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Adaptive ML Framework for Predicting Digital Payment Acceptance Among Retail Merchants

[1]Palliboyana Shweta Ravi , [2]G Chandrakala
[1]PG Scholar, [2]Assistant Professor, Deparment of CSE ,
Sree Rama Engineering College,Tirupati,517520.
Shwetaravi67@gmail.com ,chandrakala@sreerama.ac.in

Abstract
The purpose of this project is to use machine learning techniques to forecast the adoption of digital payment systems by retail retailers. We polled 270 merchants, mostly from small and medium-sized enterprises (SMEs), from 10 of Bangalore's most popular retail marketplaces. The study uses SVM, exploratory factor analysis, and multiple regression to identify three important adoption drivers: perceived usefulness, social effect, and compatibility. The results show that perceived social effect and usefulness are the most significant factors, whereas perceived technical support and simplicity of use are very irrelevant. Results from applying the SVM model to forecast platform adoption were only somewhat accurate. The study evaluates customer satisfaction with various digital payment methods and uses ARIMA models to forecast future trends. The study's findings will likely influence companies' strategies for accepting digital payments.
Keywords- Digital payment adoption, retail vendors, machine learning, exploratory factor analysis, support vector machine, ARIMA.

INTRODUCTION

The rapid proliferation of digital technology has had a profound impact on the retail industry, particularly on consumers' payment options. Traditional cash-based payments are being supplanted by digital payment systems due to their convenience, speed, and security [1]-[3]. However, there could be a wide range of approaches used by different retail companies while using these platforms. Since legislators, platform providers, and merchants might all benefit from this knowledge, it is critical to understand these features [4]-[6]. Digital payment systems like PhonePe, Paytm, GooglePay, and AmazonPay are undeniably rather popular in India [7], [8]. Despite the convenience of digital payment systems, small and medium-sized retail enterprises have been slow to fully adopt them. A number of factors influence adoption, including perceived usefulness, compatibility, social effect, and ease of use [1], [9]. This study will use machine learning to examine the aforementioned characteristics and predict the likelihood of adoption by retail retailers.

Bangalore is a dynamic metropolitan area with a broad retail landscape, which is perfect for our study. Both organized and unorganized vendors may be found in Bangalore's retail sector, which exhibits a broad variety of vendor types and behaviors [4], [10]. If you accomplish this with one market sector in India, you can probably apply what you learn to other similar urban markets. Data was gathered using structured questionnaires, analyzed statistically using tools like exploratory factor analysis (EFA) and multiple regression, and predictions were made using support vector machines (SVM). The technique utilized in the study is strong. Furthermore, it added ARIMA models to the mix, using Google patterns data to foretell digital payment usage patterns [11][13]. If the study's results are useful in influencing policy and practice, digital payment systems could become more widely used. In order to make informed decisions on the payment and service solutions they promote, stakeholders may use the study's assessment of adoption variables. Ultimately, our goal is to facilitate the acceptance of digital payments by shops, allowing them to enhance their efficiency and competitiveness.

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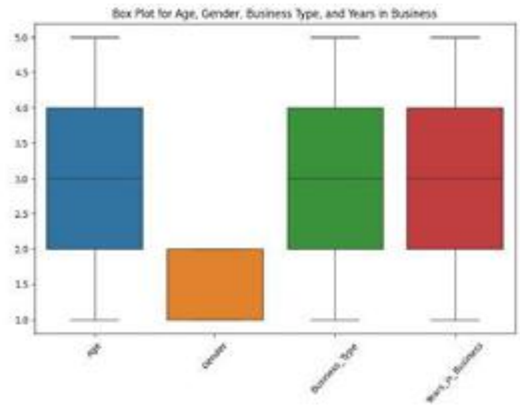
LITERATURE REVIEW

Due to the critical importance of analyzing and improving the digital shift in retail, digital payment systems have been the focus of several recent studies. Several studies that have investigated the adoption process have shown that retailers' decisions to accept digital payment methods are influenced by factors such as the Technology Acceptance Model, perceived ease of use, and perceived usefulness.The extent to which a user believes a certain technology will need little to no effort from them is one way to define perceived ease of use.How much a user believes that using the technology would make their workday more efficient is called its perceived utility [14].[14] The first TAM model, which incorporates enabling conditions and social effect, was outlined here. It was also discovered that social influence—"the extent to which a person believes that significant others think he or she should use the new systems" [15]—was a key contributing factor. The Unified Theory of Acceptance and utilize of Technology (UTAUT) paradigm states that social influence has a significant role in influencing the behavioral intention to utilize [16].

Lots of research have looked at how quickly stores are adopting digital payment platforms. Retailers' faith in the security and dependability of mobile payment systems is crucial when deciding whether or not to accept them [5]. This agrees with the results of [9], which also emphasize the importance of trust in situations involving financial transactions and the use of technology. Compatibility, or how well an innovation fits with the current beliefs, experiences, and needs of the potential user, is another important consideration. The rise of online banking has prompted compatibility analyses that digital payment systems should follow suit with. An increasingly popular area of research in recent years has been the use of machine learning to the problem of anticipating the adoption and usage of new technology.



In sections 7 and 17. Support vector machines (SVMs) and other machine learning techniques have been used to unearth patterns in complex datasets that traditional statistical approaches might have failed to notice. When it comes to forecasting when and how individuals will use new technology, machine learning performs better than more traditional approaches.

Research Gap

The factors that influence consumers' adoption of digital payment systems have been the subject of extensive research, but the use of machine learning to predict whether or not merchants will embrace such systems has received much less attention. Previous research largely used antiquated statistical approaches, which may have overlooked more complex interrelationships. Consequently, the objectives of this study were as follows.

Research Objectives

Learn the ins and outs of digital payment systems and assess their usefulness to retailers. 2. Use these metrics and machine learning algorithms to predict the likelihood of adoption. 3. Ascertain the extent to which various digital payment methods satisfy customers and foretell their future use.

Methodology

From mom-and-pop shops to larger establishments, small and medium-sized vendors in Bangalore city may choose from ten different huge retail marketplaces. The study might use a sample size of around 30,000 merchants if the city is considered in its entirety[18], [19]. Based on a rigorous sample approach that adhered to these standards, 270 individuals were chosen for the research: Level of confidence: 90%, margin of error: 5%, and population proportion: 50% [20]. The 270 vendors that comprised the sample were hand-picked from 10 of the busiest retail markets in Bangalore using a stratified random selection technique with equitable allocation. To make sure every market is represented, 27

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merchants from each market will make up the sample. Merchants have been selected at random from

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                            OLS Regression Results
==============================================================================
Dep. Variable:        Business_Type_2   R-squared:                       0.003
Model:                            OLS   Adj. R-squared:                 -0.009
Method:                 Least Squares   F-statistic:                    0.2356
Date:                Fri, 19 Jul 2024   Prob (F-statistic):              0.871
Time:                        02:46:49   Log-Likelihood:                -135.36
No. Observations:                 270   AIC:                             278.7
Df Residuals:                     266   BIC:                             293.1
Df Model:                           3
Covariance Type:            nonrobust
==================================================================================
                             coef    std err          t      P>|t|      [0.025
----------------------------------------------------------------------------------
const                      0.2447      0.092      2.667      0.008      0.064
Digital_Platforms         -0.0014      0.018     -0.077      0.939     -0.036
Number_of_Transactions    -0.0145      0.017     -0.836      0.404     -0.049
Day_Transaction            0.0007      0.017      0.040      0.968     -0.032
==============================================================================
Omnibus:                       61.599   Durbin-Watson:                   1.864
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              101.142
Skew:                           1.494   Prob(JB):                     1.09e-22
Kurtosis:                       3.249   Cond. No.                         21.0
==============================================================================
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both organized and unorganized sectors within each market.

Results are based on information collected via in-person surveys using standardized questionnaires. In order to protect the privacy of the respondents, we anonymized the data we gathered after obtaining informed permission from all participants. Ethical standards for research involving human beings were met by the study.

ANALYSIS AND INTERPRETATION

Explanations Based on Statistics A comprehensive analysis of vendor demographics, including gender, age, firm type, and years in operation, is provided by Descriptive Statistics of Retail Vendors. Key metrics such as mean, median, mode, and standard deviation round out the examination.Data Analysis.

TABLE 1: DESCRIPTIVE STATISTICS OF RETAIL VENDORS

Variable	mean	std	min	25%	50%	75%	max
Age	3.00	1.446	1	2	3	4	5
Gender	1.55	0.497	1	1	2	2	2
Business Type	3.13	1.397	1	2	3	4	5
Years in Business	3.15	1.437	1	2	3	4	5

Fig.1 Box Plot

Through careful analysis, the following details on the merchants' demographics have been revealed: Vendor ages are somewhat diverse, with a standard variation of 1.45 and an average age of around 3.00. Gender distribution is roughly even, with a harsh esteem of 1.56, which indicates a majority of one sex. There is a brutal kind of commerce that goes along with a long history of trade. The fact that their means are 3.13 and 3.16, with a standard deviation of around 1.40 for each, indicates that the two modes of trade and the level of merchant participation are distinct. In general, these measures capture the ages, genders, company kinds, and years of experience of merchants. Section B: The Way Individuals MAKE USE OF E-Payments The authors of Digital Payment Platform Usage Patterns explore the factors that impact the preferences of various kinds of organizations regarding digital platforms, daily transaction volume, and transaction amounts, among other usage indicators, using multiple regression analysis. This study aims to classify businesses by examining the impact of different digital payment platform behaviors.

TABLE 2: DIGITAL PAYMENT PLATFORM USAGE PATTERNS

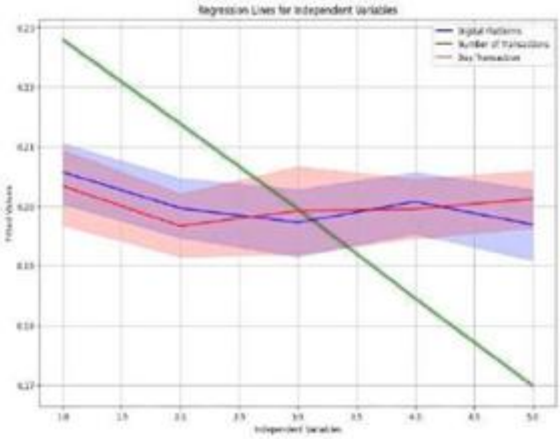

FIG.2 REGRESSION LINES

Table 2 displays the results of a multiple regression analysis that examines the impact of various digital payment platform patterns on the classification of various company types. Based on the usage data included in the research, the model fails to explain for almost all of the variance in firm type, with an R-squared value of only 0.003. Since the F-statistic is not statistically significant (p = 0.871), we may infer that digital platforms, transaction volume, and daily transaction amounts do not vary between organization types. There is little bearing on the classification of business types from the assessed attributes in this setting.

Factors Influencing Adoption

Factors Influencing Adoption uses Exploratory Factor Analysis (EFA) to identify important factors influencing the adoption of digital payment systems. These factors include perceived security, compatibility, social impact, utility, simplicity of use, and enabling circumstances. We hope that by identifying underlying connections and groupings among these elements, we might get a better understanding of how they affect adoption.

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TABLE 3: FACTORS INFLUENCING ADOPTION

Factor Loadings	1	2	3
Perceived Ease of Use	-0.0259	-0.071091	-0.023457
Perceived Usefulness	-0.0427	0.986660	-0.123304
Social Influence	0.1480	0.065481	0.625152
Facilitating Conditions	-0.0444	0.013980	0.173343
Perceived Security	0.0200	-0.067307	0.007109
Technical Support	0.0296	0.047800	-0.149576
Compatibility	1.0006	-0.104033	-0.116390

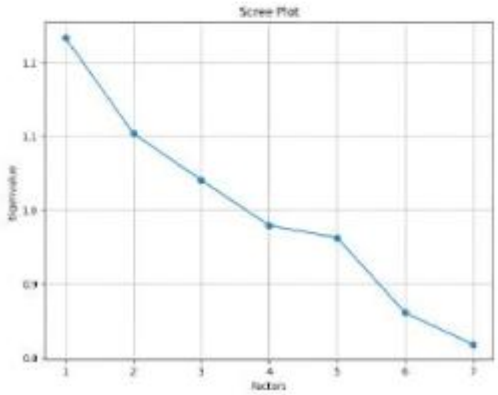

Fig.3 Scree plot

Exploratory factor analysis (EFA) results, shown in Table 3, suggest many classes for the elements impacting the uptake of digital payment systems. Perceived utility, a highly loaded variable on Factor 2 (0.987), is a key component in deciding adoption. Factor 3's heavy loading on social effect (0.625) demonstrates the importance of this variable in influencing user behavior. Factor 1's high loading of compatibility (1.001) indicates its significance in the adoption process. Lower loadings for other factors indicate that they are less relevant in this context. Perceived safety, ease of use, enabling circumstances, and technical support are all examples of such factors. You can observe which factors are influencing adoption the most from these data.

Performance Metrics of Machine Learning Models

Considerations such as perceived security, compatibility, enabling conditions, utility, ease of use, and social impact are incorporated into the support vector machine (SVM) model's predictions of digital platform adoption. The model's accuracy, precision, recall, and F1 score are utilized in this process. Our dependent variable is digital platforms, and we want to test the model's predictive abilities.

TABLE 4: PERFORMANCE METRICS OF MACHINE LEARNING MODELS

Sl. No	Metric	Value
1	Accuracy	0.566667
2	Precision	0.593751
3	Recall	0.666667
4	F1 Score	0.662471

The results given in Table 4 demonstrate that the SVM model can accurately predict when digital platforms will be used. The accuracy of the model's predictions is fairly high, standing at 56.67 percent. When it comes to predicting a specific digital platform, the model is correct around 59.38% of the time. The model correctly identifies 66.67% of the actual digital platform adoptions, as shown by the recall of 66.67%. The SVM model did a decent job of predicting the adoption of digital platforms using the given variables, as seen by an F1 score of 66.25%, which strikes a nice combination of recall and accuracy.

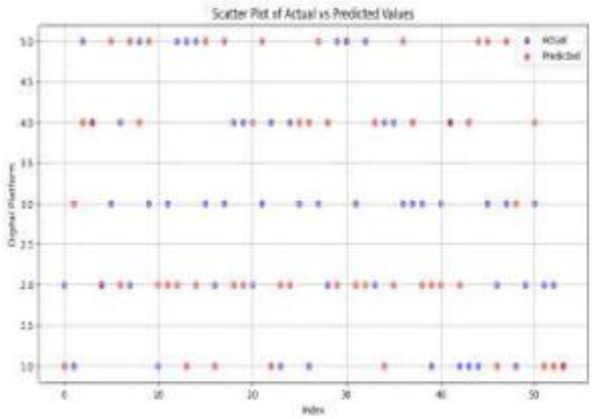

Fig.4 Scatter plot

Evaluation of Digital Platforms' Performance Based on User Satisfaction Using average satisfaction ratings, we compare and contrast various digital platforms. Our ultimate goal is to gauge user satisfaction with different digital

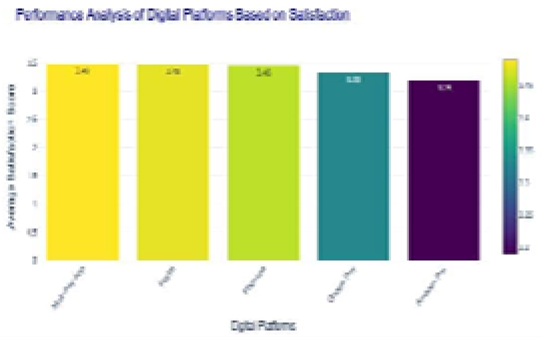

Fig.5 Performance analysis

Customer satisfaction with the "Multi-Pay App" was 3.49 out of 5, making it the clear winner among the platforms tested. Even in second place, "Paytm" has a 3.48 user acceptance score, which is excellent. With a score of 3.46, "PhonePe" is somewhat below average, although "GooglePay" and "AmazonPay" are much lower at 3.33 and 3.19, respectively. While the majority of digital platforms enjoy widespread popularity, the findings demonstrate a notable disparity in customer happiness, with "AmazonPay" receiving the lowest rating.

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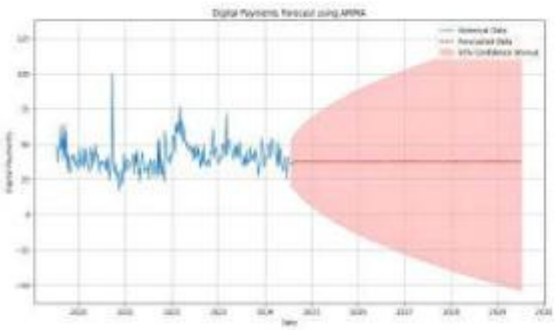
Predicting Digital Payments trends through Google trends

This study aims to forecast digital payment trends for the future five years by analyzing Google Trends data from the last five years. Quarterly data and the ARIMA model may be used to identify and project digital payment interest trends. This information is important for fintech sector strategic planning and market dynamics prediction.



Predicted values from July 21, 2024, to May 23, 2027, consistently show an anticipated value of around 37.30 with a progressively growing upper confidence interval (CI) and a declining lower CI. Without further investigation, the anticipated value will stay at 37.30 as the lower confidence interval increases from around 20.24 to approximately -32.28 on May 23, 2027. Conversely, the upper confidence interval starts at 54.16 and may go as high as 106.87 during the same time period. The overall trend seems to be that the level of uncertainty is rising in direct correlation with the potential value debate.

FINDINGS AND SUGGESTIONS

In terms of retail retailers' adoption of digital payment systems, the research states that perceived usefulness is the most crucial feature. If suppliers believe a platform may improve their operations or customer experience, they are more likely to use it. It has a major effect on one's social network as well. The vendors are affected by the vendor community members who use and advocate for digital payment methods. The UTAUT notion is consistent with this, which is a major consideration in and of itself [2, 8, 21]. Timbers that can be easily integrated with the existing infrastructure of the business. For suppliers, the ideal technology would be one that doesn't need them to drastically alter their present procedures in order to include it. The influence of perceived usability and technical support on adoption choices was under-considered[6, 10, 17]. What this means is that suppliers are open to fixing usability issues if they think there will be big benefits. Perceived security is an issue, but it did not seem to play a significant role in determining adoption rates. This may be because people are becoming more confident in the safety features offered by popular online payment processors. There is no correlation between the number or value of transactions processed each day and how firms are classified, according to studies of digital payment habits. There is no association between the acceptability of digital payment methods and the volume of daily transactions, according to this data. The Support Vector Machine (SVM) model predicted the adoption of digital payment systems with impressive accuracy (66.67%), precision (59.38%), recall (66.67%), and F1 score (66.25%). It follows that the model works generally, however its predictions might be more accurate [22], [23].

When comparing satisfaction ratings across several digital payment systems, "Multi-Pay App" and "Paytm" came out on top, with "PhonePe" following closely after. Despite receiving lower satisfaction percentages overall, the findings show that "GooglePay" and "AmazonPay" have the potential to improve the user experience and solve specific problems encountered by sellers [7]. The ARIMA model predicts that in the next years, digital payment trends will have a stable central estimate and an increasing range of uncertainty [3]. There seems to be ongoing curiosity in digital payment systems, even if this could be skewed by outside forces. Providers of digital payment platforms should emphasize the many advantages their product offers, such as faster transactions, improved customer support, and interaction with other company tools. Case studies and testimonials from other vendors might further emphasize these benefits [4, 6, 21]. The backbone of every advertising effort has to be peer referrals and social evidence. Platforms should set up community forums or user groups so vendors may talk about their experiences and share what they've learnt. It is crucial to make sure that digital payment systems work with many different kinds of corporate procedures that are in use today. Providers should provide flexible integration options and support for several business models [3, 9]. Even if they weren't the main motivators, providing strong technical assistance and making the product easier to use might increase satisfaction and lessen resistance to adoption. Making user interfaces more intuitive and providing specialized help channels are two potential options [8], [23]. Even if security is not a big concern, keeping suppliers informed about contemporary security procedures helps generate trust and alleviate any lingering anxieties. Businesses with low satisfaction ratings, such as "GooglePay" and "AmazonPay," need to find out what suppliers really need and fix it. Regularly conducting satisfaction surveys and responding to feedback could assist achieve that goal.

CONCLUSION

This study sheds light on the factors that motivate Bangalore-based retail retailers to use digital payment solutions. This study integrates classical statistical approaches with state-of-the-art machine learning techniques to identify the most important factors influencing adoption: perceived value, social effect, and compatibility. The study also covers other subjects, such as the average SVM model prediction accuracy and the different levels of satisfaction with different digital payment methods. In order to increase adoption rates, it is essential to meet vendor-specific expectations and preferences, as stated in the study. Issues with usability and security, compatibility with existing systems, showcasing the real benefits of their services, and capturing social influence should be providers of digital payment platforms' key priorities. Consequently, retail sellers become more efficient and competitive, and the shift to digital payments is smoother.

FUTURE RESEARCH

Research in the future may investigate the use of other machine learning techniques, including neural networks or ensemble approaches, to improve the accuracy of adoption estimates even more. Combining several models might lead to better and more dependable outcomes. Research that follows participants over time to see how their adoption habits evolve may provide light on the factors influencing this behavior. By comparing adoption patterns across different geographic locations, we may be able to uncover specific difficulties and regional disparities. Focus groups and in-depth interviews are examples of qualitative research methodologies that could help provide light on the challenges and aspirations of the suppliers. By addressing these issues, future studies may build on this one's findings and complete our knowledge of how retailers employ digital payment methods. This has the potential to inform policies and tactics that encourage the use of digital payment methods, which would benefit businesses and the economy overall.

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