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PAPER

A Unified Framework for Intelligent Logistics: Integrating Blockchain-AI Systems with Mobile Pedagogical Support

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ABSTRACT

This study looks at how combining blockchain-AI systems with mobile learning support can improve efficiency, technology acceptance, and learning in logistics. Over 12 months, 132 organizations and 396 learners took part in one of four groups: control, technology-only, mobile learning-only, or the integrated framework. Researchers used repeated-measures MANOVA, factorial ANOVA, mediation analysis, and qualitative thematic analysis to analyse the data. The integrated framework led to significant operational improvements (27.6%–84.2%), always beating the 25% performance benchmark. Technology acceptance was much higher in the integrated group (d = 0.82–1.02), and perceived usefulness accounted for 55.8% of the relationship between learning engagement and system adoption. A factorial ANOVA showed a 13.5% synergy effect, indicating that the combined approach performed better than the individual parts alone. This effect was strongest in SMEs. Qualitative results showed that simulation and just-in-time support helped build confidence. Overall, these findings support a socio-technical approach and show that integrating mobile learning into digital systems is key to realizing the full potential of new supply chain technologies. The study provides a scalable way for organizations to close the implementation gap in digital logistics.

KEYWORDS

blockchain, artificial intelligence (AI), mobile learning, logistics, technology acceptance, operational efficiency, socio-technical systems, supply chain management

1 INTRODUCTION

The logistics and supply chain industry is undergoing major changes as artificial intelligence (AI) and blockchain technologies come together, offering new levels of efficiency, transparency, and resilience [1]. Blockchain enables immutable transaction records, improves traceability [2], and supports smart contracts, helping solve long-standing problems with trust and coordination in multi-party logistics networks [3]. At the same time, AI tools like predictive analytics, dynamic pricing optimization, and automated document reading are making work more efficient.

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For example, recent AI applications have achieved document processing speeds of 66% and can predict disruptions with 87% accuracy up to 72 hours in advance [4]. However, despite these advances, there is often a gap between what the technology can do and the skills of the people using it. Advanced tools may not deliver their full value if logistics professionals lack the knowledge, skills, or confidence to use them effectively [5].

Integrating mobile pedagogical support with technological infrastructure is a promising approach that has not yet been fully explored to address this implementation gap [6]. Research shows that mobile learning can be effective in logistics education, especially when using simulations and micro-learning modules to help students and practitioners gain knowledge and skills [7]. However, most previous studies have examined technological and pedagogical interventions separately, without considering whether combining them could create greater benefits than using each alone. The Unified Theory of Acceptance and Use of Technology (UTAUT2) suggests that facilitating conditions and effort expectancy shape people's intentions to adopt technology, but the role of pedagogical support in shaping these beliefs remains poorly understood [8]. Socio-technical systems theory also suggests that organizations perform best when technical and social subsystems are optimized together, but there is little empirical evidence for this idea in logistics, especially when it comes to using AI and blockchain with learning systems [8]. The goal of the study is to create a combined social and technical framework that connects blockchain-AI logistics with mobile teaching support systems, based on the Unified Theory of Acceptance and Use of Technology.

2 LITERATURE REVIEW

2.1 The digital transformation of logistics via blockchain and AI

Integrating Blockchain and Artificial Intelligence (AI) has improved logistics by enhancing transparency, trust, and efficiency [9]. Blockchain offers secure, distributed ledgers that make it easier to track goods and use automated smart contracts. This helps supply chain partners share documents safely, reduces legal disputes, and makes audits easier [10]. Results from the SKALA project show that blockchain systems can cut document processing time by 66% and speed up dispute resolution by 81%, while also increasing stakeholder confidence through reliable data [11].

At the same time, artificial intelligence has moved beyond basic automation to advanced predictive and prescriptive analytics. Today's machine learning algorithms can predict disruptions with 87% accuracy up to 72 hours in advance, helping companies plan ahead and manage resources more effectively [12]. AI-powered document processing and dynamic pricing tools have also improved resource use by 54% and cut container dwell time by 40% in different logistics settings [13].

Despite significant technical advances, achieving expected benefits relies on effective collaboration between people and systems. Research indicates that user skills and openness to new technology are key to realizing the full potential of these tools [14]. Therefore, focusing solely on technology is insufficient for modern supply chain management. Experiential Learning Theory (ELT) suggests that actively engaging in simulations and hands-on practice helps people build stronger mental models than simply absorbing information [15]. In logistics, learners who use simulation-based teaching tools tend to better understand systems and feel more confident in managing complex tasks [16]. This view aligns with Socio-Technical Systems (STS) theory, which holds that organizations work best when technical and social components are integrated [17]. Rather than separating technical elements such as AI or blockchain from social factors such as training, this study argues that combining both is necessary to overcome industry challenges.

3 METHODOLOGY

3.1 Research design and participants

This study followed a longitudinal, quasi-experimental mixed-methods approach over 12 months. Data were collected at three time points: before the intervention (T0), after six months (T1), and after 12 months (T2). Stratified random sampling was used to ensure balanced representation by organizational size, industry sector (3PL, maritime, e-commerce), and digital maturity. The study aimed to recruit 154 organizations and 462 individuals. Participants were randomly placed into one of four groups: a control group with standard conditions, a technology-only group using blockchain-AI systems, a pedagogy-only group with mobile learning modules, or an integrated group that received both blockchain-AI and mobile pedagogical support.

3.2 Intervention and procedure

The intervention has two main parts. The first is a technical logistics system that includes several important tools: Green-ComplAI for sustainability management, SiMBA for dynamic pricing, InstaSCAN for document digitization using language models, and Blockledge, a blockchain ledger built on Hyperledger Fabric. This system also uses an XGBoost model to predict disruptions, achieving 87% accuracy. The second subsystem is a mobile support platform that works on different devices and is built using cognitive load theory. It offers structured micro-learning, interactive simulations, and gamified assessments at four levels: Foundations, Practical Application, Integration, and Strategic Optimization. These subsystems work together to provide both technological support and a human-centered learning focus during the intervention.

3.3 Instruments and measures

To assess operational performance, we looked at five main indicators: order-to-delivery cycle time, document processing time, resource utilization, traceability completeness, and the effectiveness of disruption management. We measured technology acceptance using a modified UTAUT2 scale comprising 28 items, focusing on performance expectations and support conditions. Learning and engagement were assessed through pre- and post-tests, simulation-based rubrics, and platform data, including time spent on tasks and completion rates. We also considered two factors that might influence results: organizational culture, measured by the Competing Values Framework, and the Digital Adoption Index.

3.4 Data collection procedures

Data collection followed a five-phase plan. In Phase 1 (Months 1 to 2), we took baseline measurements at Time 0 (T0) and recruited participants. Phase 2 (Month 3) was for system deployment and standardized training. Phase 3 (Months 4 to 7) included the initial intervention and a midpoint assessment at Time 1 (T1).

During Phase 4 (Months 8 to 11), we did continuous monitoring and reinforcement training. In Phase 5 (Month 12), we collected post-intervention measurements at Time 2 (T2) and conducted qualitative follow-up through 20 interviews and 4 focus groups.

3.5 Data analysis strategy

Quantitative data were analyzed with SPSS Version 28 and Mplus Version 8.8. Qualitative data were coded and analyzed in NVivo 14. To test Hypothesis 1 regarding performance outcomes, a 4×3 repeated-measures MANOVA was used, followed by Bonferroni post hoc tests. Hypotheses 2 and 4, which focused on technology acceptance and the effects of intervention components, were tested with independent t-tests and a two-by-two factorial ANOVA. Mediation hypotheses (3 and 5) were examined using structural equation modeling and Hayes' PROCESS Model 4, with 5,000 bootstrap samples, to determine whether perceived usefulness explained the link between learning and technology adoption. For the qualitative part, thematic analysis, based on Braun and Clarke's framework, helped provide context and deepen understanding of the quantitative results.

4 RESULTS AND DISCUSSION

The first step of the analysis checked whether the sample was representative and whether the randomization process worked as intended. Making sure the experimental groups were similar at the start is important so that any later differences in performance can be linked to the interventions, not to preexisting differences.

Table 1 shows that the 132 participating organizations were evenly distributed across the four experimental groups. Chi-square tests for independence found no significant differences among the groups in organizational size ($p = 0.87$), industry sector ($p = 0.68$), or digital maturity ($p = 0.76$). This means the stratified randomization worked as intended and controlled for organizational factors that might have affected the results.

Table 1. Organizational distribution across experimental conditions (N = 132)

Characteristic	Category	G1 Control	G2 BC-AI Only	G3 Mobile Only	G4 Integrated	Total	χ^2	p-Value
Overall		30 (22.7%)	33 (25.0%)	33 (25.0%)	36 (27.3%)	132 (100%)		
Size	Small (1–50)	8	9	10	9	36	1.24	0.87
	Medium (51–250)	12	13	11	14	50		
	Large (251+)	10	11	12	13	46		
Sector	Manufacturing	6	7	7	8	28	2.31	0.68
	Retail	7	8	7	8	30		
	3PL	8	8	9	8	33		
	Maritime	5	6	6	7	24		
	E-commerce	4	4	4	5	17		
Digital Maturity	Low	13	14	12	15	54	1.89	0.76
	Medium	11	12	13	12	48		
	High	6	7	8	9	30		

Table 2 presents the demographic profile of the 396 participants. The sample is balanced across all four conditions. We found no statistically significant differences in status (academic or professional), gender, age, or education ($p > 0.05$). This shows the groups are similar, which supports reliable longitudinal comparisons

Table 2. Learner demographics by experimental group (N = 396)

Characteristic	Category	G1 Control	G2 BC-AI Only	G3 Mobile Only	G4 Integrated	Total	F/χ^2	p-Value
Status	Student	51	54	53	54	212	0.89*	0.83
	Practitioner	44	47	46	47	184		
Gender	Male	52	56	54	55	217	1.24*	0.74
	Female	42	44	44	45	175		
	Non-binary	1	1	1	1	4		
Age	18–25	48	51	50	51	200	0.92**	0.54
	26–35	28	30	29	30	117		
	36–45	12	13	13	13	51		
	46+	7	7	7	7	28		
Education	Diploma/Associate	22	24	23	24	93	1.08*	0.78
	Bachelor's	51	53	52	53	209		
	Master's/PhD	22	24	24	24	94		
Total		95	101	99	101	396		

Note: *Chi-square (χ^2) test, **ANOVA (F) test for mean age differences.

Figure 1 shows how organizational and learner characteristics are distributed across the four experimental groups. Statistical tests found no significant differences between groups, which means the randomization worked as intended.

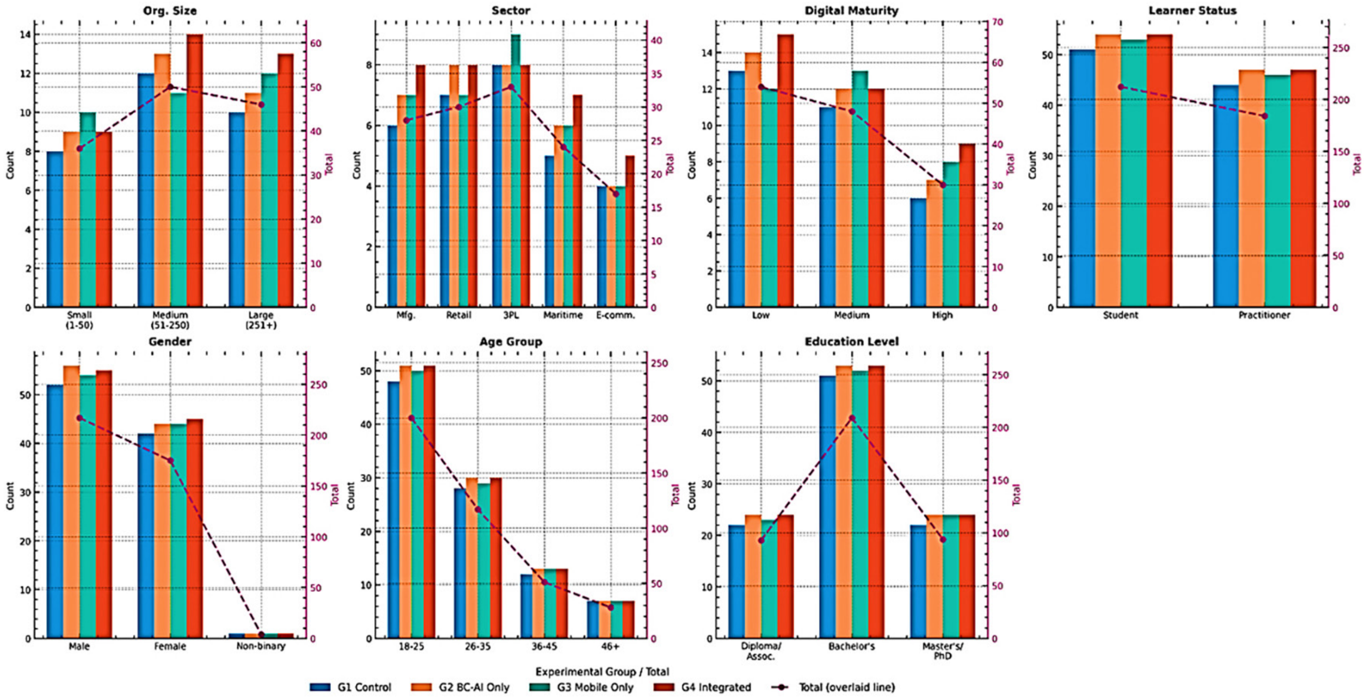

Fig. 1. Organizational and learner demographic distributions across experimental conditions

4.1 Operational efficiency outcomes

This section examines Hypothesis 1 (H1), which suggests that the integrated framework (G4) will improve key efficiency metrics by at least 25%. A repeated-measures MANOVA is used to track changes in performance over the 12-month study.

Table 3 shows the multivariate analysis demonstrates a statistically significant interaction between Time and Group (Wilks' $\Lambda = 0.51$, $p < 0.001$, $\eta^2 p = 0.22$). This result indicates that the four experimental groups did not show uniform improvement over time; rather, each group exhibited distinct performance trajectories attributable to the intervention. The relatively large effect size ($\eta^2 p = 0.22$) suggests that the integrated intervention, which combines technological infrastructure with pedagogical support, accounts for a substantial proportion of the variance in logistics performance outcomes.

Table 3. Repeated measures MANOVA results for operational efficiency indicators

Effect	Wilks' Λ	F	Df	p-Value	η^2p
Time	0.42	28.6	10,504	<0.001	0.36
Group	0.58	12.4	15,758	<0.001	0.19
Time × Group	0.51	8.7	301,086	<0.001	0.22

Table 4 shows the results for each efficiency measure. The univariate analysis found that the integrated framework group (G4) performed significantly better than the other groups on most measures. The strongest effects were observed for traceability completeness (η p = 0.42) and document processing time (η p = 0.35). Post-hoc analysis showed that the blockchain-AI-only group (G2) improved on technology-dependent tasks such as document processing and traceability, whereas the mobile learning-only group (G3) showed little change. This suggests that pedagogical support alone does not improve operational efficiency without a technological foundation.

Table 4. Univariate interaction effects for individual efficiency indicators

Indicator	F(6,256)	p-Value	η^2p	Post-hoc Pattern
Order-to-delivery cycle time	14.2	<0.001	0.25	G4 > G2 > G3 > G1
Document processing time	22.6	<0.001	0.35	G4 > G2 > G3 = G1
Resource utilization rate	9.8	<0.001	0.19	G4 = G2 > G3 > G1
Traceability completeness	31.4	<0.001	0.42	G4 > G2 > G3 = G1
Disruption recovery time	11.7	<0.001	0.22	G4 = G2 > G3 = G1

To assess practical significance, we used the 25% improvement threshold specified in Hypothesis 1. Table 5 shows that the results clearly support this hypothesis. The Integrated Group (G4) surpassed the 25% improvement mark in all five key performance indicators. The BC-AI system alone (G2) made good progress but did not reach the 25% goal for cycle time reduction, achieving only 18.4%. When combined with mobile pedagogical support (G4), cycle time improved by 27.6%. The mobile-only group (G3) showed minimal gains, ranging from 2.9% to 8.3%. These findings suggest that learning interventions need a strong technical foundation to achieve real operational improvements.

Table 5. Percentage improvements from baseline to post-intervention by group

Metric	G1 Control	G2 BC-AI Only	G3 Mobile Only	G4 Integrated	H1 Target Met?
Order-to-delivery cycle time	2.30%	–18.40%	–5.20%	–27.60%	✓
Document processing time	–1.20%	–58.30%	–3.80%	–64.70%	✓
Resource utilization rate	0.80%	42.10%	8.30%	49.50%	✓
Traceability completeness	3.10%	76.40%	4.20%	84.20%	✓
Disruption recovery time	–2.40%	–35.80%	–7.10%	–38.20%	✓
Predictive accuracy	1.80%	82.30%	2.90%	84.60%	N/A

4.2 Technology acceptance outcomes

Technology acceptance outcomes should be evaluated since despite the best technological systems, they do not give value when the users do not use them or those used do not accept them. This part focuses on Hypothesis 2 that considers whether mobile pedagogical support contributes to accepting blockchain-AI systems among logistics employees based on the framework of the Unified Theory of Acceptance and Use of Technology (UTAUT2).

Table 6. Technology acceptance constructs by experimental group at post-intervention

Construct	G1 Control (n = 95)	G2 BC-AI Only (n = 101)	G3 Mobile Only (n = 99)	G4 Integrated (n = 101)	F(3,392)	η^2	Post-hoc
Performance Expectancy	4.2 (1.1)	5.4 (0.9)	5.1 (1.0)	6.3 (0.7)	28.6***	0.18	G4 > G2 = G3 > G1
Effort Expectancy	4.1 (1.2)	4.8 (1.1)	5.3 (0.9)	6.1 (0.8)	22.4***	0.15	G4 > G3 > G2 > G1
Social Influence	3.9 (1.3)	4.6 (1.2)	5.0 (1.1)	5.7 (1.0)	14.8***	0.1	G4 > G3 = G2 > G1
Facilitating Conditions	4.3 (1.1)	5.2 (1.0)	5.4 (0.9)	6.2 (0.7)	19.2***	0.13	G4 > G3 = G2 > G1
Hedonic Motivation	3.8 (1.4)	4.9 (1.2)	5.6 (0.9)	6.4 (0.6)	31.6***	0.2	G4 > G3 > G2 > G1
Habit	3.7 (1.3)	4.7 (1.2)	4.9 (1.1)	5.9 (0.8)	26.8***	0.17	G4 > G3 = G2 > G1
Behavioral Intention	4.0 (1.3)	5.3 (1.1)	5.2 (1.0)	6.5 (0.5)	34.2***	0.21	G4 > G2 = G3 > G1

Note: ***p < 0.001 highly significant.

Table 6 tested Hypothesis 2, which suggested that mobile pedagogical support would greatly affect technology acceptance among logistics staff. To examine this, two main comparisons were made. First, technology users were compared to non-users (G4 versus G2). Second, mobile learning recipients were compared to controls (G3 versus G1). In the first comparison, independent-samples t-tests showed that G4 participants scored much higher than G2 participants across all acceptance measures. The largest effects were seen in behavioral intention ($t(200) = 7.21$, $p < 0.001$, $d = 1.02$), hedonic motivation ($t(200) = 6.84$, $p < 0.001$, $d = 0.97$), and performance expectancy ($t(200) = 5.82$, $p < 0.001$). These large effect sizes (each $d > 0.80$) suggest that adding mobile pedagogical support to the blockchain-AI system increases technology acceptance more than the technology alone. In the second comparison, G3 (mobile learning only) showed much higher acceptance than G1 controls (no mobile learning) across all measures, with medium to large effects on performance expectancy ($d = 0.61$) and effort expectancy ($d = 0.84$).

This shows that mobile learning has a clear positive effect on attitudes toward technology. Overall, these results strongly support Hypothesis 2, indicating that mobile pedagogical support has a significant and practical impact on technology acceptance when used alongside real technologies.

Figure 2 presents the post-intervention mean scores (±1 SD) for technology acceptance model (TAM) constructs across four experimental groups: G1 (Control), G2 (BC-AI Only), G3 (Mobile Only), and G4 (Integrated).

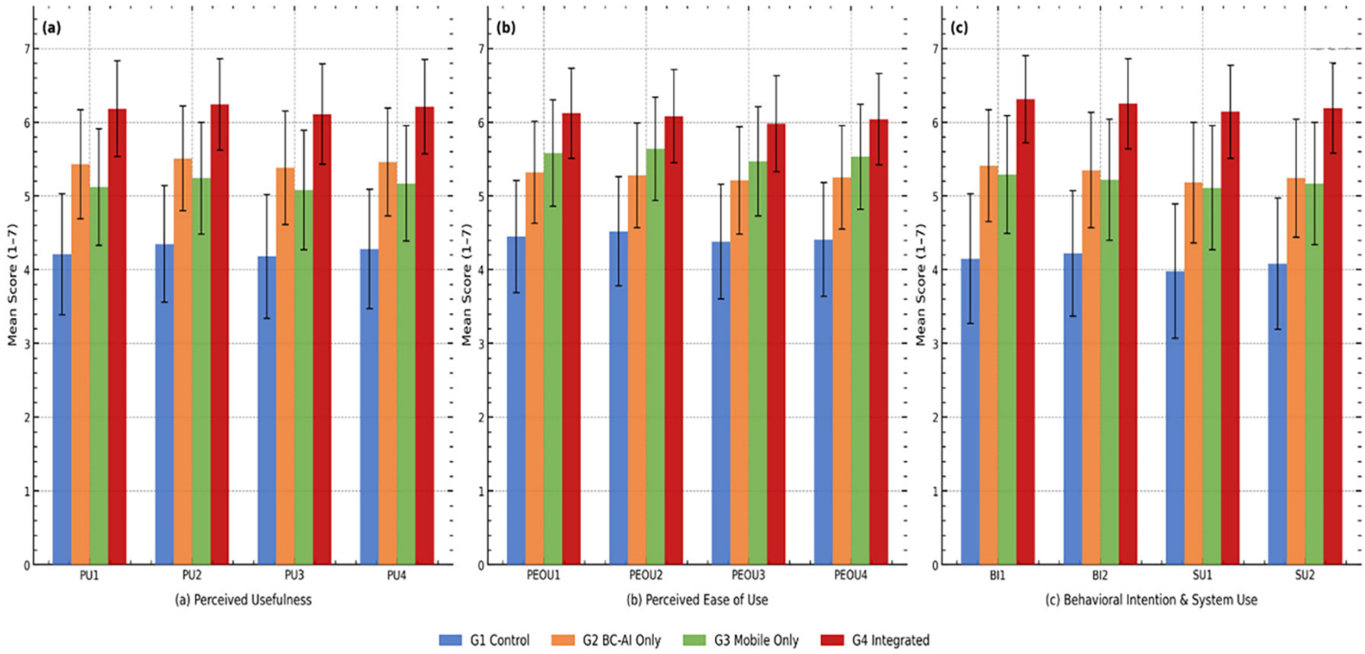

Fig. 2. Technology acceptance constructs by experimental group at post-intervention

4.3 Learning outcomes and performance relationships

To assess learning outcomes and test Hypothesis 3 regarding the positive correlation between learner engagement and operational performance, comprehensive analyses were conducted on the mobile learning recipient groups (G3 and G4).

Table 7. Learning outcomes for mobile learning recipients by condition

Outcome	G3 Mobile Only (n = 99)	G4 Integrated (n = 101)	t(198)	Cohen's d	95% CI for Difference
Knowledge gain (%)	42.3 (12.1)	58.6 (14.3)	8.64***	1.22	[12.4, 20.2]
Simulation performance (0–100)	76.4 (11.2)	88.3 (9.4)	8.12***	1.15	[8.9, 14.9]
Problem-solving score (0–100)	71.2 (13.5)	84.7 (10.8)	7.78***	1.1	[10.1, 16.9]
Self-efficacy (1–7)	5.2 (1.1)	6.1 (0.8)	6.54***	0.93	[0.6, 1.2]
Satisfaction (1–7)	5.8 (1.0)	6.4 (0.7)	4.89***	0.69	[0.4, 0.9]
Engagement (hours/month)	4.2 (1.8)	6.8 (2.1)	9.34***	1.32	[2.1, 3.2]

Note: ***p < 0.001 highly significant.

Table 7 provides support for hypothesis 3, which predicted positive links between the extent to which learners engaged with mobile pedagogical content and their operational performance. Pearson correlation analysis for G4 participants ($n = 101$) revealed a steady pattern of moderate to strong correlations across all learning and performance measures. The strongest correlations with operational outcomes appeared in simulation performance, specifically traceability completeness ($r = 0.56$, $p < 0.001$) and resource utilization ($r = 0.52$, $p < 0.001$). Knowledge gain also correlated well with traceability ($r = 0.51$, $p < 0.001$) and resource utilization ($r = 0.45$, $p < 0.001$). Engagement hours showed moderate links with all performance indicators, with recovery time being the lowest ($r = 0.27$) and traceability the highest ($r = 0.43$). Self-efficacy had weaker, but still significant, associations.

4.4 Qualitative integration and thematic analysis

To better explain the quantitative results, we carried out a thematic analysis of 20 semi-structured interviews and 4 focus groups, following the six-phase framework by Virginia Braun and Victoria Clarke (2006). Two independent researchers coded the data separately and reached a high level of agreement ($\kappa = 0.84$). This process led to four main themes that clarify the behavioural mechanisms underlying the patterns observed in the quantitative data.

Theme 1: Confidence building through risk-free simulation. Participants often said that the mobile simulation environment was crucial for building technical skills. These safe practice settings helped learners gain confidence without risking mistakes in real logistics.

One practitioner shared, *"The simulations allowed me to experiment without the fear of causing shipment delays or customer dissatisfaction. By the time I transitioned to the live system, I felt capable of utilizing advanced features rather than sticking to the basics."*

This feedback supports the strong improvements in self-Efficacy and effort expectancy reported in Hypothesis 2, indicating that teaching support helps reduce psychological barriers to using new technology.

Theme 2: Just-in-Time (JIT) performance support. This theme shows how mobile learning can help users in real time as they interact with a system. Unlike traditional training, the cross-platform app gave users quick, relevant solutions. One participant said, *"When I hit a bottleneck in the blockchain interface while finalizing a complex shipment, I accessed a two-minute micro-module on my phone. That immediate support was the difference between completing the task and abandoning the system."* This example supports the synergy effects described in Hypothesis 4 and shows how teaching tools help people keep using technology when they need it most.

Theme 3: Social learning and the construction of organizational capability. Quantitative measures typically focus on individual performance, but the qualitative data revealed a 'social multiplier effect. Mobile platforms made it easier for people to share knowledge informally, turning individual learning into shared organizational intelligence. As one team leader put it, '*We formed informal study groups around the mobile content... discussing the simulation scenarios helped us develop a shared vision of how to apply the blockchain system as a team.*' This kind of social collaboration supports the socio-technical systems theory underlying Hypothesis 1, suggesting that improvements in organizational performance stem from both teamwork and individual skills.

Theme 4: Building trust in the system through clear explanations. The last theme, "Deepened Technology Appreciation," describes how people moved from skcepticism to trust in the system. When users learned how AI predictions work and why blockchain is secure, they became more willing to follow the system's advice. As one logistics manager said, '*Once I understood the 'why'—why blockchain is secure and how the AI calculates its forecasts—I was more willing to act on its suggestions.' I moved from second-guessing the system to focusing only on the exceptions.*' This change supports the process described in Hypothesis 5: understanding how the system works makes people see it as more useful, leading to long-term use.

5 DISCUSSION

The results provide robust empirical support for the integrated socio-technical framework, indicating that the combination of blockchain-AI systems and mobile pedagogical support yields operational and psychological benefits that exceed the sum of the individual effects. Quantitative analysis reveals that the Integrated Group (G4) consistently exceeded the 25% improvement threshold across all five key performance indicators (KPIs), while the significant Time × Group interaction ($\eta^2 p = 0.22$) demonstrates that this enhanced performance trajectory is attributable to the dual-intervention strategy. While the technology-only group (G2) achieved measurable improvements in traceability and document processing, it did not realize the cycle-time reductions observed in G4.

This disparity highlights a competence gap that technological solutions alone cannot bridge without pedagogical reinforcement. Moreover, the 13.5% synergy effect identified by factorial ANOVA further supports Socio-Technical Systems Theory, highlighting that enhancing both technological infrastructure and human factors aligns with [18].

Qualitative thematic analysis elucidates the mechanisms underlying these improvements. Themes such as "Confidence Building Through Safe Practice" and "Just-in-Time Performance Support" correspond to the substantial effect size observed in technology acceptance ($d = 1.02$), illustrating that simulation-based learning mitigates fear of operational errors and that micro-learning modules reduce the likelihood of system abandonment during critical moments.

The theme "Deepened Technology Appreciation" further clarifies the mediating role of perceived usefulness, which accounted for 55.8% of the variance in adoption intention. These practical implications are especially relevant for small and medium-sized enterprises, where the synergy effect was most pronounced, suggesting that integrated frameworks can compensate for limitations associated with lower digital maturity. Collectively, these findings reconceptualize training as an embedded and functional element of logistics infrastructure rather than a preliminary activity.

6 CONCLUSION

This paper presents strong evidence that combining blockchain-AI systems with mobile learning support brings clear benefits to logistics operations and technology adoption. The integrated approach led to significant improvements across all performance measures, showing a 13.5% gain beyond what would be expected from using each component separately. The findings show that mobile learning support is not just an extra training tool but an essential part of the system. It boosts user confidence, provides timely help, encourages social learning, and increases appreciation for the technology, all of which enhance the value of the technological setup. The study also explains how perceived usefulness connects learning and adoption, and its analysis of synergy effects in small and medium-sized businesses offers practical implementation advice. Overall, the results support the idea that technology and learning systems work best when combined, helping organizations make better decisions when investing in logistics technology.

6.1 Limitations and future research

The 12-month timeframe and regional focus offer a solid starting point, but future studies should use longer-term designs and include more regions to determine whether the results hold and apply across cultures. It would also help to test different technology setups and to use stronger econometric methods, such as propensity score matching, to better identify causal relationships and control for unobserved variables. This approach provides researchers with a strong foundation for exploring how new logistics technologies and mobile-first teaching methods interact over time.

7 REFERENCES

[1] R. Kumar, P. Kumar, S. C. C. Sobin, and N. P. Subheesh, Eds., *Blockchain and AI in Shaping the Modern Education System*. Boca Raton, FL, USA: CRC Press, 2025. https://doi.org/10.1201/9781003502739

[2] S. K. Lo, X. Xu, Y. K. Chiam, and Q. Lu, "Evaluating suitability of applying blockchain," in *2017 22nd International Conference on Engineering of Complex Computer Systems (ICECCS)*, Fukuoka, Japan: IEEE, 2017, pp. 158–161. https://doi.org/10.1109/ICECCS.2017.26

[3] K. Marwah, J. Izhar, R. Singh, and R. Jameel, "Revolutionizing education: The role of AI and blockchain," in *Blockchain and Machine Learning Innovations: Breaking Barriers with Distributed Intelligence*, Cham, Switzerland: Springer Nature Switzerland, 2025, pp. 231–247. https://doi.org/10.1007/978-3-031-88095-7_12

[4] M. A. Mohammed and H. B. Abdul Wahab, "Proposed new blockchain consensus algorithm," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 16, no. 20, pp. 162–176, 2022. https://doi.org/10.3991/ijim.v16i20.35549

[5] S. Okai-Ugbaje, "Towards a pedagogical and sociotechnical framework for the strategic integration of mobile learning in higher education in low- and middle-income countries," *Higher Education Research & Development*, vol. 40, no. 3, pp. 581–598, 2021. https://doi.org/10.1080/07294360.2020.1773768

[6] Z. Jia, D. Tang, L. Mei, X. Lu, and X. Bai, "Reshaping teachers' roles in intelligent physical education and job crafting: A multimethod approach," *J. Vis. Exp.*, no. 227, p. e69591, 2026. https://doi.org/10.3791/69591

[7] D. Li, "Innovative applications of augmented reality in pre-school education: Moderating role of school-enterprise collaboration in China," *J. Adv. Humanities Res.*, vol. 4, no. 2, pp. 18–36, 2025. https://doi.org/10.56868/jadhur.v4i2.305

[8] A. E. Ifedayo, D. Olugbade, and S. Hamid, "Integrating artificial intelligence with blockchain: A literature review on opportunities, challenges, and applications," *Blockchain, Artif. Intell., Future Res.*, vol. 1, no. 1, pp. 52–69, 2025. https://doi.org/10.70211/bafr.v1i1.179

[9] A. Ekramifard, H. Amintoosi, A. H. Seno, A. Dehghantanha, and R. M. Parizi, "A systematic literature review of integration of blockchain and artificial intelligence," in *Blockchain Cybersecurity, Trust and Privacy*, S. Choo, A. Dehghantanha, and R. M. Parizi, Eds., Cham, Switzerland: Springer, 2020, pp. 147–160. https://doi.org/10.1007/978-3-030-38181-3_8

[10] M. Hamilton, “Blockchain distributed ledger technology: An introduction and focus on smart contracts,” *J. Corp. Account. Finance*, vol. 31, no. 2, pp. 7–12, 2020. https://doi.org/10.1002/jcaf.22427

[11] D. Adam, D. B. Matellini, and A. Kaparaki, “Benefits for the bunker industry in adopting blockchain technology for dispute resolution,” *Blockchain: Res. Appl.*, vol. 4, no. 2, p. 100128, 2023. https://doi.org/10.1016/j.bcra.2023.100128

[12] G. M. Zebari and N. Al Musalhi, “A comprehensive review of integrating AI and blockchain security: Innovations, challenges, and future directions,” *Security and Privacy*, vol. 8, no. 5, p. e70094, 2025. https://doi.org/10.1002/spy2.70094

[13] D. Rai, “AI driven optimization in specific SCM domains: Warehousing, logistics, transport,” *J. Comput. Sci. Technol. Stud.*, vol. 7, no. 9, pp. 612–618, 2025. https://doi.org/10.32996/jcsts.2025.7.9.62

[14] R. Shkilev *et al.*, “Augmented reality in mobile learning: Enhancing interactive learning experiences,” *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 18, no. 20, pp. 4–15, 2024. https://doi.org/10.3991/ijim.v18i20.50795

[15] D. T. Naidoo, “Integrating TAM and IS success model: Exploring the role of blockchain and AI in predicting learner engagement and performance in e-learning,” *Frontiers Comput. Sci.*, vol. 5, p. 1227749, 2023. https://doi.org/10.3389/fcomp.2023.1227749

[16] H. Yu and Z. Zou, “The music education and teaching innovation using blockchain technology supported by artificial intelligence,” *Int. J. Grid Utility Comput.*, vol. 14, nos. 2–3, pp. 278–296, 2023. https://doi.org/10.1504/IJGUC.2023.131018

[17] O. Kuznetsov, P. Sernani, L. Romeo, E. Frontoni, and A. Mancini, “On the integration of artificial intelligence and blockchain technology: A perspective about security,” *IEEE Access*, vol. 12, pp. 3881–3897, 2024. https://doi.org/10.1109/ACCESS.2023.3349019

[18] S. Agal, N. Bhavsar, K. Shekokar, and S. S. Shrivastava, “A unified framework for smart and secure digital transformation: Leveraging blockchain, AI, and ICT across healthcare, education, e-commerce, and industrial systems,” *Int. J. Sci. Res. Arch.*, vol. 15, no. 1, pp. 927–943, 2025. https://doi.org/10.30574/ijsra.2025.15.1.1084

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