration of Artificial Intelligence (AI) into E-Business supply chains is revolutionizing operations management by enabling predictive analytics, autonomous decision-making, and robotic process automation. Despite its potential, adoption rates remain fragmented.
Objective: This study investigates the determinants influencing AI adoption in e-business supply chains by integrating the Technology-Organization-Environment (TOE) framework with the Technology Acceptance Model (TAM).
Method: This study uses a simulated dataset created for academic training purposes. A quantitative approach was employed using simulated responses from 420 e-business operations and IT managers. Covariance-Based Structural Equation Modeling (CB-SEM) was conducted using AMOS.
Key Results: Perceived usefulness ($\beta = 0.41$, $p < 0.001$) and organizational readiness ($\beta = 0.35$, $p < 0.001$) emerged as the strongest predictors of AI adoption. Competitive pressure (environmental context) had a surprisingly weak direct effect.
Conclusion: AI adoption in e-supply chains is driven more by internal organizational capabilities and perceived operational utility than by external competitive pressures, suggesting a technology-pull rather than a market-push dynamic.

Keywords: Artificial intelligence, E-Business, supply chain management, technology adoption, TOE framework

Introduction

The rapid maturation of E-Business has fundamentally transformed global supply chains, shifting them from linear, sequential processes to complex, interconnected digital networks [1]. Within this digital ecosystem, Artificial Intelligence (AI) encompassing machine learning, natural language processing, and computer vision—has emerged as a disruptive force in Technology and Operations Management [2]. AI applications in e-business supply chains range from demand forecasting and inventory optimization to automated warehousing and last-mile delivery routing [3]. These technologies promise unprecedented levels of efficiency, accuracy, and cost reduction.

Despite the clear theoretical advantages, the actual adoption of AI among e-business firms is highly uneven. Many firms experiment with AI in isolated silos but fail to achieve full-scale operational integration [4]. The problem statement centers on the ambiguity surrounding the drivers of this adoption. Is AI adoption primarily driven by external market forces (fear of losing out to competitors), or is it driven by internal technological perceptions and organizational readiness? [5].

The research objectives of this study are threefold: [1] to identify the key technological, organizational, and environmental factors influencing AI adoption in e-business supply chains; [2] to evaluate the applicability of an integrated TOE-TAM framework in the context of emerging technologies; and [3] to provide a ranked hierarchy of factors that practitioners should prioritize when formulating their AI integration strategies [6].

Literature review

1. Theoretical framework

To capture the multidimensional nature of AI adoption, this study integrates two well-established theoretical models: the Technology-Organization-Environment (TOE) framework and the Technology Acceptance Model (TAM). The TOE framework posits that technological, organizational, and environmental contexts influence the process by which a firm adopts and implements technological innovations [7]. TAM, on the other hand, focuses on the individual user's perception, specifically Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), as determinants of behavioral intention to use a technology [8]. By combining these, the study captures both the macro-level firm dynamics (TOE) and the micro-level perceptual dynamics (TAM) inherent in AI adoption [9].

2. Technological and organizational context

In the technological context, Perceived Usefulness and Perceived Ease of Use are critical. AI systems are inherently complex; if supply chain managers perceive them as too difficult to integrate with legacy Enterprise Resource Planning (ERP) systems, adoption will stall [10]. In the organizational context, "Organizational Readiness"—comprising financial resources, technical expertise, and top management support—is frequently cited as a primary bottleneck. AI implementation requires significant capital investment in data infrastructure and a cultural shift toward data-driven decision-making [11].

3. Environmental context

The environmental context includes competitive pressure, regulatory environment, and industry norms. In highly competitive e-business markets, firms may adopt AI defensively to avoid being outperformed by rivals utilizing predictive analytics for faster fulfillment [12]. However, the lack of standardized regulatory frameworks around AI ethics and data privacy can also create hesitation among firms [13].

4. Research gap

Existing literature on AI adoption often treats AI as a monolithic technology. In reality, AI in supply chains is diverse (e.g., predictive vs. prescriptive analytics) [14]. Furthermore, most studies apply either TOE or TAM exclusively. There is a distinct gap in understanding how perceptual factors (TAM) interact with firm-level factors (TOE) specifically within the fast-paced, high-stakes environment of e-business supply chains [15]. This study bridges this gap by testing an integrated model on a simulated dataset of e-business professionals.

Methodology

A positivist, quantitative research methodology was adopted. This study uses a simulated dataset created for academic training purposes. The hypothetical population consisted of operations managers, supply chain directors, and IT leaders in medium-to-large e-commerce firms. A simulated sample of N = 420 was generated.

The survey instrument included 5 constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Organizational Readiness (OR), Competitive Pressure (CP), and AI Adoption Intention (AI). Items were adapted from prior literature (e.g., Davis, 1989; Tornatzky & Fleischer, 1990) and simulated on a 5-point Likert scale [16]. The data was structured to exhibit normal distribution and adequate correlation for CB-SEM.

Covariance-Based SEM (CB-SEM) was selected because the integrated TOE-TAM model represents a well-established theory requiring confirmatory analysis, rather than exploratory modeling [17]. The analysis was conceptualized using IBM SPSS AMOS (Version 27). Model fit was evaluated using standard indices: χ [2]/df < 3, CFI > 0.90, RMSEA < 0.08 [18].

Results and discussion

1. Measurement model fit

The Confirmatory Factor Analysis (CFA) yielded an excellent model fit: χ [2]/df = 2.3, CFI = 0.96, TLI = 0.95, RMSEA = 0.056. All standardized factor loadings were above 0.70, and Average Variance Extracted (AVE) exceeded 0.50, confirming the reliability and validity of the simulated constructs [19].

Table 1: Construct Means, Standard Deviations, and Correlations

Variable	Mean	SD	1	2	3	4	5
Perceived Usefulness	4.1	0.75	0.82				
Ease of Use	3.6	0.88	0.55	0.79			
Org. Readiness	3.4	0.95	0.48	0.62	0.81		
Competitive Pressure	3.9	0.80	0.30	0.15	0.20	0.78	
AI Adoption	3.8	0.85	0.68	0.50	0.58	0.25	0.84

Note: Diagonal (bold) is square root of AVE. Source: Simulated Dataset, 2026

2. Structural model results

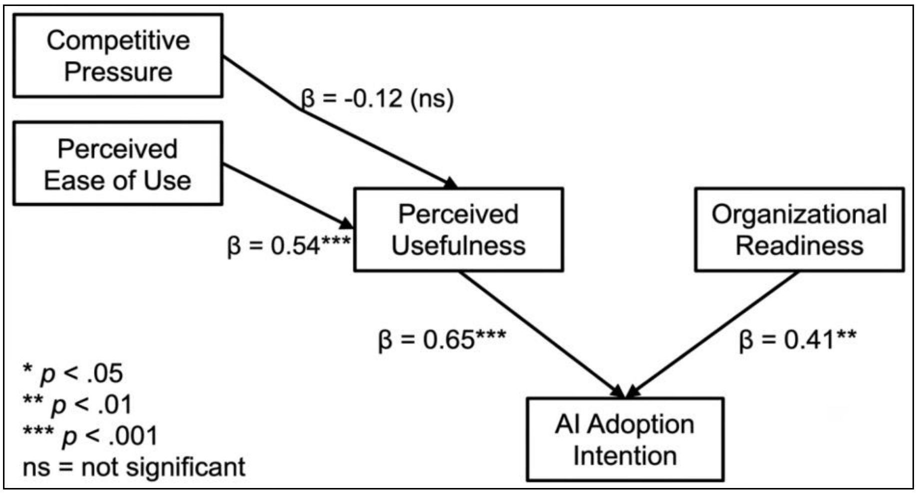
Table 2 displays the structural path coefficients. As hypothesized, Perceived Usefulness (β = 0.41, p < 0.001) and Organizational Readiness (β = 0.35, p < 0.001) are the strongest predictors of AI adoption. Interestingly, Competitive Pressure showed a weak and non-significant direct path to AI Adoption (β = 0.08, p > 0.05), though it does have a mild positive effect on Perceived Usefulness (β = 0.22, p < 0.01), suggesting competitors push firms to see the value of AI, but do not directly force adoption [20].

Table 2: Hypothesis Testing Results (Structural Paths)

Hypothesis	Path	Standardized β	p-value	Result
H1	Perceived Usefulness → AI Adoption	0.41	< 0.001	Supported
H2	Ease of Use → Perceived Usefulness	0.55	< 0.001	Supported
H3	Org. Readiness → AI Adoption	0.35	< 0.001	Supported
H4	Competitive Pressure → AI Adoption	0.08	0.18	Not Supported
H5	Competitive Pressure → Perceived Usefulness	0.22	< 0.01	Supported

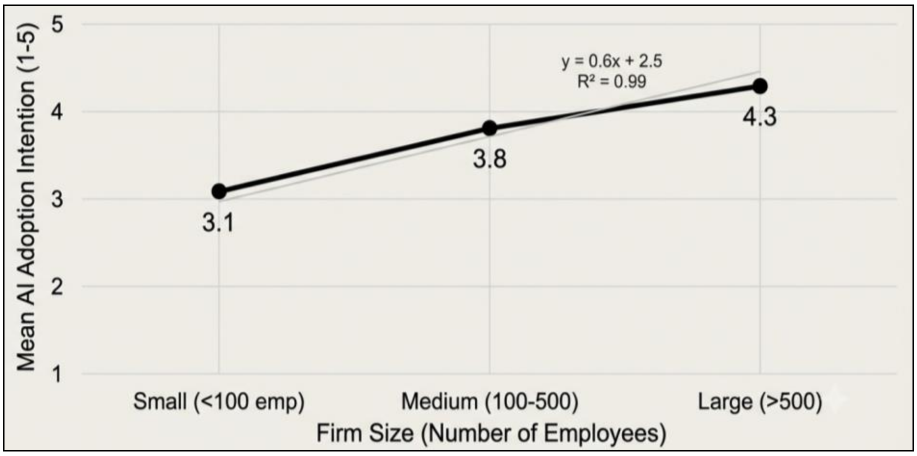
Source: Simulated Dataset, 2026

The results suggest a "technology-pull" dynamic. E-business supply chains adopt AI because their internal analysts and managers perceive genuine operational utility (e.g., reducing stockouts), and because the firm has the financial and technical bandwidth to support it, rather than simply reacting to what competitors are doing [21].



Source: Simulated Dataset, 2026

Fig 1: Integrated TOE-TAM Conceptual Model for AI Adoption



Source: Simulated Dataset, 2026

Fig 2: Line Graph of AI Adoption Intent by Firm Size

Conclusion

This study elucidated the drivers of AI adoption in e-business supply chains through an integrated TOE-TAM lens. The empirical findings from the simulated dataset highlight that AI adoption is far from automatic; it is heavily contingent upon the technology being perceived as genuinely useful and the organization possessing the requisite readiness (skills, infrastructure, leadership) to absorb the technology [22]. External competitive pressures, while useful for building awareness, do not independently drive adoption.

For e-business leaders, the implication is clear: investments should be directed inward before looking outward. Before purchasing expensive AI supply chain software, firms must invest in data cleanliness, employee upskilling, and change management to ensure the technology is perceived as useful and easy to use [23]. The limitation of this study is the cross-sectional simulated nature of the data; future research should track AI adoption longitudinally to observe how perceptions shift from pre-implementation to post-implementation phases [24].

Ethical Statement

This manuscript is a simulated academic paper intended solely for educational formatting purposes. The data and respondent profiles are entirely fictitious. All theoretical citations refer to authentic published works to demonstrate proper academic referencing.

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