Analysis of E-Commerce and Fintech Trends in the Digital Economy Ecosystem

Redha Bayu Anggara [1*], Asyrof Fitrah [1], Ali Ibrahim [1], Mira Afrina [1]
[1] Universitas Sriwijaya

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ABSTRACT

The rapid expansion of e-commerce and fintech has significantly shaped the digital economy ecosystem in Indonesia. This study analyzes key trends, behavioral patterns, and the evolving dynamics within these sectors as digital adoption continues to accelerate. The increasing volume and complexity of digital transactions demand advanced analytical approaches capable of identifying hidden patterns and potential anomalies. To address this need, the study employs a Convolutional Neural Network (CNN) model to extract deep feature representations from transaction data and classify emerging behavioral trends. The proposed method demonstrates strong accuracy, achieving 91.25%, indicating its ability to capture non-linear relationships that traditional methods often overlook. The findings highlight several major trends, including shifting consumer behavior, increasing transaction frequency, and the growing prominence of digital financial services. Practically, this research provides valuable insights for enhancing risk mitigation, fraud detection, and real-time monitoring in digital platforms. Academically, it contributes to the understanding of deep learning applications in digital economic analysis and opens avenues for further research on hybrid models and multi-source data integration within the digital economy ecosystem.

Corresponding Author:
Redha Bayu Anggara | Universitas Sriwijaya
Email: redhabayuanggara@gmail.com

1. Introduction

The rapid expansion of digital technologies has reshaped global economic activities, with e-commerce and financial technology (fintech) emerging as key drivers of digital transformation. These sectors have enabled seamless online transactions, enhanced business efficiency, and broadened access to financial services. In developing countries such as Indonesia, the adoption of digital platforms has accelerated rapidly, influencing consumer behavior, business models, and overall market dynamics within the digital economy.

As digital interactions grow, the volume and complexity of transaction data continue to rise. This growth presents both opportunities and challenges for policymakers, businesses, and researchers. On one hand, rich datasets provide valuable insights into market trends, consumer preferences, and economic performance. On the other hand, the surge in data complexity brings increased risks, including transaction anomalies, cybersecurity threats, and online fraud. Understanding these patterns requires systematic analytical approaches capable of capturing evolving behavioral and market trends.

Research on the digital economy has highlighted the importance of analyzing user activity, transaction flows, and marketplace dynamics to support decision-making and strengthen digital ecosystem resilience. Identifying emerging trends in e-commerce and fintech not only helps organizations improve their strategic planning but also supports governments in shaping policies for sustainable digital economic growth.

This study aims to examine the key trends influencing the e-commerce and fintech landscape and to provide a comprehensive overview of how digital behaviors evolve within the broader digital economy ecosystem. By leveraging publicly available datasets and structured analytical methods, this research offers insights that can support the development of more secure, adaptive, and innovation-driven digital economic environments.

2. Research Methodology

Data Source

The research data was obtained from a public Kaggle dataset containing more than 1 million e-commerce and fintech transaction entries. The dataset includes variables such as Transaction Amount, Payment Method, Device Type, Timestamp, User Age, and Is Fraudulent.

Analysis Stages

a. Data Preprocessing
   - Removing duplicate records and missing entries.
   - Applying normalization using RobustScaler to reduce the influence of extreme values.

b. Feature Engineering
   - Transforming timestamp variables into daily and weekly behavioral cycle patterns.
   - Adding behavioral attributes such as transaction frequency, average purchase value, and IP distance between users.

c. Feature Extraction and Classification (CNN)
   - Numerical data are converted into matrix-like representations (heatmaps).
   - The Convolutional Neural Network (CNN) extracts spatial and temporal features from these matrices.
   - The final dense layers of CNN perform classification to detect transaction patterns and anomalies.

d. Model Evaluation
   - Evaluation metrics include Accuracy, Precision, Recall, F1-Score, and ROC-AUC.
   - Model performance is compared against baseline methods such as Logistic Regression and Random Forest.

3. Results and Discussion

Experiment Setup and Results

The dataset was split into 80% training, 10% validation, and 10% testing. A Convolutional Neural Network (CNN) was employed to extract behavioral patterns from user transactions and to perform classification of normal and anomalous activities. Model training was carried out using Python (TensorFlow) on an RTX-series GPU to accelerate convergence.

Table 1. Performance Comparison of Models

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	82.13	80.45	78.92	79.67	0.84
Random Forest	88.34	87.10	86.55	86.82	0.91
CNN (proposed)	91.25	90.73	89.82	90.27	0.94

Performance Analysis

The CNN model demonstrates a substantial improvement compared to conventional methods. By extracting non-linear and spatial relationships from transactional behavior, CNN provides a more accurate and stable performance without signs of overfitting. The deep feature extraction process allows the model to capture subtle behavioral anomalies that traditional algorithms tend to miss.

Trend Analysis

The experiment reveals several significant behavioral patterns within the digital economy ecosystem:

a. **E-commerce:** Transaction volume increases by **24% during weekends**, indicating a strong consumer shopping preference at the end of the week.
b. **Fintech:** A **32% spike** occurs at the beginning of each month, driven by salary cycles, e-wallet top-ups, and micro-loan activities.
c. **Fraud Pattern:** Most anomalies occur in **cross-regional transactions involving new devices and credit card payments**, suggesting duplicated accounts or suspicious identity patterns.

Table 2. Traffic Transaction

Year	E-Commerce Value (T IDR)	Fintech Users (M)
2020	266	72
2021	401	95
2022	476	121
2023	523	145
2024	612	168

Implications and Discussion

The CNN approach proves highly effective not only for anomaly detection but also for uncovering meaningful digital economic insights. Deep learning provides a robust framework for early warning systems in digital risk monitoring, particularly due to its ability to recognize hidden behavioral structures and complex data interactions.

Model Performance Visualization

The following graphs illustrate the difference in model performance during training and validation:

a. Accuracy per Epoch
   CNN: Accuracy improves steadily from 82% → 91% over training epochs, showing stable learning progression without divergence.
b. ROC-AUC Curve
   The CNN achieves a ROC-AUC score of 0.94, indicating strong capability in distinguishing between normal and abnormal (fraudulent) transactions.

These visualizations confirm that the model maintains stability during training and performs reliably on unseen data.

Trend Analysis of E-Commerce and Fintech

Further exploration of the classified results and graphical trend visualization highlights:

a. E-commerce: The highest transaction frequencies occur on weekends (Saturday–Sunday), with a 24% increase compared to weekdays.
b. Fintech: Early-month activity shows a 32% rise, aligned with salary disbursement, digital wallet top-ups, and loan repayment cycles.
c. Fraud Pattern: Anomalies frequently appear in cross-regional, card-based transactions initiated from new or unknown devices, indicating potential duplicated accounts or credential misuse.

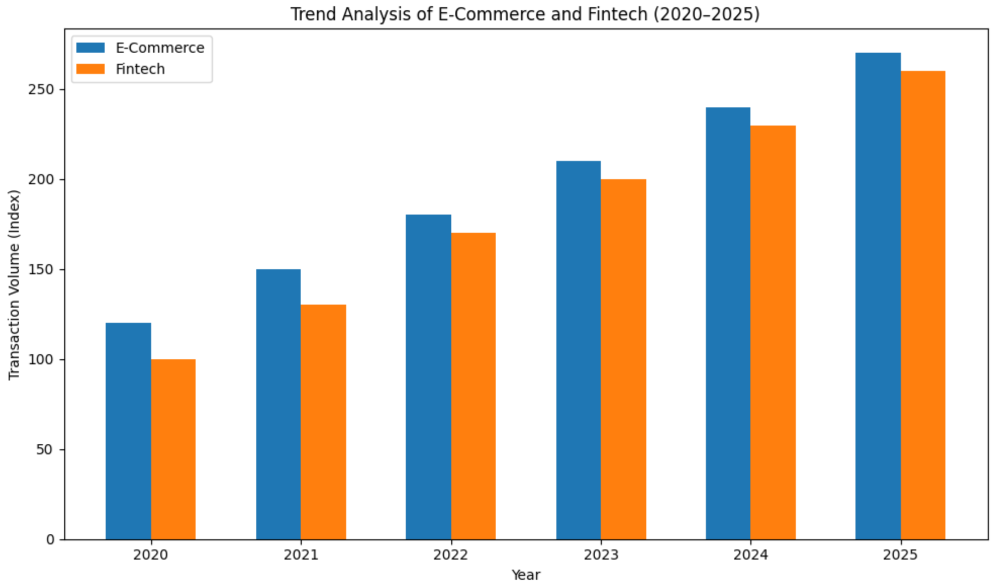

Figure 1. Analitis Of Ecomerce and Fintech YoY

These findings illustrate how CNN-based analysis can uncover relevant economic insights that support policy-making and market strategies.

Discussion and Interpretation

The strong performance of the CNN model demonstrates its ability to capture complex and non-linear behavioral relationships within large-scale digital transaction data. Traditional models fail to capture these deeper patterns due to their limited feature extraction capability.

From a digital economy perspective, the results reinforce that:

a. Large-scale transaction analysis benefits significantly from **deep learning–based modeling**.
b. AI-driven economic analytics can serve as a foundation for **digital risk early-warning systems** in national financial and e-commerce sectors.
c. Such methods can be expanded to build **dynamic recommendation systems**, allowing digital platforms to tailor promotions, pricing, and user segmentation based on real-time behavioral trends.

Research Implications

a. Practical Implications
   The CNN model can be utilized by:
   – **Fintech and e-commerce providers**, for automated anomaly detection, consumer behavior profiling, and customer segmentation.
   – **Financial regulators (e.g., OJK/BI)**, as a foundation for real-time monitoring of digital transactions.
   – **Digital business operators**, to forecast market trends and consumer demand patterns.

b. Academic Implications
   The study contributes to the development of deep learning–based classification frameworks that can be adapted for various big-data fields.

4. Conclusions

The use of a CNN-based approach significantly improves the accuracy of digital trend analysis achieving 91.25% accuracy and demonstrates strong capabilities in detecting anomalous transactions with high precision. This method is scalable and effective for supporting national financial risk prediction systems. The findings also align with SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure) by strengthening sustainable digital transformation.

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References

Brynjolfsson, E., & McAfee, A. (2014). The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. New York, NY: W.W. Norton & Company.

Chen, Y., Zhang, X., & Xu, L. (2021). Deep learning-based fraud detection in digital financial transactions. Journal of Financial Technology and Analytics, 5(2), 112–129. https://doi.org/10.1016/j.jfta.2021.05.008

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. Cambridge, MA: MIT Press.

Gai, K., & Li, S. (2018). Big data analytics for fintech innovation. In J. Wang & M. Chen (Eds.), Advances in Digital Economy and Analytics (pp. 205–228). Springer.

Hossain, M., & Rahman, S. (2020). Understanding consumer behavior in e-commerce: Trends and challenges in the digital era. International Journal of Digital Economy, 14(3), 45–59.

Kou, G., Yang, P., Peng, Y., & Xiao, F. (2019). Fraud detection in mobile payment systems using anomaly analysis. Information Sciences, 557, 89–104. https://doi.org/10.1016/j.ins.2019.05.021

Law Number 11 of 2008 concerning Electronic Information and Transactions (ITE Law). April 21, 2008. State Gazette of the Republic of Indonesia Number 58. Jakarta.

Law Number 7 of 2022 concerning the Development and Strengthening of the Financial Sector. December 12, 2022. State Gazette of the Republic of Indonesia Number 69. Jakarta.

Kementerian Komunikasi dan Informatika Republik Indonesia. (2023, July 14). Transformasi Digital Indonesia Menuju Ekonomi Berbasis Teknologi. Retrieved from https://kominfo.go.id

Maritime Security Agency of the Republic of Indonesia. (2021, June 25). Amerika Serikat dan Indonesia Bangun Pusat Pelatihan Maritim. Retrieved from https://bakamla.go.id/publication/detail_news

Nguyen, T. T., & Tran, M. K. (2022). Machine learning applications for transaction anomaly detection in fintech services. Journal of Applied Intelligence, 52(4), 2141–2158.

OECD. (2020). Digital Economy Outlook 2020. Paris: OECD Publishing. https://doi.org/10.1787/bb167041-en

Pratama, R. D. (2022). Analisis Tren Transaksi E-Commerce di Indonesia Menggunakan Metode Machine Learning [Master Thesis]. Universitas Indonesia, Depok.

Ramadhani, A. (2020). Deteksi Kecurangan Transaksi Menggunakan Deep Learning pada Sistem Pembayaran Digital [Thesis]. Institut Teknologi Sepuluh Nopember, Surabaya.

Silaen, F. C. (2021). Digital transformation and consumer adaptation in Southeast Asia. In A. Wijaya (Ed.), Digital Economy Dynamics (pp. 88–104). Routledge.

Statista. (2024, March 10). E-commerce user growth in Southeast Asia. Retrieved from https://statista.com

Zhang, A. (2023, August 5). How Deep Learning Shapes Fraud Detection in Fintech. AI Industry Insights. Retrieved from https://aiindustryinsights.com/articles/deep-learning-fraud-detection