Exploring Mobile Payment Adoption in Egypt: Challenges, Behaviors and Predictions

Original Article

Omnia Elrashidy[1,2], Hager Selim[2] and Hebatalla Kaoud[3]

[1]Faculty of Business, Alamein International University
[2]School of Information Technology and Computer Science (ITCS), Nile University
[3]The Graduate School of Management of Technology, Nile University

ABSTRACT

This study investigates mobile payment adoption in Egypt. Egypt's transition to electronic payment systems is beset with difficulties. This research thoroughly examines adoption patterns, cultural perspectives, and predictive models for forthcoming patterns. Convenience sampling was used in a survey to investigate mobile payment awareness in Egypt in 2024. There were 175 participants in the research. After participant profiles were obtained through data analysis, mobile payment awareness behaviors were predicted using machine learning approaches such as K-Nearest Neighbors, Support Vector Machine, Stochastic Gradient Descent, and Neural Network algorithms. This study fills in some of the gaps in the literature on the adoption of mobile payments by providing insightful information that will help policymakers, businesspeople, and academics better understand the dynamics of mobile payment acceptance in Egypt.

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Corresponding Author: Hebatalla Kaoud, The Graduate School of Management of Technology, Nile University, **Tel.**: +2 010 0477 7773, **E-mail:** hkaoud@nu.edu.eg

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INTRODUCTION

The rapid evolution of the internet has transformed traditional business practices, giving rise to E-Business and electronic payments. As the complexities of E-Business models and supporting technologies increase, mobile payment systems emerge as the natural successors to traditional electronic payment methods. These mobile payment solutions leverage the capabilities of wireless media, offering advanced business and customer services. In the realm of electronic payments, trust, and security play pivotal roles. Mobile payments, viewed as an evolutionary step from existing E-payment schemes, are expected to complement traditional methods. Unlike E-Business, where transactions often involve multi-user machines, mobile payment transactions occur on personal trust devices (PTD), typically owned, and managed by a single user. This distinction enhances identification, security, and trust within the mobile payment domain. The context of mobile payments is broad, encompassing payments initiated, activated, or confirmed using any mobile device. While mobile payments extend beyond mobile phones to devices like tablet PCs, PDAs, and mobile payment terminals, the term generally refers to transactions involving devices with mobile phone capabilities, such as smartphones[1,2].

Mobile payments, as a revolutionary approach to financial transactions, leverage the ubiquitous presence of mobile devices to facilitate purchases and monetary exchanges with unprecedented convenience and speed. Characterized by their ability to transcend traditional temporal and geographical limitations, these payment methods employ a variety of technologies, including but not limited to Near Field Communication (NFC), dedicated mobile applications, and e-wallets, to provide users with a seamless transaction experience[3]. The shift towards mobile-centric financial activities is not only indicative of the technological advancements in the field but also reflects a changing consumer behavior, where the value propositions of ease of use, security, and immediacy are increasingly prioritized. This evolving landscape is further shaped by factors such as perceived usefulness and societal norms, which play pivotal roles in influencing user adoption and the overall acceptance of mobile payments in the marketplace[4].

In the global economic landscape, fast, secure, and accessible financial transactions are crucial for the development of developing countries. Egypt is transitioning from a predominantly cash-based society to one embracing e-payment systems. Despite the government's efforts, challenges persist in internet infrastructure, website user-friendliness, and integration with the banking sector. The adoption of e-payment services in Egypt is seen as a potential solution to combat corruption, increase economic prosperity, and drive financial inclusion[5].

Machine learning, a subset of artificial intelligence, focuses on empowering machines to proficiently execute tasks through intelligent software. Statistical learning methods serve as the foundation for developing machine intelligence. The contemporary surge in demand for machine learning is driven by the abundance of available datasets. Machine learning involves knowledge acquisition through experience enhancement using computational methods. Knowledge engineering, facilitated by expert performance, has resulted in the creation of numerous AI expert systems. Its widespread application spans various industries and domains. Machine learning's popularity in different applications is attributed to its capability to learn from initial exposure and subsequently operate automatically when presented with similar types of data or input[6].

This research is to investigate Egypt's adoption of mobile payments. It looks at how demographics affect adoption patterns, covers a range of geographical areas to investigate cultural viewpoints, uses cutting-edge techniques to gain a deeper understanding of user motivations, creates predictive models to foresee future trends in the adoption of mobile payments, and investigates why some Egyptians are reluctant to use these platforms. This study aims to provide valuable insights into mobile payment behaviors in Egypt for academia, industry, and policymakers.

LITERATURE REVIEW

Examining the telecommunications sector in Egypt since its establishment in the 19th century, Kamel (2004) provides a comprehensive overview. The paper traces the historical evolution, detailing development phases leading to significant infrastructure growth in the 1980s and 1990s, coinciding with the emergence of mobile technology for public use. It discusses ongoing competition dynamics and outlines future development and growth plans within the industry. Emphasizing liberalization efforts, the paper highlights broad industry changes and specific enhancements in telecommunication services. The focus extends to both quantitative and qualitative improvements in infrastructure, including the incorporation of various value-added services[7].

In their 2011 study, Elbadrawy and Aziz address the resistance faced by mobile banking (m-banking) adoption in Egypt, identifying three distinct non-adopter groups: postponers, opponents, and rejectors. The objective is to investigate the reasons behind the resistance to m-banking services and assess variations among these customer groups. The research utilizes questionnaires and employs statistical tests like Chi-square, Kruskal-Wallis H, and one-way ANOVA. Results reveal significant differences among non-adopter groups concerning usage, value, and image barriers, while risk and tradition barriers show no statistical significance. Notably, risk barriers received the highest overall mean. The study highlights noteworthy associations between usage, risk, and image barriers with gender and education levels, offering insights into cultural dimensions mapped by Hofstede[8].

In their investigation on the adoption of e-payment technology in emerging economies, conducted in 2015, Dr. Maha Mourad and Hussam Farouk Sherif aim to explore the extent to which e-payment innovations contribute to enhancing service quality and organizational innovativeness. Focusing particularly on Egypt as a representative of an emerging economy, the research seeks to understand the factors influencing e-payment acceptance and adoption from the customer's perspective. Employing a mixed-methods approach, the study begins with exploratory qualitative research involving key decision-makers in the telecom and banking sectors to validate the research framework. Subsequently, a survey is conducted to examine various factors such as ease of use, usefulness, risk, privacy, and compatibility, drawing on established models like the Self-Service Technology (SST) model and integrating relevant factors from Mallat's (2005) model to suit the Egyptian context. The analysis, conducted using SPSS with 378 responses, reveals a positive relationship between attitude towards e-payment technology and perceived ease of use, usefulness, and compatibility, while demonstrating a negative association with perceived risk. Surprisingly, the need for personal interaction does not significantly impact the adoption attitude. Moreover, the introduction of Personal Innovativeness in IT as a moderating variable neutralizes the effect of compatibility, suggesting that early adopters are more inclined towards embracing e-payment options. This study offers valuable insights into the dynamics of e-payment adoption in emerging economies, particularly in Egypt, contributing to both academic research and industry practice in the communication sector[9].

In their 2018 research, Ramadan and Aita aim to explore the impact of perceived satisfaction with mobile payment applications on brand loyalty and future use behavior among Arab consumers. Utilizing a theory-based integrative model, the study employs mixed research methods, including focus groups for qualitative insights and structural equation modeling for quantitative analysis. The research involves 305 consumer participants from nine Middle Eastern countries, examining satisfaction's influence on use experience, expectations, loyalty, and purchase intentions. The findings highlight the importance of mobile payment application quality in enhancing user experience and shaping consumer expectations, ultimately influencing loyalty and future usage. The study recommends that service providers prioritize features like usability, availability, reliability, adaptability, accessibility, responsiveness, and security when developing mobile applications. This research contributes significantly to the limited empirical knowledge on mobile payment consumer behavior in the Arab world, offering insights across multiple countries in the region[10].

In 2019, Gohary conducted a study investigating the influence of fintech, covering e-payment services, bills e-payment, payment methods, and bank accounts with e-government, on enhancing e-government services in terms of availability, accessibility, efficiency, and responsiveness. To address the limited research in this area, a survey involving 400 respondents in Egypt was undertaken to evaluate the impact of fintech components on various dimensions of facilitating e-government services. The results suggest that bank accounts with e-government do not significantly affect any facilitating services dimension, while other fintech components display varying effects. The analysis highlights challenges faced by respondents, including weak internet networks, inadequately skilled e-government portal personnel, and system ineffectiveness. In conclusion, the implementation of fintech emerges as a factor influencing facilitating e-government services, albeit with diverse effects across its components[5].

In this study Hussein (2020) underscores the pivotal role of mobile payments in Egypt's commitment to financial inclusion, as outlined in the Sustainable Development Strategy for 2030. The research evaluates the Government of Egypt's preparedness to embrace financial technology (fintech) for advancing financial inclusion, revealing a notable absence of a clear vision and strategic roadmap. The study underscores the importance of collaborative efforts among stakeholders to address data gaps, shedding light on Egypt's relative lag in financial inclusion. With a flourishing fintech landscape, the government is urged to focus on cultivating an environment conducive to financial literacy, taking on roles as a regulator and incubator. Overcoming constraints and supporting fintech startups becomes crucial in bridging gaps in diverse financial services. The study delves into various themes such as Regtech, recruitment, transportation, health, micro-lending, and e-commerce amid a surge in fintech startups. Contributing to theoretical knowledge on fintech, the research aims to fill existing gaps and provide policy recommendations for the ongoing digital transformation of financial services[11].

In their 2021 study, Chen, Walker, McCalman, Elkhouly, and AbdElDayem highlight the growing global prevalence of e-payment services and the imperative to comprehend factors influencing their adoption. The research, conducted through a survey at Ain Shams University in Cairo, Egypt, delves into the adoption of e-payment services among students and staff. Applying theoretical models such as TAM, TRA, and social norms, the study's results closely align with patterns observed in Western societies. Six constructs related to adoption and four demographic backgrounds were examined, utilizing three questions to measure usage. Bivariate analysis underscores the significance of constructs including incentive, perceived usefulness, ease of use, social influence, perceived risk, and trust. Demographic variables like age, working status, education, and gender were found to correlate with e-payment usage, with gender and perceived usefulness emerging as crucial factors in multivariate analysis. Acknowledging the study's university-centric and English-language focus, the authors recommend a broader and more diverse sample for future research in Egypt[2].

Research Gap

Previous research on mobile payment adoption in Egypt has provided valuable insights into the influence of demographic variables such as age, gender, and employment status on adoption behaviors. However, these studies have often exhibited limitations in their sample diversity, focusing on specific segments like academia or certain age groups. Consequently, their findings might lack generalizability to the broader Egyptian population. A critical need exists for comprehensive studies encompassing a broader range of demographics. Such studies could shed light on how factors beyond age and gender, such as income levels and occupation, distinctly impact mobile payment adoption and usage behaviors among Egyptians[2,8,12,13].

Moreover, the geographic representation in these studies has been limited, with a focus on specific regions within Egypt. This narrow focus restricts the generalizability of findings regarding mobile payment adoption behaviors across the entire country. A broader, more geographically dispersed sample, representative of various regions in Egypt, would offer a more comprehensive understanding. Furthermore, exploring the cultural perspective and decision-making processes among different segments of the population could provide crucial insights into the barriers and concerns influencing resistance to mobile banking adoption, thus aiding in the design of more effective marketing strategies[7,10,14].

Additionally, methodological limitations have been evident in existing research, primarily relying on self-reporting methods and closed-ended questionnaires. Future studies should aim for methodological enhancement by employing mixed method approaches that combine qualitative and quantitative techniques. This approach would validate and enrich the understanding of drivers and barriers to mobile payment adoption, facilitating a deeper exploration of user experiences, perceptions, and motivations related to mobile payment usage in Egypt[10,12,14].

Ultimately, even though some studies have indicated the predictive ability of variables such as perceived utility, further research is required to design and test strong predictive models utilizing machine learning techniques in order to forecast future trends in Egypt's adoption of mobile payments. Future research can make a substantial contribution to a more thorough knowledge of Egypt's adoption of mobile payments.

METHODOLOGY

The quantitative research method was chosen for this study. For this research, researchers used convenience sampling, in which this sampling technique carried out by obtaining respondents who are easily available[15]. Samples in this research were devoted to mobile users who have been actively using digital payment services in Egypt.

Dataset Description

In 2024, an online survey using google form was distributed through email and social media channels.

Notably, the survey questions draw inspiration from the research conducted by[2]. Researchers used a Likert scale that may indicate the attitude of respondents by looking at how much respondents agree or disagree with the statements that have been formed starting from very positive to negative attitudes. The survey successfully garnered responses from approximately 175 individuals, providing a robust dataset for analysis. It's important to note that the survey instrument was constructed in the English language to ensure consistency and accessibility for a diverse range of participants.

In the first section of the survey, participants are required to provide essential demographic information, including their gender, age, current governorate of residence and occupation. Subsequently, the survey branches into two distinct paths based on respondents' awareness of mobile payment technology. If a participant selects "Yes, I'm aware of mobile payment technology," they are directed to a subsequent section focusing on their usage patterns and attitudes towards mobile payments. This includes inquiries about the specific mobile payment platforms they primarily use, their likelihood of recommending their chosen platform to others, the main purposes for which they utilize mobile payments, the frequency of their transactions, and the monetary amount spent monthly in Egyptian Pounds (EGP).

Data Analysis AND Interpretation

The objective of this research was to investigate customer awareness of mobile payment in Egypt. The information was gathered through questionnaire responses and subsequently analyzed. The necessary data for this study was acquired using readily available tools, and customer engagement was crucial in obtaining insights into the posed questions.

Table 1.1: shows that 39.4% of respondents are male and 60.6% of respondents are female.

Table 1.1: Profile of the respondent

GENDER	NO. OF RESPONDENTS	% OF RESPONDENTS
MALE	69	39.4
FEMALE	106	60.6
TOTAL	175	100

Table 1.2: shows that 1.1% of respondents are in 18-years, 40.6% of respondents are in 19-25 years, 35.4% of respondents are in 26-35 years, 20.6% of the respondents are in 36-45 years and 2.3% of respondents are in above 46 years categories.

Table 1.2: Age of the respondent

AGE GROUP	NO. OF RESPONDENTS	% OF RESPONDENTS
18-	2	1.1
19-25	71	40.6
26-35	62	35.4
36-45	36	20.6
46+	4	2.3
TOTAL	175	100

Table 1.3: shows that 27.4% of respondents are from Cairo, 24.6% are from Giza, 18.9% are from Alexandria, 4.6% are from Dakahila, 4% are from Al-Buhayrah, 3.4% are from Fayoum, 2.9% are from Sharqia and 14.2% from another city in Egypt.

Table 1.3: Governorate of the respondent

CITY	NO. OF RESPONDENTS	% OF RESPONDENTS
Cairo	48	27.4
Giza	43	24.6
Alexandria	33	18.9
Dakahlia	8	4.6
Al-Buhayrah	7	4
Fayoum	6	3.4
Sharqia	5	2.9
Other	25	14.2
TOTAL	175	100

Table 1.4: shows that 30.9% of respondents are students, 56.6% of respondents are employees, 11.4% of respondents are Unemployed and 1.1% of respondents are Retired.

Table 1.4: Occupation of the respondent

Occupation	NO. OF RESPONDENTS	% OF RESPONDENTS
Student	54	30.9
Employed	99	56.6
Unemployed	20	11.4
Retired	2	1.1
TOTAL	175	100

Machine Learning

In various scientific fields, the primary goal often involves creating a model that captures the connection between a set of observable factors (inputs) and another set of variables associated with them (outputs). Once such a mathematical model is established, it becomes feasible to predict the values of the target variables through the measurement of the observables. Unfortunately, many real-world phenomena are too intricate to be directly modeled as a straightforward input-output relationship. Machine learning offers techniques capable of automatically constructing a computational model for these intricate relationships by processing available data and optimizing a performance criterion specific to the problem. This automated model-building process is termed "training," and the data used for this purpose is referred to as "training data." The trained model not only provides insights into how input variables are linked to the output but also allows predictions for novel input values not included in the training data[13,16,17,18].

Types of Machine Learning

Machine learning is usually classified into two types based on the availability of the data and the input given to the learning system; these include supervised learning and the unsupervised learning approach. A third type of learning approach, rather less frequently used, is the reinforcement learning approach[19].

Algorithm Used

A. K-Nearest Neighbor (KNN)

The KNN algorithm is a straightforward method that stores all available cases and categorizes new instances by assessing their similarity using measures such as distance functions. KNN, initially employed in statistical estimation and pattern recognition in the early 1970s, operates on a non-parametric basis. In this algorithm, a case is categorized by a majority vote from its neighbors, with the classification being determined by the class most prevalent among its K nearest neighbors, as determined by a distance function. When K equals 1, the case is simply assigned to the class of its closest neighbor. The algorithm utilizes three distance metrics for continuous variables: Euclidean (2), Manhattan (3), and Minkowski[20].

$$\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \qquad (1)$$

$$\sum_{i=1}^{k}|x_i - y_i| \qquad (2)$$

$$\left(\sum_{i=1}^{k}(|x_i - y_i|)^q\right)^{1/q} \qquad (3)$$

$$D_H = \sum_{i=1}^{k}|x_i - y_i| \qquad (4)$$

B. Support Vector Machine (SVM)

The SVM Algorithm, introduced in 1995, is a widely used classification method. In typical classification tasks, data is divided into training and testing sets, where each entry in the training set includes a "target value" and multiple "attributes." SVM aims to create a predictive model, using the training data, that can forecast the target values of the test data solely based on the attributes of the test data[20].

$$\min w, b, \xi \quad \frac{1}{2}w^T w + C\sum_{i=1}^{i} \xi_i \qquad (5)$$

$$\text{subject to } y_i(w^T\phi(x_i) + b) \geq 1 - \xi_i, \xi_i \geq 0 \ (6)$$

C. Stochastic Gradient Descent (SGD)

The SGD algorithm simplifies the computation of the gradient of E_n (f_w) by estimating it in each iteration based on a randomly selected example, denoted as z_t:

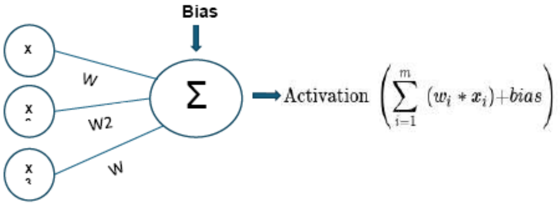
$$w_{t+1} = w_t - \gamma_t \nabla_w Q(z_t, w_t) \qquad (7)$$

Where t represents the iteration index. In the context of large-scale machine learning, the stochastic process {w_t, t = 1, ...} is influenced by the randomly selected examples at each iteration. The hope is that, despite the noise introduced by this simplified approach, the process behaves like its expectation.

As the stochastic algorithm doesn't require memory of previously visited examples, it can efficiently process examples on the fly in a deployed system. In such scenarios, stochastic gradient descent directly optimizes the expected risk since the examples are randomly drawn from the ground truth distribution[21].

D. Neural Network

A neural network is a sequence of algorithms designed to identify inherent connections within a dataset, mimicking the functionality of the human brain. Whether composed of organic or artificial neurons, these networks can adjust to varying inputs, producing optimal outcomes without the necessity of redefining output criteria. Originating from artificial intelligence, the concept of neural networks is rapidly gaining traction, particularly in the evolution of trading systems. Similarly, an artificial neural network operates with three layers: the input layer receives input, the hidden layer processes it, and the output layer transmits the calculated result[22].



(8)

Following the detailed examination of demographic variables, advanced analytical methodologies were employed to unravel deeper insights. Machine learning models, specifically K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Stochastic Gradient Descent, and Neural Network algorithms were applied to the dataset. These models were utilized within the context of respondents' awareness of mobile payment technology, a pivotal variable in the study. Among the participants, 164 indicated awareness, while 11 reported being unaware of mobile payment technology.

The utilization of these ML models, particularly about the "Are you aware of mobile payment technology?"

variable, provides a platform for exploring the predictive capabilities of each algorithm. This exploration unveils insights into the determinants of awareness within the surveyed population, enriching the study's capacity to discern complex relationships and predict behavioral patterns.

RESULTS AND DISCUSSION

The survey revealed that the paper's primary role was to gauge customer awareness of mobile payment technology. The findings indicated that most respondents were familiar with various mobile payment platforms, including Vodafone Cash, Orange Money, Fawry, Bee, Aman, Halan, ValU, Innoveyda, MaxAB Wallet, Masary, Paymob, PaySky, Porto Pay, Tasdeed by CIB, Qash, YallaPay, PayNas, TPAY Mobile, and Instapay.

Post-survey analysis identified Vodafone Cash as the most widely used platform because The fee for transferring funds to a Vodafone Cash wallet is 1 LE. When transferring funds to other wallets, a fee of 0.5% is applied, with a minimum charge of 1 LE and a maximum cap of 15 LE. The first money transfer transaction each month is free, provided that the transferred amount is less than 2000 LE. Withdrawal fees amount to 1% of the withdrawal amount, with a minimum charge of 3 LE. Customers have the flexibility to transfer money with a minimum amount of 5 LE and a maximum limit of 60,000 LE.

The survey results provide compelling evidence that Vodafone Cash is the most widely used platform. With 175 responses from individuals residing in various regions of Egypt, it was evident that when posed with the question "Which mobile payment platforms do you primarily use?" approximately 83% indicated Vodafone Cash as their primary choice.

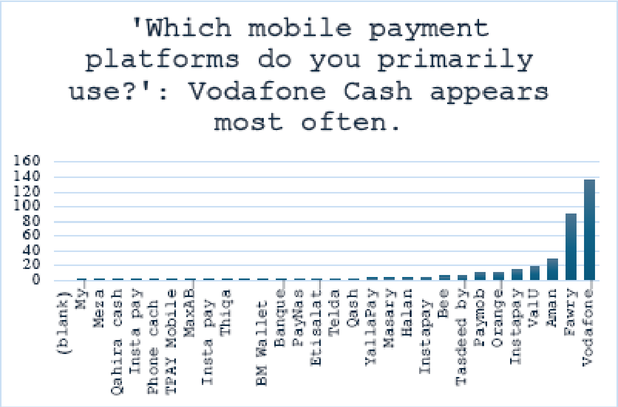


Fig. 1: Show Which mobile payment platforms you primarily use

Additionally, when people were surveyed with the question "How likely are you to recommend your chosen mobile payment platform to others?" We discovered that 41% provided a full recommendation rating of 5. This outcome strongly suggests a positive trend, indicating a high likelihood that people will increasingly adopt mobile payment platforms in the future.

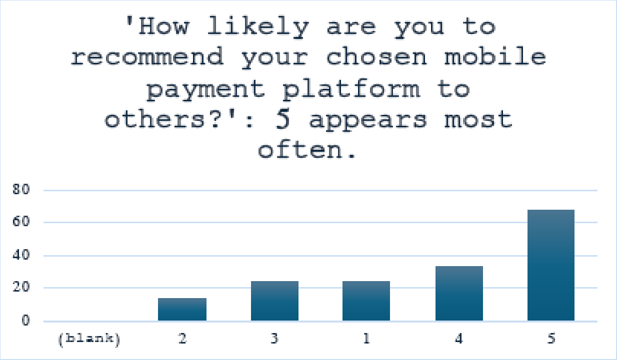


Fig. 2: Show How likely are you to recommend your chosen mobile payment platform to others

Furthermore, when individuals were questioned about the primary purposes for using mobile payments, it was observed that a significant 82% of respondents utilize mobile payments for money transfers.

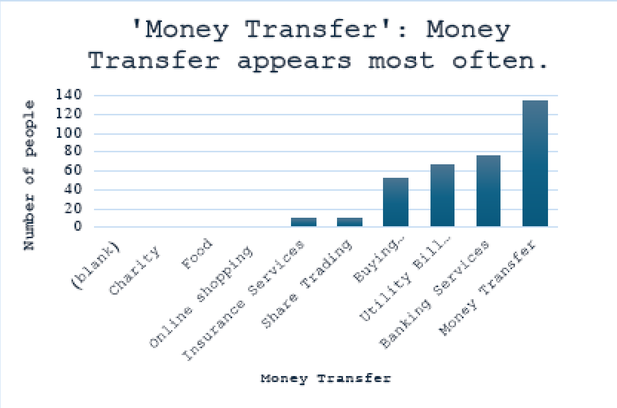


Fig. 3: Show What purposes do you primarily use mobile payments for

Three questions were posed to gauge awareness of e-payment among Egyptians: "How often do you use mobile payment platforms in your monthly transactions? Approximately ___ times per month," and "How much money do you spend via mobile payment per month? (in EGP)." The survey results indicate that 64% of respondents use e-payment 1-6 times per month, with 17% using it 1-2 times. On average, Egyptians tend to engage in e-payment around 19.44 times per month. Regarding the amount spent per month via e-payment, over 75% of respondents spent less than 5,000 EGP. Approximately a quarter spent between 201-800 EGP, while about a third spent between 1,200-5,000 EGP. This suggests that e-payment is primarily used for Money Transfers, not to buy goods and services.

Table 2: Descriptive Statistics for Dependent Variables

Variables	Frequencies	Percentage	Mean	S. D
Monthly Transaction			19.44	14.55
0	2	1.1		
1-2	31	17.7		
3-4	47	26.9		
5-6	32	18.3		
7-8	14	8		
9-10	19	10.9		
11-12	5	2.9		
13 and over	14	8		
Missing	11	6.3		
TOTAL	175			
Money Spent			15.90	7.66
0	3	1.7		
1-200	16	9.1		
201-400	17	9.7		
401-800	25	14.2		
801-1,200	22	12.5		
1,201-2,500	23	13.1		
2,501-5,000	27	15.4		
5,001-8,000	12	6.8		
8,001-12,000	8	4.5		
12,001 and over	11	6.2		
Missing	11	6.2		
TOTAL	175			

Following this outcome, the study explored customer awareness of mobile payment. Now, the study will delve into the reasons behind customers not being aware of mobile payment. Initially, the study posed two questions to customers: "What are the primary reasons for your reluctance to use mobile payment platforms?" and "What improvements could mobile payment platforms make to encourage adoption?".

Many factors were mentioned by respondents who were asked why they didn't utilize mobile payments as often. These included a preference for conventional payment methods, ignorance about mobile payment possibilities, lack of trust in technology and security concerns, restricted access to cellphones or Internet connectivity, and cultural or sociological reasons.

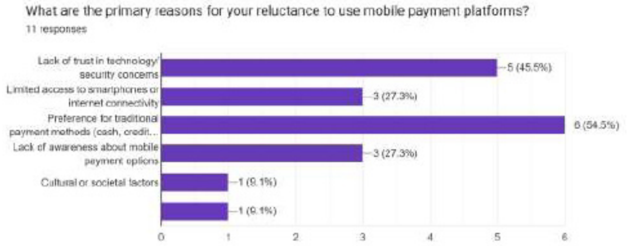


Fig. 4: Show What are the primary reasons for your reluctance to use mobile payment platforms

We discovered that individuals questioned about What improvements could mobile payment platforms make to encourage adoption. These include better education and awareness campaigns, Enhanced customer support services, Simplified user interfaces, Stricter security measures, and Tailored incentives or promotions.

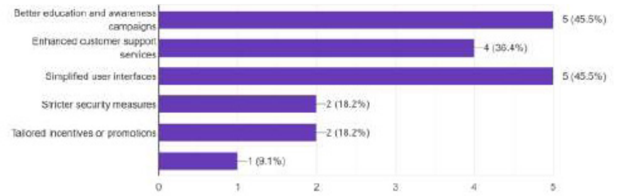


Fig. 5: Show What improvements could mobile payment platforms make to encourage adoption

To predict future awareness of mobile payment platforms, our machine learning models were fed a comprehensive set of features derived from survey responses and user behavior data. These features include:

User Demographics

Age, gender, income level, and geographic location. These aspects help in understanding the user base's diversity and potential preferences.

Usage Frequency: The number of times users engage with mobile payment platforms within a given timeframe, offering insights into user reliance on these platforms.

Transaction Amounts

Ranges of money spent through mobile payments per month, highlighting the platforms' role in users' financial activities.

Platform Preference: Users' preferred mobile payment platforms, providing a direct indicator of market dominance and user satisfaction.

Recommendation Likelihood: How likely users are to recommend their chosen platform to others, which is a qualitative measure of user satisfaction and platform reliability.

Purpose of Use

The primary reasons users opt for mobile payments, such as money transfers, bill payments, or shopping, indicating the platforms' versatility and utility in everyday transactions.

These features were carefully selected to capture a broad spectrum of factors influencing mobile payment platform adoption and satisfaction. By analyzing these features, the machine learning models aim to identify patterns and trends that can predict future user awareness and adoption of mobile payment technologies.

The predictive process began with preprocessing the gathered data to normalize feature scales and handle missing values, ensuring the models' effective learning. Subsequently, the dataset was split into training and testing sets, with the training set used to train the models and the testing set to evaluate their predictive performance.

The evaluation of models—KNN, SVM, Stochastic Gradient Descent, and Neural Network—involved comparing their accuracy in predicting user awareness, using metrics like AUC (Area Under the ROC Curve), F1 Score, Precision, Recall, and MCC (Matthews Correlation Coefficient). This comprehensive evaluation framework enabled the identification of the most effective model in forecasting future trends in mobile payment platform awareness.

The outcomes obtained from the k-nearest Neighbor, Support Vector Machine, Neural Network, and Stochastic Gradient Descent are presented hereafter.

The dataset undergoes two rounds of testing: first on cross-validation with 10 folds, and second on a random sample with a 70% training set and a 30% testing set. Four distinct algorithms are employed and evaluated using metrics such as AUC, F1, Recall, CA, Precision, and MCC.

Table 3: Statistics of Algorthim with 10 K-Fold

Model	AUC	CA	F1	Precision	Recall	MCC
KNN	0.861	0.972	0.955	0.965	0.972	0.339
SVM	0.927	0.970	0.955	0.940	0.970	0.000
Stochastic Gradient Decent	0.680	0.978	0.974	0.975	0.978	0.531
Neural Network	0.906	0.972	0.961	0.973	0.972	0.297

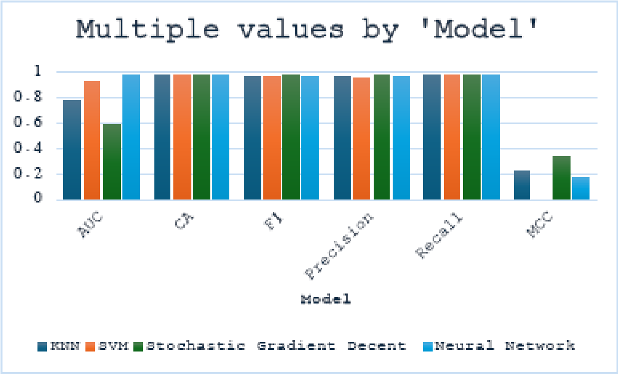


Fig. 6: Dataset Performance chart with 10 k-fold

The table and graph illustrate that the top-performing model, achieving a high accuracy of 92.7%, is SVM. Following closely, the second-best is the Neural Network with an accuracy of 90.6%, while the third-ranking model is KNN with an accuracy of 96.1%. In contrast, the least effective model is Stochastic Gradient Descent, which attains a modest accuracy of 68%.

Table 4: Statistics of Algorthim with 70/30 Data Split

Model	AUC	CA	F1	Precision	Recall	MCC
KNN	0.768	0.972	0.963	0.962	0.972	0.215
SVM	0.928	0.972	0.959	0.946	0.972	0.000
Stochastic Gradient Decent	0.582	0.975	0.968	0.970	0.975	0.337
Neural Network	0.975	0.972	0.962	0.961	0.972	0.175

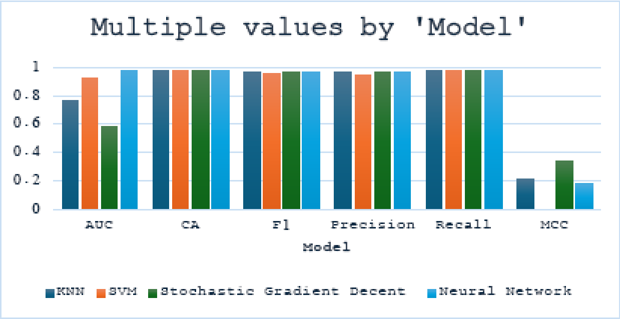


Fig. 7: Dataset Performance chart with Data Split 70/30

The table and graph illustrate that the top-performing model, achieving a high accuracy of 97.5%, is Neural Network. Following closely, the second-best is the SVM with an accuracy of 92.8%, while the third-ranking model is KNN with an accuracy of 76.8%. In contrast, the least effective model is Stochastic Gradient Descent, which attains a modest accuracy of 58.2%.

The results using k-fold were very similar, and sometimes better than the 70/30 data split, and it also maintained the same hierarchy.

The survey aimed to assess consumer awareness and utilization of mobile payment technologies. The overwhelming preference for Vodafone Cash by 83% of respondents, out of 175 individuals surveyed across Egypt, underscores its dominant market position. This preference can be attributed to Vodafone Cash's competitive fee structure, including a low fund transfer fee and the absence of charges for the first transaction each month under certain conditions. These findings suggest a strong market presence of Vodafone Cash, supported by consumer perception of value and convenience offered by its fee structure.

The high likelihood of recommending the used mobile payment platform, as indicated by a 41% full recommendation rate, hints at a significant positive user experience. This satisfaction level could be influencing the growing adoption of mobile payment solutions, reflecting a trend towards digital financial solutions.

An interesting insight from the survey is the primary use of mobile payments for money transfers, indicated by 82% of respondents. This suggests that, currently, mobile payment platforms are primarily seen as tools for personal fund transfers rather than comprehensive financial management solutions including purchases and bill payments.

CONCLUSION

In conclusion, this research investigated customer awareness and adoption behaviors regarding mobile payment technology in Egypt, employing a survey and advanced machine learning models. The survey results highlighted Vodafone Cash as the most widely used platform, with 83% of respondents choosing it as their primary mobile payment option. Notably, the survey revealed that 41% of participants provided a full recommendation rating of 5 when asked about recommending their chosen mobile payment platform to others. This positive trend suggests a high likelihood of increasing adoption in the future, fueled by favorable user experiences.

The survey identified key reasons for reluctance to adopt mobile payment platforms, including trust and security concerns, limited access to smartphones or internet connectivity, preference for traditional methods, lack of awareness, and cultural factors. Respondents suggested improvements such as better education, enhanced customer support, simplified interfaces, stricter security measures, and tailored incentives.

While this research offers valuable insights into mobile payment adoption behaviors in Egypt, several limitations should be acknowledged. Firstly, the reliance on a convenience sample, particularly with a small number of respondents, raises concerns regarding the representativeness of the findings. The limited sample size may not adequately capture the full spectrum of attitudes and behaviors towards mobile payment technology within the Egyptian population. Consequently, caution should be exercised when generalizing the results beyond the sampled demographics. Additionally, the study's focus on a specific geographic region and demographic profile further restricts the applicability of its findings to broader contexts. Future research endeavors should aim for larger and more diverse samples to enhance the validity and generalizability of conclusions drawn about mobile payment adoption dynamics in Egypt.

Machine learning models, including k-nearest Neighbor, Support Vector Machine, Neural Network, and Stochastic Gradient Descent, were employed to predict future awareness levels. The results indicated that SVM and Neural Networks outperformed other models, achieving accuracies of 92.7% and 97.5%, respectively. These models demonstrated potential for predicting mobile payment awareness and could guide strategies for increasing adoption.

The methodology encompassed a diverse sample of 175 individuals from various regions in Egypt, providing valuable insights into demographic factors influencing mobile payment adoption. Studies are needed, nevertheless, to support the necessity for more thorough research using a variety of approaches, diverse geographic representation, and a wider range of demographics. Subsequent research endeavors may augment the comprehension of mobile payment practices, so facilitating the formulation of efficacious strategies to foster acceptance and bolster the continuous shift in the nation from currency-based to electronic transactions.

CONFLICT OF INTERESTS

There are no conflicts of iterest.

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الملخص العربى

" استكشاف تبني الدفع عبر الهاتف المحمول في مصر: التحديات، السلوكيات، والتوقعات "

أمنية الرشيدي[١,٢]، هاجر سليم[٢]، هبة الله قاعود[٣]

[١]كلية العمال جامعة العلمين الدولية
[٢]كلية تكنولوجيا المعلومات وعلوم الحاسب ، جامعة النيل
[٣]كلية الدراسات العليا في إدارة التكنولوجيا، جامعة النيل

لقد أدى التطور السريع للإنترنت إلى تحويل الممارسات التجارية التقليدية، مما أدى إلى ظهور الأعمال التجارية الإلكترونية والمدفوعات الإلكترونية. مع تزايد تعقيدات نماذج الأعمال الإلكترونية والتقنيات الداعمة لها، تظهر أنظمة الدفع عبر الهاتف المحمول كخليفة طبيعي لطرق الدفع الإلكترونية التقليدية. تبحث هذه الدراسة في اعتماد الدفع عبر الهاتف المحمول في مصر. يواجه تحول مصر إلى أنظمة الدفع الإلكترونية صعوبات. يدرس هذا البحث بدقة أنماط التبني، ووجهات النظر الثقافية، والنماذج التنبؤية للأنماط القادمة. تم استخدام عينات الراحة في دراسة استقصائية لدراسة الوعي بالدفع عبر الهاتف المحمول في مصر في عام 2024. وكان هناك 175 مشاركًا في البحث. بعد الحصول على ملفات تعريف المشاركين من خلال تحليل البيانات، تم التنبؤ بسلوكيات الوعي بالدفع عبر الهاتف المحمول باستخدام أساليب التعلم الآلي مثل K-Nearest Neighbors وSupport Vector Machine وStochastic Gradient Descent وخوارزميات الشبكة العصبية. تسد هذه الدراسة بعض الثغرات في الأدبيات المتعلقة باعتماد الدفع عبر الهاتف المحمول من خلال توفير معلومات ثاقبة من شأنها أن تساعد صناع السياسات ورجال الأعمال والأكاديميين على فهم ديناميكيات قبول الدفع عبر الهاتف المحمول في مصر بشكل أفضل.

الكلمات الدالة: مصر، الدفع عبر الهاتف المحمول، التعلم الآلي، التنبؤات، اعتماد التكنولوجيا