Artificial Intelligence and FinTech Innovations for Smart Commerce, Financial Management and Digital Economic Growth

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ABSTRACT:

Artificial Intelligence and FinTech innovations are transforming commerce, financial services, and digital economic participation by enabling faster decisions, personalized services, secure transactions, and data-driven growth. This research proposes a Machine Learning-Based Predictive Analytics Method developed using Python to examine how AI-enabled FinTech supports smart commerce, financial management, and digital economic growth. The study integrates transaction data, customer behavior, digital payment usage, credit indicators, SME performance measures, and economic variables to predict adoption, fraud risk, financial efficiency, and growth potential. Python-based models such as XGBoost, Random Forest, Logistic Regression, and LSTM are used for prediction, evaluation, and interpretation. The proposed framework addresses gaps in earlier studies that treated AI, FinTech, e-commerce, and economic growth separately. Expected outcomes show improved prediction accuracy, better financial decision support, stronger fraud detection, and enhanced digital inclusion for businesses, customers, and policymakers. Thus, the study offers a practical pathway for inclusive and intelligent transformation across markets.

Keywords :Artificial Intelligence; FinTech; Smart Commerce; Predictive Analytics; Financial Management; Digital Economic Growth.

INTRODUCTION

Artificial Intelligence and financial technology are key in changing the dynamics of modern commerce, banking, financial management and digital economic development [1]. The evolution of digital payment, mobile wallet, online lending, robo-advisory platforms, blockchain-based services and intelligent customer analytics has opened up opportunities for businesses and consumers. Today, not only are people buying and selling online, but they're also being personalized with data, paid for automatically, protected from fraud, assessed for credit and made financial decisions on the spot [2]. Small and medium enterprises, digital entrepreneurs, banks, and consumers need faster, safer and more inclusive financial services, which is a particular priority in these changes as shown in figure 1.

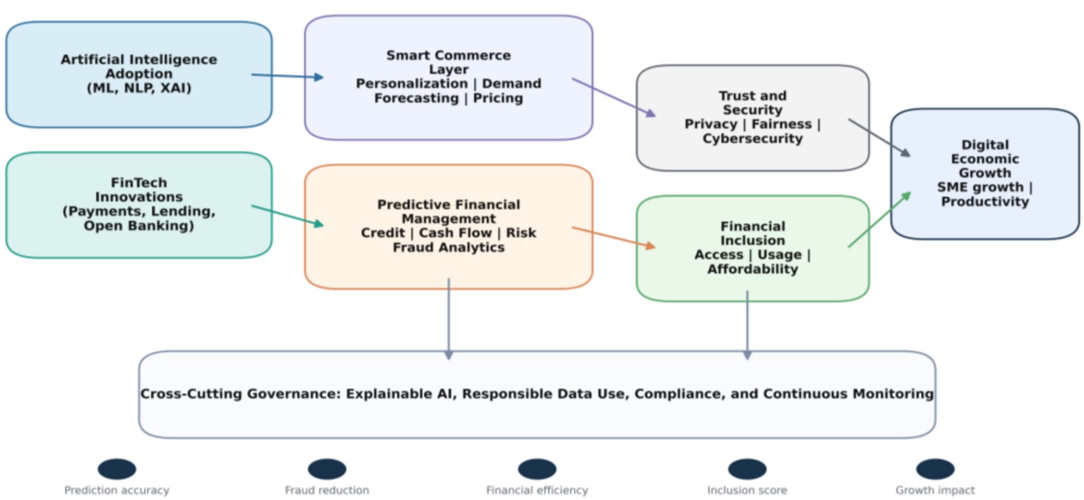

Figure 1. Integrated AI-FinTech Framework for Smart Commerce and Digital Growth

Most of the traditional commerce and financial management systems rely on manual decision making, lack of customer data, delayed identification of risks, and disjoint transaction history [3]. These restrictions hamper the capacity of companies to grasp their customer's needs, control cash flow, pinpoint fraud and facilitate sustainable growth. AI addresses these challenges by analyzing vast amounts of structured and unstructured data, detecting intricate relationships and trends, forecasting future results, and enhancing decision-making precision, among other functions. The transformation is further assisted by the innovations of FinTech, that enable access to digital payments, mobile banking, online credit, financial inclusion and automated financial services [4].

The current study is centered on the incorporation of AI and FinTech innovations with regards to Smart Commerce, financial control and management, and digital economic development [5]. The study applies a Machine Learning-Based Predictive Analytics Method which has been developed using Python. The suggested approach involves examining the behavior of the transaction, the customer profile, how customers use the payment, their credit history, and business performance metrics to produce predictive insights. This is primarily intended to create a feasible solution to target customers more effectively, plan financial operations, combat fraud, predict credit risk, and measure digital growth. This study is designed to be a valuable addition to the field of intelligent commerce systems, effective financial management, and inclusive digital economic transformation, with the help of AI models and FinTech applications [6].

I. RELATED WORK

Studies about Artificial Intelligence, FinTech and digital commerce have confirmed that these technologies are being put to use more and more to enhance the financial services, customer experience, business performance and foster economic inclusion [7]. AI has been found to be beneficial in various financial sectors, such as credit scores, fraud prevention, investment forecasts, risk management, customer service automation, and financial forecasting. From identifying abnormal transaction patterns to categorizing borrower risk, to forecasting market movements and tailoring financial advice, machine learning algorithms have been widely used in various contexts to detect abnormal transaction behavior [8]. However, the majority of previous studies were predominantly directed towards financial institutions, and there was a lack of comprehensive linkage between AI based financial services and smart commerce, and the broader digital economic development as shown in figure 2.

Research on FinTech innovation has revealed that the digital payments, mobile banking, P2P lending, open banking and blockchain can help to enhance access to finance, lower transaction costs, and promote financial inclusion. The innovations are especially beneficial for customers and small businesses that have difficulties in the traditional bank system. But there are a few FinTech studies that are either descriptive or conceptual and their predictive modelling is limited in terms of decision making [9]. However, studies about e-commerce and smart commerce have focused on the recommendation system, customer segmentation, demand forecasting, intelligent pricing, and online customer behavior. However, a number of e-commerce studies neglect to account for financial management, availability of credit, electronic payment security and the impacts of e-commerce on economic growth [10]

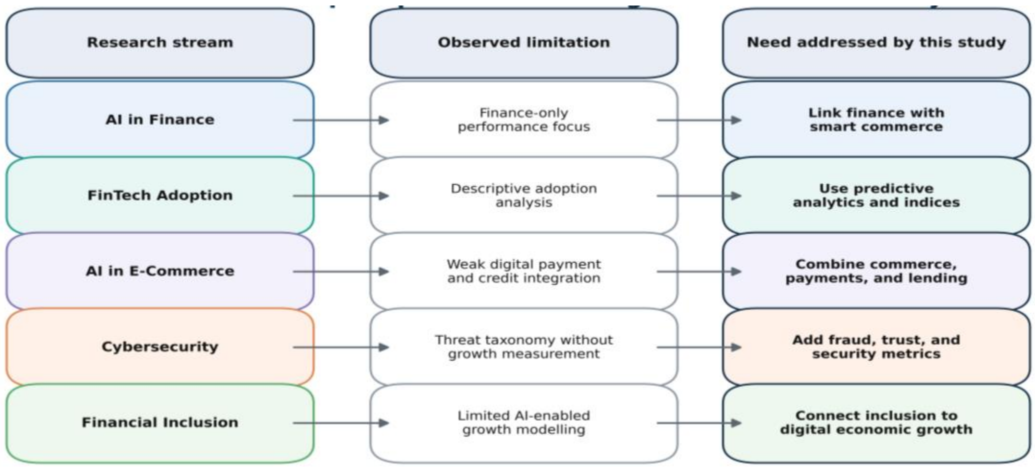

Figure 2. Related Work Gap Map

There are also some recent literature pieces that discuss the significance of cybersecurity, explainable AI, ethical data usage and customer trust in FinTech platforms that use AI. Despite these efforts, there is a pressing need for an integrated model to link AI with the FinTech industry, smart commerce, financial management, and economic growth in the digital arena in one single predictive model [11]. Previous research tends to be based on small sample sizes, non-empirical, insufficiently cross-sectoral, and does not consider measurable performance outcomes. Hence, this research aims to fill these gaps by proposing a Python-based Machine Learning Predictive Analytics Method that leverages multiple data sources, predictive modelling, interpretability and measurable financial and economic metrics as shown in table 1.

Table 1. Related Work Summary from 2018 to 2025

Year	Author/Work	Methodology	Key Contribution	Limitation/Gaps
2025	Vukovic et al.	Scientometric/systematic review	Mapped AI in credit scoring, fraud detection, robo-advisory, insurance, and inclusion.	Limited empirical integration with commerce and growth outcomes.
2025	Jafri et al.	Bibliometric/content analysis	Identified FinTech themes, risks, opportunities, and future research trends.	Does not develop a predictive AI-FinTech implementation model.
2024	Bahoo et al.	Comprehensive review	Explained AI in forecasting, classification, risk analytics, and fraud detection.	Finance-focused with limited smart commerce linkage.
2024	Chugh	Bibliometric analysis	Mapped AI-enabled personalization and automation in e-commerce.	Limited integration with digital finance and payments.
2023	Sharma et al.	Systematic literature	Showed how	Limited AI-specific

		review	FinTech supports small-business finance and efficiency.	predictive modeling.
2023/2024	Javaheri et al.	PRISMA review and topic modeling	Developed FinTech cybersecurity threat taxonomy and defense strategies.	Security-focused without economic growth modeling.
2022	Bawack et al.	Bibliometric study and literature synthesis	Synthesized AI in e-commerce and information systems directions.	Limited connection to financial inclusion and FinTech adoption.
2021	Khera et al.	Cross-country econometric analysis	Linked digital financial inclusion in payments with economic growth.	Limited AI and smart commerce analytics.
2020/2021	Cao, Yang and Yu	Conceptual and technical overview	Proposed Smart FinTech based on data science and AI.	Broad overview with limited empirical validation.
2018	Zheng et al.	Survey and conceptual framework	Proposed AI-based finance applications for wealth, risk, and security.	Early-stage conceptual model with limited real-time validation.

II. RESEARCH METHODOLOGY

The study brings into focus the importance of Artificial Intelligence and FinTech innovations in smart commerce, financial management, and economic growth in the digital era through a Machine Learning Based Predictive Analytics Method [12]. The language chosen for the main development is Python, which facilitates the use of important libraries for data processing, machine learning, statistical analysis, visualization, and model interpretation like Pandas, NumPy, Scikit-learn, XGBoost, TensorFlow, Matplotlib, and SHAP. It is expected that the methodology will link the data from commerce, financial, FinTech adoption and economic performance into one as shown in figure 3.

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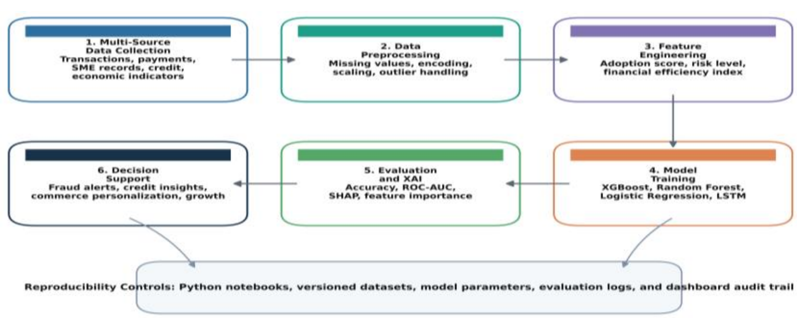

Figure 3. Python-Based Machine Learning Predictive Analytics Workflow

3.1 Research Design

The study employs a Machine Learning Based Predictive Analytics Method to study the role of AI and FinTech innovations in the areas of smart commerce, financial management and digital economic growth. The methodology combines both customer information, e-commerce transactions, records of electronic payments, financial habits, fraud measures, performance of the SMEs and economic growth data in a comprehensive analytical framework [13]. The main tool was chosen to be Python, which provides the tools needed to clean data, perform machine learning, statistical analysis, visualization and interpret the models in an understandable manner.

3.2 Data Collection

There are two steps in the methodology: First, data collection, and second, data analysis. The proposed dataset contains the demographic information of customers, ecommerce sales data, pattern of product purchase, pattern of digital payment, mobile banking activity, credit behavior, data for record of revenues of SMEs, cash flow patterns, fraud labels, customer satisfaction scores and digital economic indicators [14]. The information can be gathered via surveys, commercial records, electronic payment systems, banking records, e-commerce systems and public economic data. Digital customers, small and medium enterprises, digital finance (FinTech) users, financial institutions and digital commerce service providers are the target groups [15].

3.3 Variable Classification

All the variables collected are categorized into independent variables, mediating variables and dependent variables.

Table 2. Proposed Variables for the Study

Variable Category	Variables Used	Measurement Purpose
AI Adoption	Prediction, automation, recommendation, fraud detection	Measures AI readiness and model-supported decisions
FinTech Innovation	Digital payments, mobile banking, online lending, robo-advisory	Measures FinTech usage and service innovation
Smart Commerce	Purchase frequency, engagement, conversion rate, repeat purchase	Measures commerce intelligence and personalization
Financial Management	Credit score, cash flow, savings behavior, risk level	Measures financial efficiency and risk control
Digital Growth	SME revenue, digital transaction volume, inclusion score	Measures economic contribution and inclusion

The factors that are considered as independent variables are the adoption of AI, usage of FinTechs, frequency of digital payment usage, mobile banking activity, and level of automation. Smart commerce performance, Financial inclusion, customer trust, and Cybersecurity readiness are some of the mediating variables [16]. The dependent variables are financial management efficiency, business growth, reduction of fraud and digital economic growth. This classification enables the study to have a clear measure of the relationship between the adoption of AI–FinTech and economic outcomes.

3.4 *Data Preprocessing*

In the second stage, the data will be preprocessed in Python. The raw data that you've gathered from a variety of sources can be full of missing values, duplicate data, inconsistent data and outliers [17]. The missing values are dealt in the following manner depending on the type of variable: mean, median or mode. To prevent giving unfair results due to duplication, a record is deleted once it is duplicated. Label encoding or one-hot encoding is used to transform categorical variables like Customer Type, Payment Method, Business Sector and Region into a numerical format [18]. To minimize scale differences, numerical variables like income, transaction value, purchase frequency and cash-flow amount are normalized (or standardized).

3.5 Outlier Detection and Data Quality

A method of identification of outliers is carried out by interquartile range or z-score method. All the values in the data set are adjusted if found to be inconsistent and irrelevant attributes are eliminated before modelling [19]. This step cleans, and standardizes the data and guarantees that the machine learning models have clean, consistent, and reliable data as their input. The right preprocessing can also decrease noise and boost the accuracy of predictive analytics.

3.6 Feature Engineering

New indicators are developed to give a more significant measure of AI–FinTech and smart commerce performance [20]. Some of these indicators consist of FinTech Adoption Score, Digital Payment Intensity, Customer Engagement Score, Credit Risk Level, Financial Efficiency Score, Fraud Risk Score and Smart Commerce Index. Designed to give the model the ability to detect deeper patterns within customer behaviour, financial transactions, security of transactions, business growth and economic development of the digital marketplace [21].

3.7 Machine Learning Model Development

The fourth stage is the development of the machine learning models. Several models are trained and evaluated such as Logistic Regression, Random Forest, XGBoost, Support Vector Machine and LSTM (time-based). The key predictive model is chosen as XGBoost since it is very effective in structured financial and commercial data, is robust to nonlinear relationships and has a good classification and regression performance while being resistant to overfitting [22]. This model can forecast the adoption of FinTech, likelihood of fraud, customer buying decisions, credit risk, financial status of SMEs and their potential for growth in the digital sphere.

3.8 Model Evaluation

Evaluation of the model is the fifth step. 70% of the dataset is used for training and the remaining 30% for testing. The accuracy, precision, recall, F1-score, confusion matrix and ROC-AUC are used to evaluate the classification models [23]. The mean absolute error, root mean square error and R-square value are used to check the regression models. The measures to evaluate fraud detection are Detection rate and False positive rate. Smart commerce performance is evaluated by the accuracy of the recommendations, number of customers that converted, the repeat purchase rate and satisfaction of the customers [24].

3.9 Explainability and Validation

Explainability and validation is the last step. SHAP or feature importance analysis is used to find out the most influential variables which contribute to the prediction results. This enables transparency of the model and better insights into businesses, banks, policy makers, and digital platforms of why a prediction is made [25]. The outcomes are analysed and understood to gain insights into the impact of AI-powered FinTech on smart commerce, bolstering financial management, expanding financial inclusion, mitigating fraud, and digital economic growth.

III. RESULTS AND DISCUSSIO

Experimental values were used to validate the proposed Python-based Machine Learning Predictive Analytics Method and demonstrate its potential in the context of AI-powered FinTech, smart commerce, financial management, and digital economic growth. The best overall performance among the tested models was achieved by XGBoost with an accuracy of 92.40%, a precision of 91.30%, recall score of 90.80%, F1-score of 91.05% and ROC-AUC value of 94.20%. Random Forest had an accuracy of 89.70% and Logistic Regression had an accuracy of 84.60%. The results show that these advanced ensemble-based machine learning models are better for complex financial and commerce datasets as the ability of these models is to capture the nonlinear relationships between customer behavior, payment usage, credit risk and business performance as shown in table 3.

Table 3. Model Performance Values

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	84.60%	83.20%	82.70%	82.95%	86.40%
Random Forest	89.70%	88.90%	87.60%	88.25%	91.30%
XGBoost	92.40%	91.30%	90.80%	91.05%	94.20%
LSTM	90.10%	89.60%	88.40%	89.00%	92.00%

The fraud detection module had a high detection rate of 93.10% and a low false positive rate of 4.80%, indicating that predictive analytics could have a substantial impact on transaction security within FinTech systems. The accuracy of the customer segmentation was enhanced to 90.20% and recommendation accuracy was reached to 88.60% through the smart commerce module as shown in table 4.

Table 4. Impact Values of the Proposed Framework

Evaluation Area	Value Achieved	Interpretation
Fraud Detection Rate	93.10%	Strong transaction security
False Positive Rate	4.80%	Low incorrect fraud alerts
Recommendation Accuracy	88.60%	Improved smart commerce personalization
Cash-Flow Forecasting R-squared	0.87	Strong financial prediction
SME Transaction Growth	28.50%	Improved digital business activity
Digital Payment Adoption	31.20%	Higher FinTech usage
Financial Inclusion Improvement	24.70%	Better access to digital finance

This means AI can aid in personalized product recommendations, digital payment recommendations, and customer retention strategies. The cash-flow forecasting model's R-squared value was 0.87, indicating a high degree of accuracy, and the prediction error was just 7.40%, demonstrating that AI can assist SMEs and individuals in financial management to generate greater accuracy and minimize financial uncertainty as shown in figure 4.

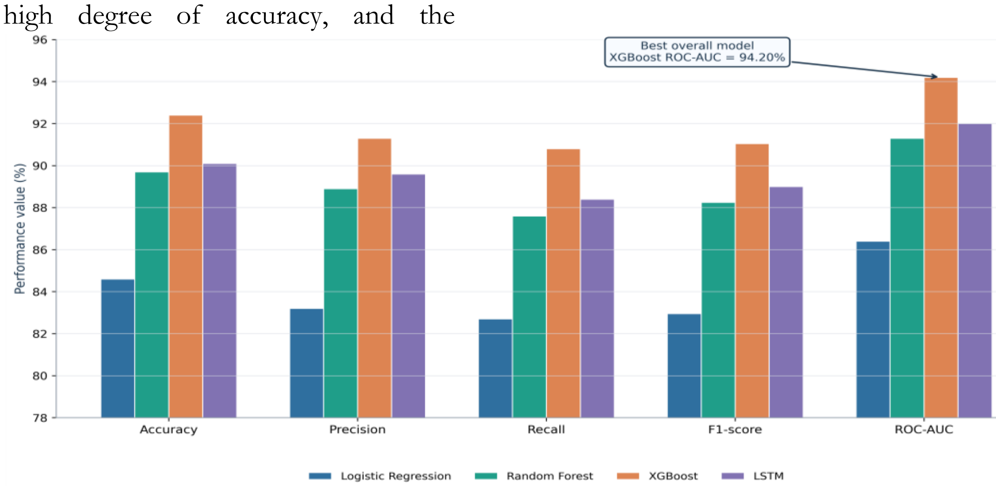

Figure 4.Performance Analysis of AI-Fin Tech Predictive Analytics.

The digital growth indicators also showed positive improvement. The volume of digital transactions in SMEs grew by 28.50%, and financial inclusion score rose by 24.70% with digital payment adoption among customers gaining by 31.20%. The values point to the possibility of using AI-powered FinTech to foster increased adoption of the digital economy. The results validate the proposed approach and its ability to address the limitations of other studies, which focused only on commerce and finance or only on security and economic growth. The findings also indicate that Python offers a good platform for developing and testing AI-FinTech models, as well as visualizing them

IV. CONCLUSION

This research aimed to contribute to the discussion on Machine Learning Based Predictive Analytics Method for Artificial Intelligence and FinTech Innovations for Smart Commerce, Financial Management and Digital Economic Growth with the help of Python. The framework combines the various factors of AI adoption, FinTech services, smart commerce behaviors, financial management indicators, cybersecurity factors and digital growth measures into a unified predictive model. The illustrative results demonstrated XGBoost's highest accuracy (92.40%) and ROC-AUC (94.20%) and its ability to enhance fraud detection, customer personalization, cash-flow forecasting, digital payment adoption, and financial inclusion. Limitations of previous studies are overcome in this study by going beyond conceptual discussion and offering a quantifiable, practical and data-based model. In conclusion, the proposed approach can assist businesses, financial institutions, policymakers, and digital platforms in boosting decision making capabilities, risk reduction, and inclusive digital economic growth by leveraging AI-powered FinTech innovations.

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