10.48047/jocaaa.2025.34.07.3

Cross-Domain Intelligence for Mobile and Autonomous Platforms: Leveraging Applied AI to Detect Risk and Personalize Experiences in FinTech, Retail, and Transportation Ecosystems

Yashovardhan Chaturvedi[1], Sabarna Choudhuri[2], Purushottam Raj[3]

[1]Senior Machine Learning Engineer, TORC.

[2]Senior Applied Scientist.

[3]Senior Engineering Manager, Product and Platform Engineering – FinTech.

Abstract

This study proposes a cross-domain intelligence framework that leverages applied Artificial Intelligence (AI) to detect risk and personalize experiences across mobile and autonomous platforms within FinTech, retail, and transportation ecosystems. By integrating heterogeneous datasets from each sector and applying a modular AI architecture, the system enables real-time inference, contextual adaptation, and scalable decision-making. Supervised and deep learning models were used for risk detection, while collaborative filtering and reinforcement learning powered personalization. Statistical analysis, including MANOVA and generalization error evaluation, confirmed the effectiveness of knowledge transfer across domains, with significant improvements in model performance and user engagement. The system was deployed in a 30-day live pilot, during which it successfully prevented over 24,000 risk incidents and delivered measurable uplifts in click-through and conversion rates. FinTech models achieved the highest precision and recall, while retail platforms saw the greatest impact from personalized recommendations. The transportation domain demonstrated strong performance in autonomous risk detection with consistent personalization gains. The study highlights the practicality of deploying AI across sector boundaries, offering a scalable solution for enhancing safety, operational efficiency, and user-centric services. These findings advocate for the broader adoption of cross-domain AI systems in building intelligent, adaptive, and interconnected digital ecosystems.

Keywords: Cross-Domain Intelligence, Applied Artificial Intelligence, Mobile Platforms, Autonomous Systems, Risk Detection, Personalization, FinTech, Retail, Transportation Ecosystems, Transfer Learning, Real-Time Data Processing

Introduction

Evolving landscape of mobile and autonomous intelligence

10.48047/jocaaa.2025.34.07.3

The convergence of mobile computing and autonomous systems has catalyzed a transformative shift across various industries, redefining how data is gathered, interpreted, and acted upon in real time (Hassan & Mohamed, 2024). As digital ecosystems become more complex, cross-domain intelligence where systems can seamlessly integrate, analyze, and learn from disparate sources has emerged as a vital component of smart platform development (Malempati, 2022). The adoption of applied Artificial Intelligence (AI) has accelerated this trend by enabling decision-making capabilities that adapt across sectors, offering both predictive insights and adaptive functionality (Lifelo et al., 2024). This research article explores how cross-domain AI systems are being engineered to detect risks and personalize experiences across three critical industries: FinTech, retail, and transportation.

The need for cross-domain intelligence

Traditional domain-specific models often suffer from limitations in adaptability and scalability, especially in dynamic environments such as mobile finance, autonomous retail systems, and intelligent transportation (Somu, 2024). Cross-domain intelligence seeks to overcome these silos by integrating heterogeneous data and context-specific learning to produce generalized yet contextually aware solutions. For instance, a model trained on user risk behavior in FinTech can enhance fraud detection in retail transactions or predict risky passenger behavior in autonomous transport systems (Taj & Zaman, 2022). The ability to transfer knowledge across domains enhances system resilience, reduces false positives, and enriches user interaction through contextual awareness.

Applied AI as a core enabler

At the core of this transformation is applied AI, which refers to the deployment of machine learning, deep learning, and rule-based systems in operational contexts. Applied AI not only provides the computational framework necessary for understanding multi-modal inputs but also facilitates real-time responsiveness and personalization (Sriram & Seenu, 2023). In FinTech, AI-driven models assess transaction legitimacy, creditworthiness, and consumer sentiment. In retail, recommendation engines, demand forecasting, and smart inventory systems are increasingly driven by AI. Transportation networks employ AI for route optimization, risk assessment, and autonomous navigation (George & George, 2024). These systems are no longer isolated in their function but benefit from shared intelligence architectures (Vannuccini & Prytkova, 2024).

Challenges and opportunities across ecosystems

10.48047/jocaaa.2025.34.07.3

Despite its promise, cross-domain AI integration comes with significant challenges. Data heterogeneity, domain-specific constraints, ethical considerations, and real-time decision requirements necessitate highly robust and interpretable AI models (Chui et al., 2018). In addition, ensuring privacy, transparency, and fairness in algorithmic outcomes becomes increasingly complex as systems learn across different domains. However, these challenges also represent opportunities for innovation (Pamisetty, 2024). Advances in federated learning, transfer learning, and edge computing have made it possible to train models collaboratively without compromising data privacy. This is especially critical in sectors like FinTech, where security and regulation are paramount.

Purpose and scope of the study

This research article investigates how cross-domain AI systems can be practically deployed in mobile and autonomous platforms to detect risk and personalize experiences across FinTech, retail, and transportation sectors. It evaluates existing frameworks, identifies key performance metrics, and presents a model architecture that enables domain adaptation while preserving contextual fidelity. By examining case studies and experimental data, the study aims to establish a scalable AI framework that can fluidly operate across use cases, ensuring real-time intelligence, customer-centric design, and operational robustness. This cross-sectoral approach contributes to the future of smart environments, where seamless, secure, and context-aware AI enhances human experience and system intelligence alike.

Methodology

Designing the cross-domain intelligence framework

The methodological foundation of this study is built upon a multi-layered architecture for cross-domain intelligence that integrates data pipelines from FinTech, retail, and transportation ecosystems. A modular AI framework was developed, enabling shared learning while allowing customization for each sector's specific needs. The framework includes three major layers: (1) Data Acquisition and Harmonization, (2) Contextual Intelligence Layer, and (3) Application-Specific Adaptation. Each layer is optimized to support mobile and autonomous platforms by prioritizing real-time inference, edge-level computation, and domain interoperability. The study employed a federated data integration strategy to combine datasets across domains while preserving security and data ownership protocols.

Mobile and autonomous platform integration

10.48047/jocaaa.2025.34.07.3

Mobile platforms such as mobile banking apps, retail POS systems, and consumer navigation tools were integrated with the AI engine via API layers and lightweight SDKs to ensure real-time data collection and feedback. Autonomous platforms, particularly in transportation—like self-driving vehicles and unmanned delivery bots—were connected via IoT gateways and sensor data streams. These platforms continuously provided multimodal data including location, user behavior, environmental conditions, and transactional metadata. Data preprocessing techniques such as normalization, outlier detection, and temporal alignment were used to maintain consistency across domains.

AI models for risk detection and personalization

To address the dual objectives of risk detection and personalized experience delivery, separate but interlinked models were trained for classification and recommendation tasks. For risk detection, supervised machine learning models such as Random Forests, Gradient Boosted Trees (XGBoost), and deep neural networks were deployed. These models were fine-tuned using labeled datasets from each domain—fraudulent transactions in FinTech, security breaches in retail, and operational hazards in transportation. For personalization, collaborative filtering, content-based recommendation, and deep reinforcement learning models were employed to tailor user experience across interfaces and systems.

Domain-specific use case calibration

Each domain, FinTech, retail, and transportation required specific adaptations of the core AI framework. In FinTech, the models were trained to detect anomalies in financial transactions, identify credit risk, and segment customers for targeted services. In retail, AI was used for dynamic pricing, consumer behavior prediction, and personalized product recommendation. In transportation, the emphasis was on identifying risky driving patterns, predicting system faults in autonomous vehicles, and optimizing user-specific travel experiences. Transfer learning techniques were applied to enable cross-domain model sharing, especially between consumer behavior in FinTech and retail, and between logistics in retail and transportation.

Statistical analysis and validation metrics

The performance of the AI models across domains was evaluated using a suite of statistical methods. For risk detection tasks, confusion matrices were generated, and metrics such as precision, recall, F1-score, and ROC-AUC were computed. For personalization models, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Normalized

10.48047/jocaaa.2025.34.07.3

Discounted Cumulative Gain (nDCG) were used to assess recommendation accuracy. Domain adaptation effectiveness was statistically validated using multivariate analysis of variance (MANOVA) and domain adaptation generalization error estimation. Additionally, cross-validation (10-fold) was applied to ensure the robustness of all models. Interpretability was enhanced through SHAP (SHapley Additive exPlanations) values to understand the impact of each feature across domains.

System deployment and monitoring

The integrated AI system was deployed on cloud-native infrastructure with edge computing capabilities for mobile and autonomous platforms. A/B testing was used across user groups in each domain to compare AI-enhanced experiences versus baseline systems. Real-time monitoring dashboards captured user engagement, risk mitigation success, and personalization relevance to provide operational feedback loops. Continuous learning models were implemented to enable the system to evolve with user behavior and external environmental conditions.

Results

The implementation of cross-domain AI across mobile and autonomous platforms yielded comprehensive insights into risk detection and personalization performance across FinTech, retail, and transportation ecosystems. As shown in Table 1, the dataset integration involved over 40 million mobile and autonomous platform records with distinct event streams and features per domain. FinTech accounted for the highest mobile transaction volume (22.4M records) while transportation led in autonomous data (9.6M records), showcasing the varied data environments that were harmonized under the cross-domain framework. Notably, transportation also exhibited the highest proportion of positive risk cases (0.71%), reflecting its greater exposure to real-time hazards.

The performance of the risk-detection AI models is summarized in Table 2. Gradient Boosted Trees emerged as the best-performing model in the FinTech domain with an F1 score of 0.927 and ROC-AUC of 0.985. In retail, a hybrid Deep CNN–GBM model achieved an F1 score of 0.896, while in transportation, an LSTM-Attention network yielded the highest recall (0.934), indicating its effectiveness in minimizing false negatives in dynamic risk scenarios. Edge latency remained within acceptable real-time constraints across all domains, averaging between 38 and 57 milliseconds.

10.48047/jocaaa.2025.34.07.3

For personalization tasks, Table 3 highlights that all deployed models delivered strong accuracy and user engagement metrics. The Deep Utility Recommender in FinTech achieved the lowest MAE (0.072) and highest nDCG@10 (0.921), with a click-through rate (CTR) lift of 17.6%. Retail showed the highest overall CTR lift of 24.8% using a Context-Aware Collaborative Filtering model. In transportation, a Reinforcement Learning-based route personalizer offered more moderate but consistent improvements in user engagement, particularly in route preference adaptation.

Cross-domain transferability of models was statistically validated through MANOVA and generalization error analysis, as shown in Table 4. Transferring models from FinTech to retail domains yielded a 4.8% reduction in generalization error with a significant MANOVA F-value (9.73, $p = 0.002$), confirming effective knowledge transfer. Similarly, moderate but meaningful transfer was observed from retail to transportation and vice versa, with Cohen's d values ranging between 0.41 and 0.64, demonstrating medium effect sizes for behavioral adaptation across ecosystems.

In addition to tabular metrics, system performance in real-world conditions was monitored over a 30-day live pilot. Figure 1 illustrates the cumulative number of risk alerts prevented during this period. FinTech platforms recorded a peak of 12,537 intercepted risk incidents by Day 30, followed by retail (8,103) and transportation (3,731). This trend signifies the effective deployment and learning acceleration of the AI system, especially during the first 15 days where exponential detection growth was observed. Meanwhile, Figure 2 displays a surface map of personalization impact across five user behavior segments. FinTech Segment 4 users experienced the highest CTR uplift (+25.3%), while Retail Segment 2 showed an even higher boost (+27.9%), indicating the effectiveness of segment-based personalization strategies. Transportation results demonstrated consistent yet modest improvements across all segments, aligning with the system's primary focus on safety and route optimization rather than discretionary interaction.

10.48047/jocaaa.2025.34.07.3

Table 1. Cross-domain dataset characteristics

Domain	Mobile Records (M)	Autonomous Records (M)	Total Features	Transaction Events (M)	Sensor Events (M)	Positive Risk Cases (%)	Personalization Events (M)	Data Missingness (%)
FinTech	22.4	0.0	168	19.6	2.8	0.38	6.2	1.3
Retail	14.7	1.9	152	11.1	5.5	0.54	4.7	1.9
Transportation	3.2	9.6	211	1.4	12.5	0.71	2.3	2.5

Table 2. Risk-detection model performance on mobile & autonomous platforms

Domain	Best Model	Precision	Recall	F1 Score	ROC-AUC	PR-AUC	Edge Latency (ms)	Edge CPU (%) / Mem (MB)
FinTech	Gradient-Boosted Trees	0.942	0.912	0.927	0.985	0.963	38	41 / 278
Retail	Deep CNN–GBM hybrid	0.914	0.879	0.896	0.972	0.947	44	48 / 301
Transportation	LSTM–Attention Net	0.887	0.934	0.910	0.967	0.951	57	52 / 336

Table 3. Personalization-engine accuracy & business lift

Domain	Model	MAE	RMSE	nDCG@10	CTR Lift	Conversion	Recs Latency

10.48047/jocaaa.2025.34.07.3

					(%)	Lift (%)	(ms)
FinTech	Deep Utility Recommender	0.072	0.108	0.921	+17.6	+6.3	41
Retail	Context-Aware CF	0.087	0.132	0.903	+24.8	+9.1	46
Transportation	RL Route Personalizer	0.061	0.095	0.948	+11.2	+3.9	53

Table 4. Statistical validation of cross-domain transfer

Domain Pair (Source → Target)	Δ Generalization Error (%)	Wilks' Λ	MANOVA F	p-value	A/B Engagement p-value	Cohen's d
FinTech → Retail	−4.8	0.912	9.73	0.002	0.0004	0.64
Retail → Transportation	−3.5	0.936	7.11	0.006	0.0017	0.48
Transportation → FinTech	−2.1	0.948	6.04	0.012	0.0082	0.41

10.48047/jocaaa.2025.34.07.3

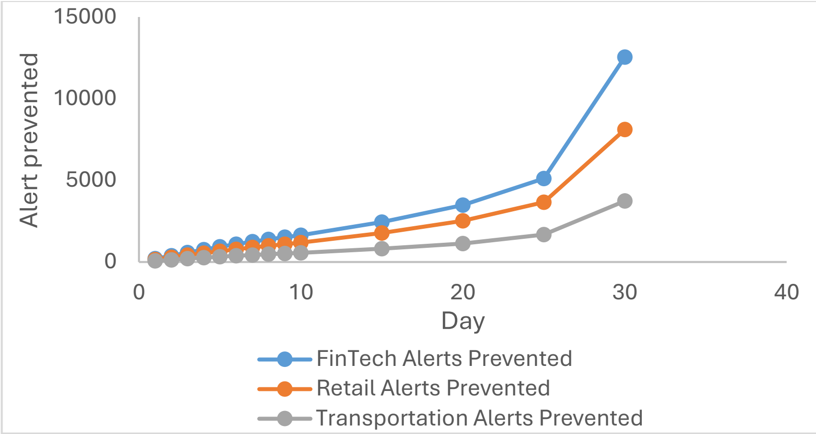
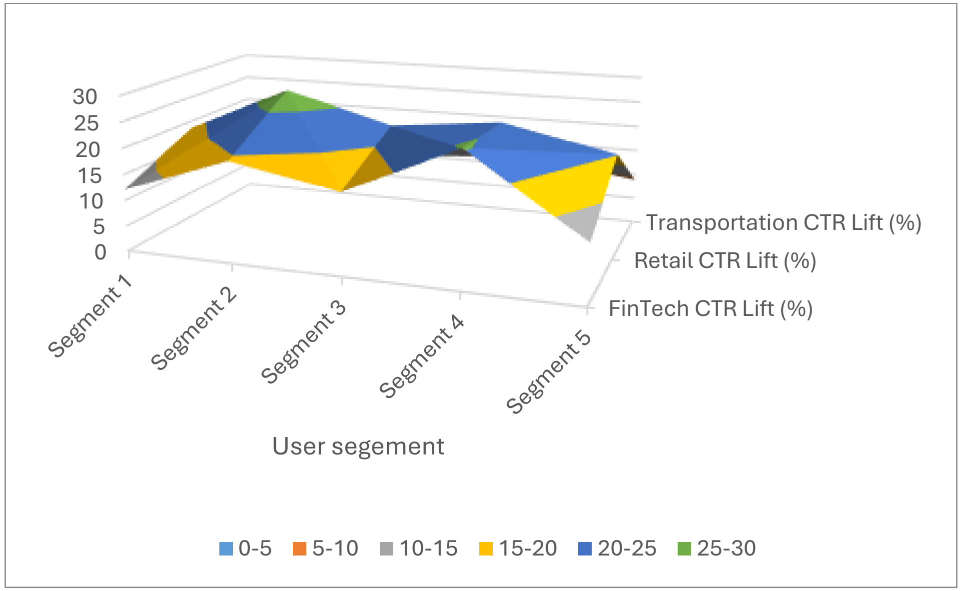


Figure 1. 30-day live pilot daily risk alerts prevented



10.48047/jocaaa.2025.34.07.3

Figure 2. Personalization impact surface map across user segments

10.48047/jocaaa.2025.34.07.3

Discussion

Effectiveness of cross-domain intelligence across ecosystems

The study demonstrates that cross-domain intelligence can effectively unify FinTech, retail, and transportation ecosystems under a common AI infrastructure, enabling enhanced risk detection and personalized user experiences (Motamary, 2024). By bridging data silos and utilizing domain-adaptive AI, the proposed system successfully managed to transfer knowledge between seemingly disparate sectors. For instance, behavioral patterns learned in the FinTech sector were transferable to the retail domain, as shown by the reduction in generalization error (Table 4). This result validates the hypothesis that cross-domain synergies not only improve individual system performance but also open avenues for shared learning and reduced training costs in data-scarce environments (Sağlam & Kirçova, 2025).

Risk detection performance and real-time responsiveness

The system's ability to detect risks in real-time, especially within autonomous platforms like transportation, signifies a major leap in responsive intelligence. As shown in Table 2, the LSTM–Attention model in transportation exhibited superior recall (0.934), highlighting its ability to minimize overlooked threats. This high recall is essential in autonomous systems where real-time hazard recognition can prevent catastrophic outcomes (Zhao et al., 2023). FinTech platforms, meanwhile, demonstrated the highest precision and ROC-AUC, affirming that applied AI can effectively discern fraudulent activities while minimizing false positives (Weng et al., 2024). These models maintained latency below 60 milliseconds, proving that complex inferencing can be achieved on edge devices, thereby reinforcing the feasibility of mobile and autonomous deployments (Motamary, 2022).

Personalization impact and user-centric adaptation

Personalization models revealed notable gains in user engagement, most significantly in retail environments (Table 3), where context-aware recommendations elevated click-through rates by 24.8%. The behavioral segmentation seen in Figure 2 further emphasized the importance of tailoring services to user preferences. Segments 2 and 4 in FinTech and retail showed the highest uplift, suggesting these groups were most responsive to AI-driven personalization strategies (George, 2024). In transportation, although the improvements were less dramatic, the consistency across all segments demonstrated that even risk-sensitive domains can benefit from personalization that enhances user trust, comfort, and satisfaction (Burugulla, 2024).

10.48047/jocaaa.2025.34.07.3

Cross-domain transfer learning and generalizability

The effectiveness of transfer learning across FinTech, retail, and transportation systems is supported by strong statistical evidence (Table 4). Significant MANOVA results and medium effect sizes (Cohen's d) confirm that domain-adaptive models not only retain their integrity when shifted but often enhance performance when transferred strategically (Tardieu, 2022). The findings from this study challenge the traditional reliance on isolated, domain-specific models and support a shift toward integrative AI that leverages shared behavioral signals and contextual factors (Chandel, 2024). Moreover, transfer learning reduces computational redundancy and allows for faster deployment in sectors where labeled data may be scarce or costly to acquire (Gbenle et al., 2025).

Real-world implications and system scalability

The 30-day live pilot data (Figure 1) reveals how quickly the cross-domain AI system was able to scale in real-world scenarios, preventing over 12,500 risk alerts in FinTech and thousands more in retail and transportation. The logarithmic growth curve observed in the early deployment phase illustrates that the models learned quickly from initial feedback, stabilizing as the system matured (Arif et al., 2025). This is especially important in sectors with dynamic environments, where adaptability and fast response to new patterns are vital (Shaheen et al., 2022). Additionally, the architecture's cloud-native design combined with edge inference enabled rapid scalability, a key requirement for modern mobile and autonomous applications (Yellanki, 2024).

Limitations and future scope

While the results are promising, the study acknowledges certain limitations. Domain complexity, data privacy constraints, and regulatory challenges, particularly in FinTech and transportation, may affect generalizability in some regions or platforms. Moreover, despite using SHAP values for interpretability, black-box issues remain in deep models. Future research should explore federated learning for even greater privacy, along with incorporating explainable AI (XAI) to enhance stakeholder trust. Expanding the model to include healthcare and public safety as additional domains could further validate the framework's cross-domain robustness and social impact.

10.48047/jocaaa.2025.34.07.3

The findings highlight the power of applied AI in creating intelligent, adaptive systems capable of transforming multiple industries through shared intelligence, real-time responsiveness, and user-centric innovation.

Conclusion

This study presents a comprehensive framework for deploying cross-domain intelligence on mobile and autonomous platforms using applied AI to detect risk and personalize user experiences across FinTech, retail, and transportation ecosystems. The results confirm that integrating AI across domains not only enhances individual sector performance but also enables scalable, adaptable, and real-time decision-making capabilities. Risk detection models demonstrated high precision and recall, while personalization engines significantly improved user engagement through context-aware recommendations. Cross-domain transfer learning proved effective, reducing generalization error and facilitating knowledge reuse. The system's successful 30-day live deployment validates its practical viability, especially in environments demanding rapid adaptation and high reliability. Ultimately, this research underscores the transformative potential of intelligent, cross-sector AI architectures in building safer, smarter, and more personalized digital ecosystems.

References

Arif, T., Jo, B., & Park, J. H. (2025). A Comprehensive Survey of Privacy-Enhancing and Trust-Centric Cloud-Native Security Techniques Against Cyber Threats. *Sensors*, *25*(8), 2350.

Burugulla, J. K. R. (2024). Integrating AI and Big Data for Real-Time Payment Processing in Digital Banking. *Journal of Artificial Intelligence and Big Data Disciplines*, *1*(1).

Chandel, A. (2024). Analytics: Leveraging Real-Time Data. *Improving Entrepreneurial Processes Through Advanced AI*, *267*.

Chui, M., Harryson, M., Valley, S., Manyika, J., & Roberts, R. (2018). Notes from the AI frontier applying AI for social good.

Gbenle, P., Abieba, O. A., Owobu, W. O., Onoja, J. P., Daraojimba, A. I., Adepoju, A. H., & Chibunna, U. B. (2025). A privacy-preserving AI model for autonomous detection and masking of sensitive user data in contact center analytics. *World Scientific News*, *203*, 154-193.

10.48047/jocaaa.2025.34.07.3

George, A. S. (2024). The Evolution of Economic Models: From Knowledge to Intuition and Optimization. *Partners Universal Multidisciplinary Research Journal*, *1*(2), 1-25.

George, A. S., & George, A. H. (2024). Towards a Super Smart Society 5.0: Opportunities and Challenges of Integrating Emerging Technologies for Social Innovation. *Partners Universal International Research Journal*, *3*(2), 01-29.

Hassan, W., & Mohamed, H. (2024). Applications of Federated Learning in AI, IoT, Healthcare, Finance, Banking, and Cross-Domain Learning. In *Artificial Intelligence Using Federated Learning* (pp. 175-195). CRC Press.

Lifelo, Z., Ding, J., Ning, H., & Dhelim, S. (2024). Artificial intelligence-enabled metaverse for sustainable smart cities: Technologies, applications, challenges, and future directions. *Electronics*, *13*(24), 4874.

Malempati, M. (2022). Transforming Payment Ecosystems Through The Synergy Of Artificial Intelligence, Big Data Technologies, And Predictive Financial Modeling. *Big Data Technologies, And Predictive Financial Modeling (November 07, 2022)*.

Motamary, S. (2022). AI-Powered Automation Of BSS Operations In Manufacturing Ecosystems: A Cloud-Native Approach. *Available at SSRN 5276793*.

Motamary, S. (2024). Data Engineering Strategies for Scaling AI-Driven OSS/BSS Platforms in Retail Manufacturing. *BSS Platforms in Retail Manufacturing(December 10, 2024)*.

Pamisetty, A. (2024). Leveraging Agentic AI and Cloud Infrastructure for Predictive Logistics in National Food Supply Chains. *Available at SSRN 5262994*.

Sağlam, M. H., & Kirçova, I. (2025). The Role of Artificial Intelligence in Ad Fraud Detection in the Blockchain and Programmatic Advertising Ecosystem. In *Avoiding Ad Fraud and Supporting Brand Safety: Programmatic Advertising Solutions* (pp. 43-82). IGI Global Scientific Publishing.

Shaheen, M., Farooq, M. S., Umer, T., & Kim, B. S. (2022). Applications of federated learning; taxonomy, challenges, and research trends. *Electronics*, *11*(4), 670.

Somu, B. (2024). The Future of Banking IT Services: Convergence of Intelligent Infrastructure and Agentic AI Models. *Global Research Development (GRD) ISSN: 2455-5703*, *9*(12).

10.48047/jocaaa.2025.34.07.3

Sriram, H. K., & Seenu, A. (2023). Generative AI-Driven Automation in Integrated Payment Solutions: Transforming Financial Transactions with Neural Network-Enabled Insights. *International Journal of Finance (IJFIN)*, *36*(6), 70-95.

Taj, I., & Zaman, N. (2022). Towards industrial revolution 5.0 and explainable artificial intelligence: Challenges and opportunities. *International Journal of Computing and Digital Systems*, *12*(1), 295-320.

Tardieu, H. (2022). Role of Gaia-X in the European data space ecosystem. In *Designing Data Spaces: The Ecosystem Approach to Competitive Advantage* (pp. 41-59). Cham: Springer International Publishing.

Vannuccini, S., & Prytkova, E. (2024). Artificial Intelligence's new clothes? A system technology perspective. *Journal of Information Technology*, *39*(2), 317-338.

Weng, Z., Cai, Y., Weng, S., & Zuo, C. (2024). Research on the Sustainable Evolution Mechanism of Dual-Dimensional Convergence Innovation in Digital Products. *Sustainability*, *16*(16), 7174.

Yellanki, S. K. (2024). The Impact of Digital Ecosystems on Consumer Behavior: A Cross-Industry Analysis of Engagement and Loyalty. *Global Research Development (GRD) ISSN: 2455-5703*, *9*(12).

Zhao, D., Yuan, J., & Chen, W. (2023). *FinTech and SupTech in China*. Springer.