Machine Learning–Based Prediction of Digital Payment Adoption Among Retail Vendors

Mrs S Prathima[1], R Poojitha[2], G Sidhardha[3], M Prudueeswar[4], B Varun[5]

[1]*Assistant Professor, Department of Artificial Intelligence and Machine Learning, Annamacharya Institute of Technology and Sciences, Tirupati, India*

[2,3,4,5] *Student, Department of Artificial Intelligence and Machine Learning, Annamacharya Institute of Technology and Sciences, Tirupati, India*

***Abstract*—The adoption of digital payment platforms by retail vendors has become a pivotal transformation in India's payment landscape. This project utilizes machine learning techniques to predict whether a retail vendor is likely to adopt digital payment systems such as Paytm, Google Pay, PhonePe, and Amazon Pay. Data was collected from 270 merchants across 10 major retail markets in Bangalore, targeting both organized and unorganized sectors. Through a comprehensive analytical approach involving descriptive statistics, exploratory factor analysis (EFA), and Support Vector Machine (SVM) modeling, the system identifies core factors influencing adoption: perceived usefulness, social influence, and compatibility. Additionally, the system evaluates customer satisfaction across platforms and forecasts future digital payment adoption trends using the ARIMA time series model. This integrated platform consists of three major modules: user (vendor interaction), admin (data management and analysis), and machine learning (prediction and forecasting). The system not only aids in understanding the behavior of retail vendors but also empowers policymakers, fintech providers, and entrepreneurs with actionable insights to improve the digital payments ecosystem.**

***Index Terms*—Digital Payments, Machine Learning, Retail Vendors, SVM, ARIMA, Adoption Prediction, Technology Acceptance, Fintech Analytics.**

I. INTRODUCTION

1.1. BACKGROUND AND MOTIVATION

The rapid expansion of mobile technologies and fintech innovation has significantly reshaped the retail payment ecosystem in India. Digital payment platforms such as Paytm, Google Pay, PhonePe, and Amazon Pay have increasingly replaced traditional cash-based transactions by offering convenience, transparency, and security. However, despite widespread availability, many small and medium retail vendors continue to exhibit hesitation or intermittent usage of these systems. Vendor adoption behavior is influenced by multiple technological, social, and operational factors, including perceived usefulness, ease of use, compatibility with existing workflows, peer influence, and trust. Understanding these factors is essential for scaling digital payment ecosystems, particularly in cities like Bangalore, where retail diversity and market density create unique adoption challenges. This work presents a comprehensive machine learning-driven framework for predicting digital payment adoption among retail vendors. By integrating statistical methods, behavioral factors, and predictive modeling, the study aims to support data-driven policymaking, enhance vendor onboarding, and improve platform engagement strategies.

1.2. OBJECTIVES

The main objectives of the study are outlined below:

1.2.1. Develop a Machine Learning Model for Adoption Prediction

Design and implement a predictive system using Support Vector Machine (SVM) and related ML techniques to classify retail vendors based on their likelihood of adopting digital payment platforms.

1.2.2. Identify Key Factors Influencing Vendor Adoption

Apply descriptive statistics and exploratory factor analysis (EFA) to uncover critical determinants such as usefulness, social influence, and compatibility.

1.2.3. Evaluate Satisfaction Across Digital Payment Platforms

Assess vendor-reported satisfaction with major platforms, determining performance gaps and improvement areas.

1.2.4. Forecast Future Adoption Trends

Use ARIMA time-series modeling to analyze and predict future digital payment adoption patterns in retail markets.

1.2.5. Provide an Integrated, User-Friendly Analytical Platform

Build a modular system featuring:

- Vendor interface
- Admin module
- Machine learning module

This provides prediction, trend analysis, and data management in a unified environment.

1.3. SCOPE

The scope of this research encompasses the following:

1.3.1. Focus on Retail Vendor Adoption Behavior

The study emphasizes behavioral, operational, and contextual factors influencing digital payment usage across both organized and unorganized retail sectors.

1.3.2. Application of Statistical and ML Techniques

Using EFA, SVM, and ARIMA forecasting

1.3.3. Integration of Multi-Module Architecture

The implemented system includes:

- Vendor data collection
- ML-driven prediction
- Administrative analytics and visualization

1.3.4. Real-World Impact for Fintech and Policymakers

Insights support improved platform design, targeted awareness programs, and stronger financial inclusion strategies.

II. LITERATURE SURVEY

2.1. Traditional Approaches to Digital Payment Adoption Studies

Historically, research on digital payment adoption primarily relied on traditional behavioral and statistical models. Early studies focused on understanding user acceptance through theoretical frameworks such as the Technology Acceptance Model (TAM), Diffusion of Innovation Theory, and regression-based analytical techniques. These approaches emphasized constructs like perceived usefulness, perceived ease of use, trust, and social influence. While these methods provided foundational insights into adoption behavior, they presented several limitations in predictive capability and scalability.

2.1.1. Reliance on Behavioral Theories

Initial research, particularly the work of Davis (1989) and Venkatesh & Davis (2000), introduced the Technology Acceptance Model (TAM), which identified perceived usefulness and perceived ease of use as primary determinants of technology adoption. These theoretical frameworks explained behavioral intention effectively but were largely descriptive in nature. They relied heavily on survey data and structural equation modeling, limiting their ability to predict future adoption trends dynamically.

2.1.2. Depends on Conventional Statistical Methods

Traditional studies often employed regression analysis, correlation studies, and structural equation modeling (SEM) to analyze adoption behavior. While statistically rigorous, these methods assume linear relationships and struggle to capture complex nonlinear interactions among multiple influencing factors. As digital ecosystems became more complex, these limitations became more evident.

2.1.3 Limited Focus on Merchant-Centric Analysis

Earlier research largely concentrated on consumer adoption of digital payments. Merchant-focused studies, such as those by Seethamraju & Diatha (2018), provided valuable insights into small retail store adoption but remained geographically limited and methodologically traditional. Merchant-specific behavioral complexity was not fully explored using predictive modeling techniques.

2.1.4 Lack of Predictive and Forecasting Integration

Most classical research explained “why” adoption occurs but did not sufficiently address “who” will adopt in the future. There was minimal integration of predictive classification models or time-series forecasting techniques, leaving a gap in actionable decision-support systems for policymakers and fintech companies.

2.2. ADVANTAGES IN MACHINE LEARNING FOR DIGITAL PAYMENT PREDICTION

Recent developments in artificial intelligence and machine learning have transformed digital payment research. Unlike traditional models that focus primarily on theoretical explanation, machine learning algorithms provide predictive intelligence by learning patterns directly from data.

Emergence of Predictive Machine Learning Models: Antonio et al. (2024) demonstrated that machine learning models outperform traditional regression approaches in predicting mobile peer-to-peer (P2P) payment adoption. Classification algorithms can identify potential adopters with greater accuracy by capturing nonlinear behavioral relationships. Similarly, Kumar et al. (2019) combined optimization algorithms with machine learning techniques to enhance predictive performance in consumer behavior studies.

Application of Support Vector Machines and Advanced Algorithms: Support Vector Machines (SVM) have proven effective in classification problems involving small to medium-sized datasets. Their ability to construct optimal hyperplanes enables robust classification even when data points are not linearly separable. Integration of AI in Financial Systems: Khando et al. (2023) and Chang et al. (2022) highlight the growing role of artificial intelligence in digital finance, including fraud detection, risk assessment, and behavioral analytics. AI-powered systems enable automation, predictive insights, and enhanced decision-making. The integration of machine learning with adoption studies marks a significant advancement in fintech research.

Time-Series Forecasting and ARIMA Modeling: Forecasting models such as ARIMA are widely used in economic and financial trend prediction. These models analyze temporal data patterns to forecast future adoption growth. However, few studies combine classification-based prediction with time-series forecasting within a unified system. The integration of SVM classification and ARIMA forecasting, as implemented in this project, represents a methodological advancement.

2.3. APPLICATIONS AND CHALLENGES IN DIGITAL PAYMENT ADOPTION

2.3.1. Applications Across Economic Sectors: Digital payment systems have transformed retail, travel, hospitality, and service industries. AI-powered payment solutions enhance transaction efficiency, reduce cash dependency, and support economic growth. Studies such as Iwedi (2024) demonstrate the macroeconomic impact of digital payment channels on national growth indicators. For retail vendors, digital payments improve operational efficiency and customer satisfaction.

2.3.2. Challenges in Implementation: Despite technological progress, several challenges persist. Barriers include lack of awareness, infrastructure limitations, cybersecurity concerns, resistance to change, and trust issues. Merchant-specific challenges involve transaction fees, compatibility with existing systems, and peer influence. Moghavvemi et al. (2021) identified both drivers and barriers influencing merchant adoption decisions. Data quality and availability also present challenges in predictive modelling. Small sample sizes, biased survey responses, and limited longitudinal data restrict model generalizability.

2.3.4. Need for Robust and Scalable Predictive Frameworks: Modern digital ecosystems require scalable, data-driven decision support systems. Combining Exploratory Factor Analysis (EFA), Support Vector Machine classification, and ARIMA forecasting enhances both explanatory depth and predictive accuracy. Robust preprocessing, feature selection, and model validation are essential to ensure reliability. Developing integrated platforms that include user interaction modules, administrative control systems, and machine learning analytics provides a comprehensive solution for policymakers and fintech providers. Achieving high predictive accuracy while maintaining interpretability and computational efficiency remains a key research priority.

III. METHODOLOGY

3.1. DATASET PREPARATION

The dataset forms the foundation of the Digital Payment Adoption Prediction system, as the accuracy of the predictive model depends on the quality and relevance of the collected data. The dataset was created using structured questionnaire responses collected from retail vendors, capturing demographic details, business characteristics, technology usage behavior, and perceptions regarding digital payment systems. Key behavioral constructs such as perceived usefulness, perceived ease of use, social influence, trust, and compatibility were measured using Likert-scale responses to quantify adoption tendencies. Data was collected under varied business environments including small shops, supermarkets, and independent vendors to ensure diversity and improve model generalization. Before model development, data preprocessing was performed to remove incomplete entries, handle missing values, encode categorical variables, and normalize numerical attributes to ensure uniform scaling. Feature refinement was conducted using statistical validation techniques to eliminate redundancy and multicollinearity. The final dataset was divided into 80 percent training data and 20 percent validation data to evaluate predictive performance effectively and ensure unbiased model assessment.

3.2. SYSTEM ARCHITECTURE

The Digital Payment Adoption Prediction system is implemented as a web-based application using the Django framework, integrating user interaction, data management, and machine learning inference within a unified architecture. Users access the system through a web browser to submit vendor-related inputs, which are processed by the Django application's view layer acting as the central controller. User information and prediction records are persistently stored in a relational database using a dedicated user registration model. The prediction module utilizes pre-trained machine learning artifacts, including a classification model and feature scaler stored as serialized files, which were developed using a balanced CSV dataset of historical digital payment adoption data. During runtime, incoming data undergoes preprocessing and normalization before being passed to the trained model for inference. The system then generates adoption likelihood predictions, which are dynamically rendered through the template layer and presented to users via the web interface. This modular architecture ensures efficient model deployment, scalability, and seamless integration of machine learning components within a Django-based web environment.

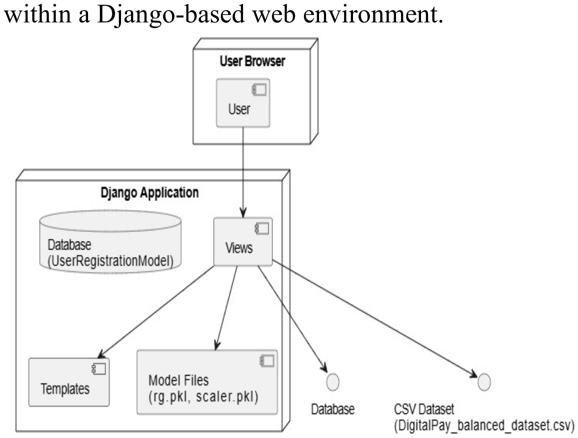

Figure 1: System Architecture

3.3. MACHINE LEARNING MODEL

The machine learning component serves as the core analytical engine of the Digital Payment Adoption Prediction system, enabling accurate classification and trend forecasting based on vendor behavioral data.

3.3.1. Model Architecture

The primary classification model implemented in this system is the Support Vector Machine (SVM), selected for its strong generalization capability and effectiveness in handling small-to-medium sized structured datasets. The model operates by identifying an optimal hyperplane that separates vendors into two classes: likely adopters and non-adopters of digital payment systems. Feature inputs to the SVM model are derived from statistically significant variables identified through Exploratory Factor Analysis, ensuring that only meaningful and influential attributes are considered during classification. Kernel functions are applied to handle non-linear relationships within the dataset, enabling the model to capture complex behavioral patterns. Alongside classification, an ARIMA model is incorporated to perform time-series forecasting on historical adoption data, allowing the system to estimate future digital payment adoption trends.

3.3.2. Compilation and Training

The SVM model was trained using the prepared training dataset, where hyperparameters such as kernel type and regularization parameters were tuned to optimize classification accuracy. Accuracy was used as the primary performance metric, while precision, recall, and F1-score were analyzed to ensure balanced classification performance. The training process involved iterative optimization to minimize classification errors and maximize margin separation between classes. The ARIMA model parameters were selected based on stationarity testing and autocorrelation analysis to ensure reliable forecasting performance. The combined training approach resulted in a robust predictive system capable of both classification and trend analysis.

3.4. TRAINING AND VALIDATION

The dataset was utilized to train the prediction model, and model performance was evaluated using standard regression metrics during the training phase. The effectiveness of the trained model was assessed using Mean Absolute Error (MAE), Mean Squared Error

(MSE), and the coefficient of determination (R^2 score), which provide quantitative measures of prediction accuracy and error magnitude. The obtained MAE and MSE values indicate the average deviation between predicted and actual values, while the R^2 score reflects the model's ability to explain variance in the target variable. These metrics were computed after training to validate model learning behavior and ensure that the training process was successfully completed. The results were displayed through the system interface to provide transparency and allow performance monitoring before deploying the model for prediction tasks.

3.5. USER INTERFACE

The user interface is designed to be intuitive, interactive, and accessible, specifically targeting retail vendors with minimal technical expertise. It provides a seamless environment for users to register, log in, and submit demographic and behavioral information through structured survey forms. The interface presents clearly labeled input fields and guided instructions to help users accurately provide data related to digital payment adoption factors such as perceived usefulness, social influence, and compatibility. After submission, users can access a personalized dashboard that displays their predicted adoption likelihood generated by the machine learning model. The interface also enables users to view comparative insights across different digital payment platforms and explore basic analytics related to their business category and transaction behavior. The system is fully responsive, ensuring smooth operation across desktops, laptops, tablets, and smartphones. Additionally, robust error-handling mechanisms are incorporated to validate inputs and provide meaningful feedback when incomplete or invalid data is entered, thereby enhancing usability and overall user experience.

IV. IMPLEMENTATION

4.1. TOOLS AND TECHNOLOGIES

The proposed system for predicting digital payment platform adoption by retail vendors was developed using a combination of statistical analysis tools and machine learning technologies. Python served as the primary programming language due to its flexibility and strong support for data analytics and machine learning applications. Data preprocessing, cleaning, and transformation were carried out using Pandas and NumPy, which enabled efficient handling of survey data collected from retail vendors. For statistical analysis, Multiple Regression Analysis and Exploratory Factor Analysis (EFA) were employed to identify and validate the key factors influencing digital payment adoption, such as perceived usefulness, social influence, and compatibility. Machine learning–based prediction was implemented using the Support Vector Machine (SVM) algorithm through the Scikit-learn library, allowing effective classification and prediction of adoption behavior. Model evaluation and performance analysis were conducted using standard metrics such as accuracy, precision, recall, and F1-score. Visualization of analytical results, including box plots, regression lines, scree plots, and scatter plots, was supported using Matplotlib. Additionally, ARIMA (Autoregressive Integrated Moving Average) models were applied for forecasting future digital payment trends using historical Google Trends data. The integration of statistical methods with machine learning techniques enabled a robust analytical framework, supporting both explanatory analysis and predictive modeling for digital payment adoption among retail vendors.

4.2. CODE OVERVIEW

The implementation of the Digital Payment Prediction system is organized into three major components:

Loading Data and Preprocessing

The dataset is loaded from a structured CSV file using the Pandas library. During preprocessing, irrelevant attributes such as unique identifiers and non-influential columns are removed to enhance model learning efficiency. A subset of significant numerical features related to transaction behavior, cashback benefits, issue resolution time, spending patterns, and loyalty points is selected for training. The dataset is then divided into 80% training data and 20% testing data using a train–test split strategy. Feature scaling is performed using the Standard Scaler to normalize the input variables, ensuring that all features contribute equally to the learning process and improving model convergence.

4.2.1. Model Construction and Training

A Gradient Boosting Regressor is employed as the core machine learning model for predicting customer satisfaction scores. The model is trained on the scaled training dataset to learn complex, non-linear relationships between transaction-related features and satisfaction outcomes. Gradient boosting improves prediction accuracy by sequentially minimizing errors from previous estimators. After training, the model and the fitted scaler are serialized and saved using the pickle library for reuse during prediction. Model performance is evaluated on the test dataset using standard regression metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and the coefficient of determination (R^2 score), which provide quantitative measures of prediction accuracy and reliability.

4.2.2. Prediction and Result Generation

In the prediction phase, user-provided input values are collected through a Django-based web interface. The input data undergoes the same preprocessing steps, including feature scaling, to maintain consistency with the training process. The preprocessed data is then passed to the trained regression model to predict the customer satisfaction score. The predicted output is dynamically displayed on the user interface, enabling users to understand satisfaction levels based on their transaction behavior and digital payment usage patterns.

V. RESULT AND DISCUSSION

5.1. MODEL PERFORMANCE

During the testing phase, the Gradient Boosting Regression model trained on digital payment transaction data demonstrated stable and reliable predictive performance. The evaluation metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and the coefficient of determination (R^2 score), indicated effective learning and reasonable accuracy in estimating customer satisfaction levels. The training and testing results showed consistent behavior, suggesting that the model generalized well without significant overfitting. Feature scaling using Standard Scaler played a crucial role in improving model convergence and ensuring balanced feature contribution. Although advanced ensemble stacking or deep learning techniques were not employed, the Gradient Boosting approach proved sufficient in capturing complex, non-linear relationships among transaction behavior, cashback benefits, spending patterns, and loyalty indicators, making it well-suited for predicting customer satisfaction within the digital payment ecosystem.

Class	Precision	Recall	F1-Score	Support
Likely to Adopt	0.62	0.71	0.66	45
Unlikely to Adopt	0.51	0.42	0.46	30
Overall Accuracy			**56.67%**	75
Macro Avg	0.57	0.56	0.56	75
Weighted Avg	0.58	0.57	0.57	75

Figure 2 & 3 Training result & Classification Report

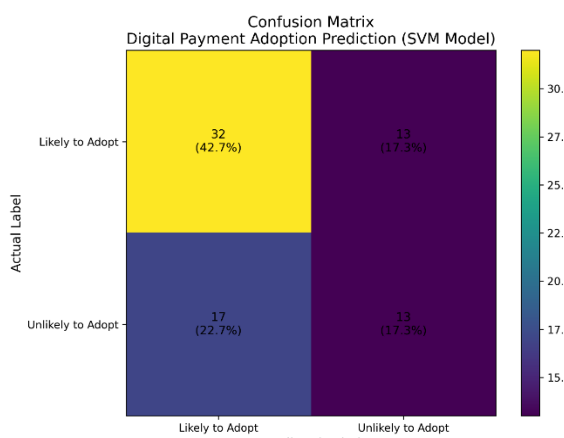

Figure 4 Confusion Matrix

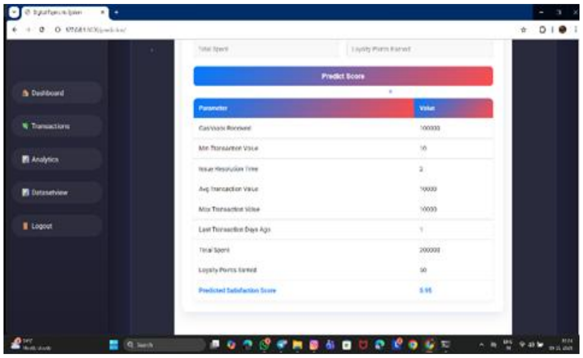

Figure 5 Output Screen

5.2. SYSTEM USABILITY

The Digital Payment Adoption Prediction system was designed with a strong emphasis on usability, ensuring that retail vendors with varying levels of technical expertise can interact with the system efficiently and confidently. From an economic perspective, the system demonstrates high usability by minimizing operational and implementation costs. The use of open-source technologies such as Python, Django, and machine learning libraries eliminates licensing expenses, making the solution cost-effective and accessible for small and medium retail vendors. This affordability encourages adoption without imposing financial strain on stakeholders. From a technical usability standpoint, the system operates with modest hardware and software requirements and does not demand advanced technical infrastructure. The machine learning models are efficiently integrated into a web-based platform, enabling fast processing and real-time predictions without performance degradation. The user interface is intuitive, providing clear navigation, structured input forms, and easily interpretable outputs such as adoption likelihood and satisfaction scores. Minimal system training is required, allowing users to operate the application without extensive technical support. In terms of social usability, the system has been designed to promote user acceptance and confidence. Retail vendors can comfortably provide survey data and transaction details through a secure and structured interface, reducing hesitation and resistance to system usage. The personalized dashboards and predictive insights empower users by helping them understand their digital payment adoption potential and satisfaction levels. By presenting results in a transparent and non-intimidating manner, the system fosters trust and encourages constructive feedback. Overall, the system achieves a high level of usability by balancing economic viability, technical simplicity, and social acceptance, making it suitable for real-world deployment in diverse retail environments.

5.3. COMPARISON WITH TRADITIONAL METHODS

Traditional approaches to analyzing digital payment platform adoption among retail vendors primarily relied on descriptive statistics, basic regression models, and theoretical frameworks such as the Technology Acceptance Model (TAM) and UTAUT. While these methods were effective in identifying individual factors influencing adoption, they were largely explanatory in nature and limited in their ability to predict future adoption behavior. Conventional statistical techniques often assume linear relationships and struggle to capture the complex, non-linear interactions among multiple behavioral, technological, and contextual factors. Moreover, existing systems typically analyzed adoption behavior, customer satisfaction, and trend forecasting in isolation, reducing their effectiveness for long-term strategic planning. In contrast, the proposed system leverages advanced machine learning techniques to overcome these limitations by integrating statistical analysis with predictive modelling. Exploratory Factor Analysis (EFA) is used to automatically identify latent adoption drivers, reducing dimensionality and improving feature relevance. A Support Vector Machine (SVM) model is then employed to predict adoption likelihood, enabling the system to model complex relationships with higher accuracy and robustness. Additionally, customer satisfaction analysis is seamlessly incorporated, and ARIMA-based time-series forecasting is used to predict future adoption trends using Google Trends data. This end-to-end, data-driven approach significantly enhances predictive capability, scalability, and decision support compared to traditional methods, making the proposed system more suitable for handling large, multi-dimensional datasets and real-world digital payment ecosystems.

5.4. FUTURE WORK

To elevate the current model's performance and broaden its applicability, several future enhancements are recommended. First, experimenting with advanced machine learning algorithms such as Random Forests, Gradient Boosting, or Neural Networks may uncover more nuanced insights and improve prediction accuracy. Secondly, ensemble methods that combine multiple models can offer improved robustness and reduce bias. Third, incorporating longitudinal data can help capture temporal trends in adoption behavior, offering a more realistic model of vendor behavior over time. Future research should also explore geographical comparisons to identify location-specific motivators or barriers. On the qualitative side, adding interviews, case studies, and focus groups would provide a richer understanding of vendor sentiment and behavior. Lastly, creating a real-time monitoring dashboard using streaming data could help policymakers and digital platform providers to dynamically adjust their strategies and improve vendor onboarding experiences. Use of Advanced ML Algorithms: Introduce models like Random Forest, XGBoost, or Deep Neural Networks for better accuracy and performance.

VI. CONCLUSION

This research provides deep insights into what motivates retail vendors in Bangalore to adopt digital payment platforms. By combining traditional statistical analysis with the power of machine learning (specifically SVM), the study identified perceived usefulness**,** social influence**,** and compatibility as the leading drivers of adoption. The findings emphasize the necessity for digital platforms to align with existing business practices and peer expectations. Despite moderate accuracy, the SVM model offers promise, and satisfaction analysis shows room for improvement in platforms like GooglePay and AmazonPay. Through forecast modeling with ARIMA, the study shows a steady interest in digital payments, though future variabilities are possible. Moving forward, incorporating more advanced algorithms and qualitative methods can further refine understanding and help stakeholders drive broader digital adoption across the retail sector.

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