



AI-Driven Predictive Modeling for Customer Acquisition in Digital Payment Platforms

Noor Alam Siddiqui¹;

[1]. Master of Science in Management Information Systems, College of Business, Lamar University, Texas, USA; Email: noor.siddiqui440@gmail.com

Doi: [10.63125/ftbwbz35](https://doi.org/10.63125/ftbwbz35)

Received: 21 January 2026; **Revised:** 22 February 2026; **Accepted:** 20 March 2026; **Published:** 06 June 2026;

Abstract

This study examines the impact of predictive modeling on customer acquisition rates in digital payment platforms, addressing the practical problem that many fintech firms generate large volumes of transaction and behavioral data but still struggle to convert those data into efficient customer acquisition strategies. The purpose of the research is to determine whether predictive modeling, supported by machine learning based transaction analysis, improves customer targeting efficiency and acquisition outcomes in cloud-based and enterprise digital payment cases. Using a quantitative, cross-sectional, case-based design, the study collected data from 218 respondents drawn from cloud and enterprise payment platform contexts, including professionals in data analytics, marketing, operations, product, and management roles. The core variables were predictive modeling, machine learning based transaction analysis, customer targeting efficiency, and customer acquisition rate. Data were analyzed using descriptive statistics, Cronbach's alpha, Pearson correlation, and regression analysis. The findings show strong reliability across constructs, with Cronbach's alpha values ranging from 0.838 to 0.881, and an overall scale reliability of 0.889. Descriptive results indicated high agreement across all variables, including predictive modeling ($M = 4.18$, $SD = 0.61$), machine learning based transaction analysis ($M = 4.11$, $SD = 0.66$), customer targeting efficiency ($M = 4.07$, $SD = 0.64$), and customer acquisition rate ($M = 4.14$, $SD = 0.59$). Correlation analysis revealed significant positive relationships between predictive modeling and customer acquisition rate ($r = 0.681$, $p < .001$), transaction analysis and customer acquisition rate ($r = 0.643$, $p < .001$), and targeting efficiency and customer acquisition rate ($r = 0.701$, $p < .001$). Regression results further showed that predictive modeling alone explained 46.4% of the variance in acquisition outcomes, while the combined model of predictive modeling, transaction analysis, and targeting efficiency explained 59.3% of the variance, with targeting efficiency emerging as the strongest predictor ($\beta = 0.374$, $p < .001$). The study implies that digital payment firms can improve acquisition performance by embedding predictive analytics into evidence-based targeting and campaign decision systems.

Keywords

Predictive Modeling, Digital Payment Platforms, Customer Acquisition Rate, Machine Learning Based Transaction Analysis, Customer Targeting Efficiency

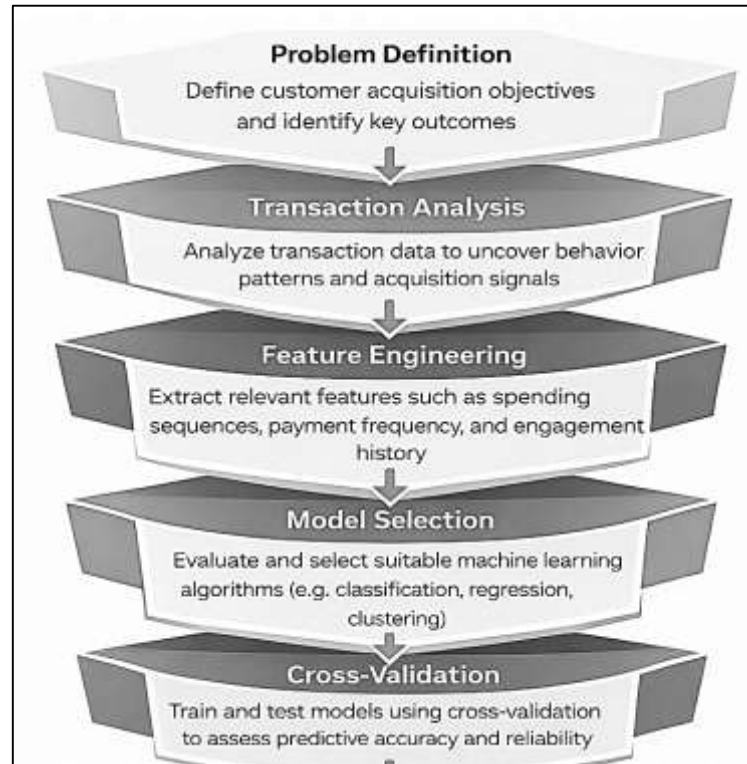
INTRODUCTION

Predictive modeling refers to the use of statistical techniques, data mining procedures, and machine learning algorithms to estimate the probability of future outcomes from historical and real-time data, while transaction analysis refers to the systematic examination of payment records, spending sequences, usage frequency, timing, channel choice, and other behavioral traces embedded in digital commerce systems (Aker & Wamba, 2016). In customer-facing markets, customer acquisition rate generally denotes the proportion of prospective or reachable users who become active customers within a defined period, and digital payment platforms refer to technology-enabled systems that facilitate transfers, purchases, merchant payments, peer-to-peer payments, and wallet-based financial interactions through mobile and online channels. These definitions matter because digital payment ecosystems have become a globally significant infrastructure for retail exchange, platform competition, financial inclusion, and data-driven market coordination (Pozzolo et al., 2018). Early mobile payment scholarship already framed payment innovation as a distinct field shaped by technological architecture, user trust, and service design rather than by payment mechanics alone. Later reviews showed that research on digital payments expanded rapidly as payment platforms moved from experimental services to central instruments of daily commerce and digital intermediation. Within this broader evolution, predictive modeling gained salience because platform operators no longer compete only on transaction completion; they compete on identifying who is likely to adopt, who is likely to transact repeatedly, and which behavioral signals indicate conversion readiness (Leong et al., 2020). Marketing and CRM scholarship has long established that customer data can be transformed into actionable knowledge for customer identification, attraction, retention, and development, with classification, regression, clustering, and forecasting serving as foundational analytical tools. Contemporary marketing analytics literature further explains that data-rich environments alter managerial decision making by shifting emphasis from descriptive reporting to predictive inference, customer-level estimation, and behavior-based intervention design (Liu et al., 2019). In digital payment platforms, this shift is internationally significant because platform expansion depends on scaling both trust and usage across heterogeneous populations, merchants, devices, and transaction contexts. For that reason, a study of predictive modeling and customer acquisition in digital payment platforms sits at the intersection of fintech adoption, data-driven marketing, and machine learning-based behavioral analysis, making the topic relevant to both emerging and mature digital economies.

The conceptual roots of predictive modeling in customer acquisition can be traced to customer relationship management and marketing analytics, where firms use observable customer characteristics and behavioral histories to identify the highest-probability targets for conversion and relationship development (Ngai et al., 2011). In the CRM literature, customer attraction is not treated as an isolated promotional act; it is a structured decision problem involving segmentation, prioritization, forecast accuracy, and efficient allocation of communication resources. Marketing analytics research subsequently expanded this logic by arguing that firms in data-rich markets are increasingly capable of linking granular behavioral data to strategic decisions on acquisition, cross-selling, engagement, and customer value creation. Big data consumer analytics was later positioned as a transformational force because real-time and high-variety customer information allows organizations to detect patterns that were previously invisible to traditional market research (Ha et al., 2024). Related work on customer engagement value also clarified that firms should evaluate customers not only by immediate transaction worth but by broader economic and network value, including referral, influence, and relational effects that shape growth trajectories. This literature is highly relevant to digital payment platforms because such platforms operate within multi-sided markets where one user's adoption may influence merchant readiness, peer recommendation, and network externalities. As a result, customer acquisition on payment platforms is inseparable from analytics capable of estimating who is most likely to adopt, which incentives are most effective, and how transaction-linked experiences affect conversion. The research tradition in predictive modeling thus provides the analytical vocabulary for this thesis: acquisition becomes a measurable dependent outcome, transaction patterns become predictive inputs, and machine learning becomes a method for converting high-volume platform data into acquisition probabilities (Hidayat-ur-Rehman et al., 2022). This perspective also supports the use of quantitative testing because predictive-modeling research commonly relies on measurable constructs, correlation

structures, classification logic, and regression-based examination of behavioral relationships. In short, the intellectual foundation of the present topic lies in the merger of CRM, analytics, and platform-market thinking, where customer acquisition is interpreted as a forecastable event shaped by behavioral evidence rather than by intuition alone (Belanche et al., 2022).

Figure 1: Predictive Modeling Process for Customer Acquisition in Digital Payments



Digital payment platforms provide an especially fertile setting for predictive modeling because they continuously generate transaction data that capture user behavior at scale. Payment timestamps, average ticket size, wallet top-up frequency, failed transactions, peer-to-peer transfer sequences, merchant category usage, geographic variance, device channel choice, and responsiveness to incentives all create a behavioral archive that can be mined for acquisition and activation insights (Carcillo et al., 2018). The e-commerce and analytics literature shows that such environments are structurally different from low-data settings because the volume, velocity, and variety of digital traces enable firms to profile customers dynamically and adapt decisions in near real time. In practical terms, this means that customer acquisition in digital payment systems is rarely a purely demographic problem. It is a behavioral prediction problem involving readiness, trust formation, perceived convenience, transactional familiarity, and friction exposure. Research on customer lifetime value and customer value segmentation reinforces this view by showing that machine learning models can identify heterogeneous customer groups from transactional records and thereby improve prioritization and resource deployment (Tanhaei et al., 2024). For payment platforms, that logic extends to acquisition because first conversion and post-adoption activation are influenced by the same kinds of behavioral regularities that later shape retention and value realization. Internationally, payment ecosystems have become central to digital retail, service delivery, and platform intermediation, which means acquisition performance is tied not only to marketing communication but also to the platform's ability to decode payment behavior quickly and accurately. Reviews of digital payment adoption likewise document that the field has matured from basic acceptance studies to more complex investigations of ecosystem structure, user heterogeneity, and strategic design (Chand & Kumar, 2024). Consequently, machine learning-based transaction analysis is not peripheral to digital payment growth; it is part of the operating core of customer expansion, because behavioral evidence can be used to detect latent interest,

tailor onboarding, refine targeting, and reduce acquisition uncertainty. This makes digital payment platforms uniquely suitable for a study that links predictive modeling directly with customer acquisition rates.

Machine learning-based transaction analysis has become particularly important in payment systems because transaction streams are complex, sequential, imbalanced, and sensitive to context. Fraud-detection scholarship is instructive here because it demonstrates how payment data reveal behavioral drift, temporal regularities, anomaly structures, and evolving user patterns that conventional static rules fail to capture (Binayan & Shakhawat, 2022; Jurgovsky et al., 2018; Abdur & Iftekhar, 2021). Sequence classification research showed that incorporating transaction order and behavioral history can improve detection quality, while other work highlighted the realism challenge in payment analytics by noting that concept drift, class imbalance, and verification latency are central characteristics of payment data. Other studies argued that combining supervised and unsupervised learning improves performance when historical patterns coexist with emerging anomalies, and scalable real-time frameworks extended this discussion to large transaction streams in operational payment environments (Dahlberg et al., 2008; Hasan & Uddin, 2022; Mohiul & Badrul, 2022). Earlier literature reviews in financial fraud detection had already established that classification, clustering, regression, and visualization are core analytical approaches for extracting intelligence from financial transaction data. Although fraud detection and customer acquisition are not the same managerial task, both rely on the same principle: transaction data contain latent behavioral information that can be modeled to anticipate user outcomes. In one case the outcome is suspicious behavior; in the other it is conversion, adoption, activation, or response to acquisition efforts (Kanti & Rony, 2022; Hossain & Uddin, 2022). This is why transaction analysis matters to the present study. It justifies the phrase “machine learning-based transaction analysis” not as a fashionable label but as a methodologically meaningful approach grounded in the proven capacity of learning systems to interpret payment-related behavioral patterns (Kumar et al., 2010). For digital payment platforms, the same analytical infrastructure used to distinguish normal from abnormal behavior can also be adapted to distinguish cold prospects from high-propensity adopters, low-engagement users from near-converters, and one-time registrants from likely active customers. Thus, the transaction-analysis literature strengthens the rationale for examining predictive modeling as a driver of customer acquisition rates in payment ecosystems that are already defined by dense, behavioral, continuously updating data (Ngai et al., 2009).

The adoption literature on mobile payments and digital payments provides another essential foundation for this research because customer acquisition in a payment platform begins with the decision to adopt or use the service. Studies across multiple countries consistently identify perceived usefulness, ease of use, trust, security, compatibility, social influence, and relative advantage as major drivers of payment adoption behavior. Trust has received especially strong attention because payment adoption involves financial risk and perceived vulnerability. Trust was conceptualized as a central mechanism in m-payment acceptance, and later work extended this perspective by showing the importance of initial trust formation in early-stage user adoption. Meta-analytic evidence also supports the stability of these relationships across settings (Chandra et al., 2010; Sany & Siful, 2022; Binte & Iftekhar, 2022). Broad consensus has been found on the significance of perceived usefulness, trust, risk, social influence, and ease of use, while broader digital-payment review work confirmed that the field is organized around recurring antecedents related to benefit, security, social context, and behavioral intention. Country-specific studies have enriched this picture by showing that payment adoption is shaped by local infrastructure, institutional trust, innovation readiness, and user psychology (Iftekhar & Binayan, 2023; Hasan & Chapal, 2023; Patil et al., 2020). Research in Portugal combined UTAUT2, DOI, and security perceptions; research in India extended Meta-UTAUT by incorporating personal innovativeness, anxiety, trust, and grievance redressal; research in Saudi Arabia examined m-wallet adoption with a SEM-ANN design; research in Colombia analyzed a payment platform from the user-network perspective; research in Fiji examined m-payment adoption through UTAUT; and another recent study integrated TAM and task-technology fit to deepen explanation of mobile payment adoption intentions (Aminul & Sheak, 2023; Shakhawat et al., 2023). Together, these studies show that customer acquisition in digital payment settings is neither random nor purely promotion-driven. It is

strongly connected to measurable psychological and behavioral predictors, many of which can be modeled quantitatively (Badrul & Mominul, 2023; Risha & Khalid, 2023). This makes adoption literature directly relevant to a research design that seeks to explain acquisition rates through predictive modeling and transaction-based evidence (Thi et al., 2024; Hossain & Binayan, 2023).

A further synthesis emerges when the customer analytics literature is read alongside digital payment adoption studies: predictive modeling contributes to acquisition not only by forecasting adoption likelihood, but also by refining the quality of market targeting and platform onboarding. In customer analytics, prediction models allow firms to identify high-value segments, estimate response propensities, and reduce acquisition waste by matching offers to likely converters (Binayan, 2024; Gao & Waechter, 2017; Sany & Uddin, 2023). In payment settings, this logic appears in studies that examine behavioral intention, recommendation intention, wallet resistance, and perceived risk because each of these outcomes can be treated as a conversion-related signal. Mobile wallet resistance has been modeled through both linear and non-linear relationships, showing that barriers to adoption are measurable and analytically tractable (Sany, 2024; Ali et al., 2024). Research on peer-to-peer mobile payment adoption demonstrated the role of perceived risk, thereby highlighting that behavioral conversion in payment platforms depends on how users evaluate control, security, and social acceptability (Binayan, 2025; Chapal, 2025; Kim et al., 2010; León, 2021). A more explicitly predictive perspective was added through machine learning analysis identifying key predictors of digital payment acceptance and usage among small retailers, illustrating how machine learning can isolate the most influential determinants from a large variable set. Additional work also showed that machine learning models such as random forest and logistic regression can achieve strong performance in forecasting customer behavior, which is directly relevant for acquisition-oriented analytics (Erevelles et al., 2016). The strategic importance of such work lies in the fact that payment platforms acquire users under conditions of high competition and limited attention. Under those conditions, predictive modeling enables the platform to identify who is likely to adopt, what message or incentive is likely to work, and which transactional or behavioral markers signal movement from awareness to active usage (Arif Uz et al., 2025; Shakhawat, 2025). In other words, the bridge from predictive modeling to customer acquisition is analytically coherent and empirically grounded: prediction improves targeting, targeting shapes onboarding, onboarding shapes adoption, and adoption is the first measurable layer of customer acquisition. This chain of reasoning supports the treatment of predictive modeling as an explanatory variable in a quantitative study of acquisition rates (Mallat, 2007; Shurovi, 2025; Kanti, 2025).

The accumulated literature therefore reveals a strong foundation for studying predictive modeling and customer acquisition in digital payment platforms, while also revealing a clear research space for the present thesis. Existing studies have richly documented payment adoption drivers, trust mechanisms, mobile-wallet resistance, transaction-analytics capabilities, and the managerial value of customer analytics. Yet much of this literature treats adoption, behavioral intention, fraud detection, customer value, and platform usage as separate conversations (Oliveira et al., 2016; Hossain, 2025; Sany, 2025). The present topic requires these conversations to be synthesized around one core question: whether predictive modeling, supported by machine learning-based transaction analysis, is associated with higher customer acquisition rates in digital payment platforms (Allen et al., 2022; Carcillo et al., 2021; Oliveira et al., 2016). Reviews of digital payment research confirm the breadth of the field, but they also show that many studies remain centered on acceptance intention, literature mapping, or single-theory adoption explanations (Ali et al., 2025; Uddin, 2025). On the other side, analytics and fraud-detection studies demonstrate the power of machine learning on transactional data, though their focal outcomes are often anomaly detection, churn, or customer valuation rather than acquisition conversion itself (Amir, 2026; Binayan, 2026). Marketing analytics scholarship explains why predictive modeling should matter for acquisition, yet it often develops this argument at a general strategic level rather than within the specific institutional and behavioral architecture of digital payment platforms (Sun et al., 2023; Wedel & Kannan, 2016). This creates the intellectual basis for the current research. A quantitative, cross-sectional, case-study-based investigation can test whether respondents working with or within digital payment platforms perceive predictive modeling as materially linked to acquisition outcomes, whether transaction-based analytics improves targeting and customer identification, and whether those

relationships are statistically visible through descriptive patterns, correlation structures, and regression effects (Chapal, 2026; Aminul, 2026; Sahi et al., 2021). The introduction to this study is therefore anchored in an international body of work that defines digital payments as data-intensive ecosystems, identifies customer acquisition as a central strategic objective, and recognizes predictive modeling as an increasingly important mechanism for transforming behavioral data into measurable growth outcomes.

Background of the Study

The background of this study lies in the rapid transformation of payment systems from cash-based and card-dominant transactions to highly digitized platform-based financial ecosystems where mobile wallets, QR payments, peer-to-peer transfers, merchant apps, and embedded financial services now shape everyday commercial activity. Digital payment platforms have become an essential part of modern economic life because they offer speed, convenience, traceability, broader market reach, and continuous access to financial transactions across personal, retail, and business settings. As competition within the fintech and digital commerce environment has intensified, customer acquisition has become one of the most critical performance priorities for digital payment providers. Platforms are no longer competing only by offering payment functionality; they are also competing through the quality of user experience, the relevance of promotional offers, the efficiency of onboarding, and the ability to identify potential customers who are most likely to adopt and actively use the service. In this environment, large volumes of transaction-related data are generated every second through user registrations, login frequency, wallet funding behavior, purchase patterns, response to rewards, merchant interactions, and repeated payment activities. These data create significant opportunities for firms to move beyond traditional marketing decisions based on intuition and broad segmentation. Predictive modeling has emerged as a powerful analytical approach that allows digital payment platforms to use historical and behavioral data to estimate customer likelihood of adoption, activation, and continued engagement. Through machine learning-based transaction analysis, firms can identify hidden patterns in customer behavior, classify users according to transaction propensity, forecast conversion outcomes, and improve acquisition strategy by targeting the right users with the right incentives at the right time. This makes predictive modeling highly relevant to customer acquisition because it supports more efficient allocation of marketing resources and reduces uncertainty in decision-making. The background of this study is therefore grounded in the increasing dependence of digital payment platforms on data-driven strategies to survive and grow in competitive markets. It reflects the need to understand whether predictive modeling actually contributes to better customer acquisition outcomes and whether transaction-based analytical capability can strengthen how platforms attract and convert new users in a measurable and statistically meaningful way.

Problem Statement

Digital payment platforms operate in a highly competitive environment where sustained growth depends not only on service availability but also on the ability to attract and convert new users efficiently. Although these platforms generate vast amounts of transactional and behavioral data, many organizations still face difficulty translating that data into effective customer acquisition strategies. In many cases, acquisition campaigns are designed around broad assumptions, generic market segmentation, promotional intensity, or short-term tactical decisions rather than analytically grounded predictions about which potential users are most likely to adopt the platform and become active transactors. This creates a serious operational challenge because customer acquisition costs can increase when firms target low-probability prospects, misread user intent, or fail to detect meaningful transaction-related signals that indicate readiness for adoption. At the same time, customer behavior in digital payment ecosystems is complex and dynamic, shaped by factors such as transaction frequency, perceived convenience, digital familiarity, responsiveness to incentives, and behavioral trust formed through platform interaction. Conventional acquisition approaches often lack the precision required to capture these patterns in a timely and structured manner. While predictive modeling and machine learning-based transaction analysis offer strong potential for identifying customer propensity, refining targeting decisions, and improving acquisition efficiency, the extent to which these tools actually influence customer acquisition rates in digital payment platforms remains insufficiently examined in a focused quantitative framework. A clear gap therefore exists in

understanding whether predictive modeling contributes significantly to acquisition outcomes, whether transaction-based analytical capabilities improve the identification of high-potential customers, and whether such improvements are visible in measurable organizational performance. This problem is important because digital payment providers need evidence-based guidance on how analytics can be used to reduce acquisition uncertainty, improve marketing resource allocation, and strengthen competitive positioning. The present study addresses this problem by investigating the relationship between predictive modeling and customer acquisition rates in digital payment platforms through a quantitative, cross-sectional, case-study-based approach grounded in descriptive statistics, correlation analysis, and regression modeling.

Research Objectives

The objective of this study is to examine how predictive modeling influences customer acquisition rates in digital payment platforms within a data-intensive and highly competitive business environment. More specifically, the study seeks to determine whether machine learning-based transaction analysis can provide meaningful support for identifying potential users, improving targeting precision, and increasing the efficiency of acquisition strategies. In line with this central purpose, the study aims to evaluate the extent to which predictive modeling helps organizations recognize behavioral patterns that are associated with customer conversion and early usage activity. It also seeks to assess the relationship between transaction-derived analytical insights and the overall effectiveness of customer acquisition efforts on digital payment platforms. Another objective is to investigate whether enhanced customer targeting efficiency acts as an important mechanism through which predictive modeling contributes to better acquisition outcomes. By focusing on measurable variables and structured respondent data, the study is designed to provide statistical evidence about the strength and direction of these relationships. The objectives are therefore not merely descriptive; they are analytical and explanatory, intended to show whether predictive modeling serves as a meaningful operational driver of growth-oriented performance. The study also aims to contribute a case-based empirical understanding of how digital payment organizations can move from intuition-led marketing to evidence-based acquisition management. In this sense, the objectives address both practical and academic concerns by linking predictive analytics capability with one of the most important success indicators in platform-based financial services. Through this objective-driven approach, the research seeks to clarify whether predictive modeling can improve customer identification, support more efficient promotional decision-making, and strengthen acquisition performance in a statistically demonstrable manner. The final objective is to provide a structured empirical basis for understanding how transaction analysis and predictive insight can be integrated into customer acquisition strategy within digital payment ecosystems.

Research Hypotheses

The research hypotheses of this study are developed from the assumption that predictive modeling can function as a significant strategic tool for improving customer acquisition in digital payment platforms. Since these platforms collect large amounts of behavioral and transactional data, it is reasonable to expect that organizations using predictive methods can better distinguish between high-potential and low-potential prospects, thereby improving the efficiency and outcome of their acquisition activities. The first hypothesis proposes that predictive modeling has a significant positive effect on customer acquisition rates. This hypothesis reflects the expectation that stronger analytical capability leads to better identification, targeting, and conversion of prospective users. The second hypothesis proposes that machine learning-based transaction analysis is positively associated with customer acquisition performance. This reflects the idea that transaction-level behavioral insights provide meaningful signals about user readiness, platform engagement potential, and likely adoption outcomes. The third hypothesis states that predictive modeling positively influences customer targeting efficiency, based on the assumption that firms with stronger predictive systems are better able to allocate offers, campaigns, and acquisition efforts to the most relevant users. The fourth hypothesis proposes that customer targeting efficiency has a significant positive relationship with customer acquisition rates, since more precise targeting is expected to reduce wastage and improve conversion outcomes. Taken together, these hypotheses establish a coherent analytical structure in which predictive modeling acts as the primary explanatory construct, transaction analysis strengthens behavioral interpretation,

targeting efficiency functions as an operational mechanism, and customer acquisition rate serves as the principal performance outcome. These hypotheses are suitable for quantitative testing because they involve measurable relationships among clearly defined variables and can be examined through descriptive statistics, correlation analysis, and regression modeling. They also align with the broader aim of determining whether data-driven analytical tools produce statistically meaningful effects in customer acquisition contexts. Through the formulation of these hypotheses, the study creates a testable framework that allows the relationship between predictive modeling and acquisition performance to be examined in a systematic, objective, and evidence-based manner.

Significance of the Research

The significance of this research can be understood from several important perspectives that reflect its academic, managerial, methodological, and practical value in the context of digital payment platforms.

- i. Academic significance: the study contributes to the growing body of knowledge on predictive analytics, machine learning, and digital payment systems by examining how predictive modeling relates specifically to customer acquisition rates, an area that remains less directly explored than adoption intention or payment usage.
- ii. Theoretical significance: the research strengthens the conceptual understanding of how behavioral transaction data can be transformed into actionable acquisition insights, thereby supporting a more structured explanation of the relationship between data-driven decision-making and customer growth outcomes.
- iii. Managerial significance: the study offers useful evidence for managers and decision-makers in digital payment platforms who must allocate marketing resources efficiently, improve targeting precision, and reduce uncertainty in acquisition strategy.
- iv. Operational significance: by focusing on transaction analysis and predictive capability, the study provides insight into how organizations can enhance day-to-day customer acquisition processes through better identification of likely adopters and better use of behavioral indicators.
- v. Methodological significance: the research demonstrates how a quantitative, cross-sectional, case-study-based design using Likert-scale data, descriptive statistics, correlation analysis, and regression modeling can be applied to evaluate analytics-driven business questions in fintech settings.
- vi. Strategic significance: the findings may help digital payment providers understand whether predictive modeling should be treated as a core growth capability rather than merely a technical support function, especially in markets where competition for new users is intense.
- vii. Policy and industry significance: the study may also be relevant to broader digital finance stakeholders by showing how evidence-based acquisition systems can support efficiency, service expansion, and more informed platform development.

Overall, the significance of this research lies in its ability to connect analytical capability with a real business outcome, thereby offering a focused and practical contribution to scholarship and to the evolving operational realities of digital payment ecosystems.

LITERATURE REVIEW

The literature review for this study examines the scholarly foundations necessary to understand the relationship between predictive modeling and customer acquisition rates in digital payment platforms. It is organized around the central idea that digital payment ecosystems are not merely financial transaction channels but data-rich environments in which customer behavior can be observed, interpreted, and strategically influenced through analytical tools. In this context, the literature becomes essential for clarifying the meanings of predictive modeling, machine learning-based transaction analysis, customer acquisition, customer targeting efficiency, and platform-based competitive growth. The review also helps position the study within existing academic debates by showing how prior research has approached digital payment adoption, transaction behavior, data-driven decision-making, customer analytics, and fintech platform performance. Since this research is quantitative and explanatory in nature, the literature review serves not only to summarize previous studies but also to establish the conceptual and theoretical basis for the variables examined in the study. It provides the foundation for understanding why predictive modeling may shape acquisition outcomes, how transaction records can function as behavioral signals, and why customer acquisition should be treated as a measurable strategic performance variable rather than a purely promotional outcome. The literature also makes it possible to identify gaps in current scholarship, especially where earlier studies have focused more heavily on user adoption intentions, trust, fraud detection, or payment acceptance, while giving comparatively less direct attention to the role of predictive analytics in acquisition

performance. In addition, the literature review supports the development of a theoretical framework that can explain the logic behind data-driven acquisition decisions, as well as a conceptual framework that defines the expected relationships among the study variables. For this reason, the review is a critical part of the study because it links the research problem with existing knowledge, clarifies how the study builds on prior scholarship, and creates the academic basis for the hypotheses and methodological choices that follow. Through this structure, the literature review provides an organized intellectual pathway for examining predictive modeling as a meaningful driver of customer acquisition in digital payment platforms.

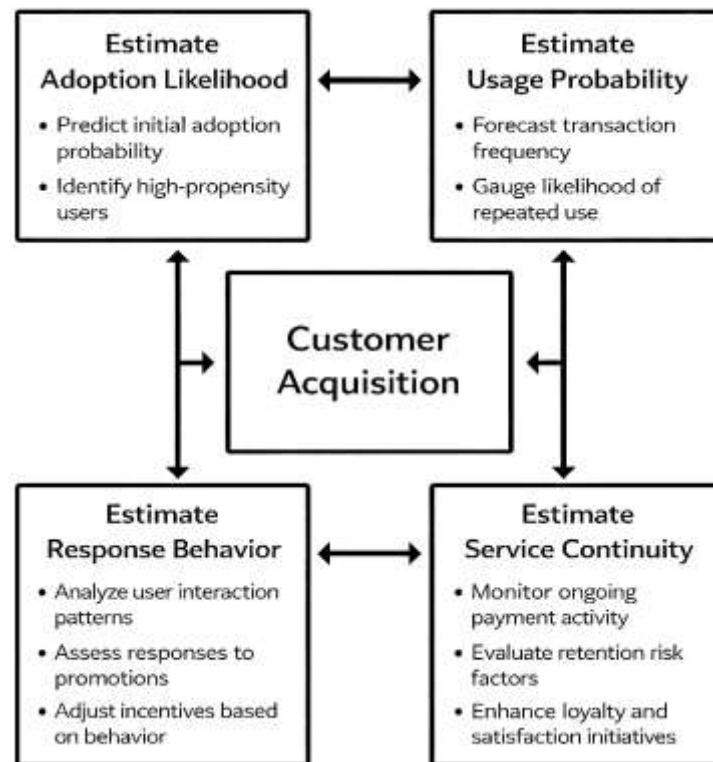
Predictive Modeling in Digital Payment Platforms

Predictive modeling in digital payment platforms refers to the use of analytical models to estimate adoption likelihood, usage probability, response behavior, and service continuity on the basis of observable customer attributes and transaction-linked signals. In the digital payment context, this analytical logic is important because payment platforms are not only processing transactions; they are also continuously generating behavioral data that can be used to identify who is likely to adopt, who is likely to intensify use, and which user segments require differentiated acquisition strategies. Earlier empirical work on mobile payment adoption showed that user decisions are shaped by an interplay of behavioral beliefs, social influences, and personal traits, and that these determinants change meaningfully between the pre-adoption and post-adoption stages (de Kerviler et al., 2016). This point is crucial for predictive modeling because it implies that customer acquisition cannot be treated as a single static outcome. Instead, acquisition-related behavior must be modeled as a staged process in which expected usefulness, ease, social approval, and individual innovativeness interact differently over time. A second line of evidence emphasized that predictive insight is equally necessary after initial adoption, because the long-term value of a payment user depends on whether the individual continues using the service regularly (Edu, 2024). Research on continuance intention found that service quality, information quality, trust, flow, and satisfaction work together to shape ongoing mobile payment usage, showing that customer-related prediction in payment systems must account for both entry and continuity. Taken together, these studies establish a core foundation for predictive modeling in digital payment platforms: customer acquisition is more accurately understood as a data-informed progression from pre-adoption disposition to actual usage and then to repeated engagement. This makes predictive modeling highly relevant for platforms seeking to identify high-propensity users, reduce inefficient promotional spending, and align acquisition campaigns with behaviorally meaningful indicators rather than broad demographic assumptions alone.

The literature also shows that predictive modeling in digital payment platforms must be sensitive to differences in payment context, because user perceptions and behavioral triggers vary across remote, in-store, and proximity payment environments. Research on remote mobile payments in the United Kingdom demonstrated that innovativeness, trust, and perceived risk materially improve explanation of adoption intention beyond standard acceptance variables, which suggests that predictive models in payment platforms gain strength when they incorporate psychological and uncertainty-related factors rather than relying on convenience alone (Slade et al., 2015). Related work on proximity mobile payments reached a similar conclusion by showing that adoption in physical retail settings is influenced by a broader value structure that includes utilitarian, hedonic, and social benefits alongside financial and privacy risks. This is important for the present study because customer acquisition in digital payment platforms depends not only on identifying technically capable users, but also on recognizing how value perceptions shape response to payment-based offers, platform onboarding, and promotional communication (Yang et al., 2012). Predictive modeling therefore becomes more useful when it is designed to reflect the actual behavioral architecture of payment usage, including trust formation, perceived risk, convenience expectations, and perceived experiential value. From a platform strategy perspective, these findings indicate that payment providers can improve acquisition precision by segmenting prospects according to the kinds of benefits and barriers that are most salient in a given payment mode. In practical terms, this means that one group of potential users may respond more strongly to trust and security assurances, while another may be more influenced by ease, speed, or experiential appeal. The literature thus supports a more refined view of predictive modeling in digital payment systems: its value lies in translating multiple behavioral drivers into more precise acquisition

probabilities, stronger targeting logic, and better alignment between platform design and user decision patterns.

Figure 2: Key Predictive Modeling Factors Shaping Customer Acquisition In Digital Payment Platforms



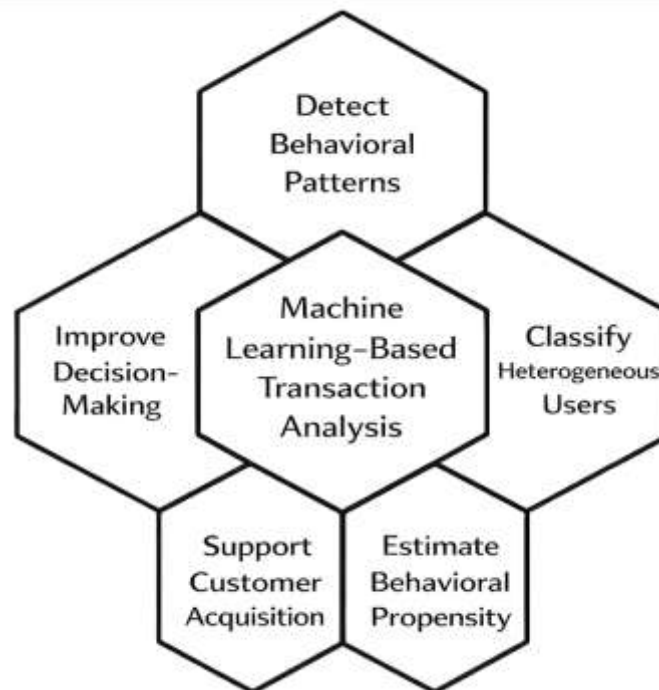
More recent scholarship strengthens this view by showing that predictive modeling in digital payment platforms should not be limited to simple linear adoption explanations, because digital payment behavior emerges through combinations of readiness, platform attributes, and post-adoption evaluations. An integrated framework developed in South Africa showed that adoption and continuance intention toward mobile payment apps can be explained more powerfully when technology readiness is examined together with expectation-confirmation processes, convenience, compatibility, perceived cost, and perceived risk. This expands the relevance of predictive modeling because it frames customer acquisition as an outcome shaped by both readiness before use and evaluative confirmation after use, allowing researchers and practitioners to link acquisition with subsequent engagement potential. A newer 2024 study on digital mobile payment platforms adds another layer by showing that usage does not always emerge from a single dominant factor; instead, different configurations of conditions can lead to acceptance and use (Edu, 2024; Shurovi, 2026; Risha, 2026). Its findings identified distinct user topologies centered on systems readiness, ease of use, affection, security, and performance expectancy, reinforcing the idea that predictive analytics in payment ecosystems should classify users into meaningful behavioral clusters rather than assume one universal pathway to adoption. For the current research, this literature is especially useful because it supports the argument that predictive modeling can enhance customer acquisition rates when platforms use transaction-related and behavioral variables to identify which prospects fit which pathway of conversion (Humbani & Wiese, 2019; Hossain, 2026; Sany, 2026). In other words, predictive modeling in digital payment platforms is not merely a technical forecasting exercise; it is a strategic capability that organizes user heterogeneity into actionable acquisition intelligence. The literature therefore positions predictive modeling as a mechanism for improving customer identification, targeting efficiency, and acquisition performance by aligning analytical insight with the complex, multi-condition reality of digital payment adoption and usage (Zhou, 2013).

Machine Learning–Based Transaction Analysis

Machine learning–based transaction analysis refers to the use of computational models to detect patterns, classify users, estimate behavioral propensity, and support decision-making from payment-related data generated through digital interactions. In digital payment platforms, transaction analysis is valuable because user behavior is recorded not only through payment completion, but also through the wider chain of actions surrounding wallet access, platform navigation, rewards response, peer transfer habits, and usage regularity (Ali et al., 2026; Uddin, 2026). Research in this area shows that machine learning contributes to payment analysis by moving beyond simple explanatory statistics toward richer prediction-oriented models. A good example is the study by Kalinić et al. (2019), which used a two-stage structural equation modeling and artificial neural network design to analyze peer-to-peer mobile payment acceptance and showed that machine learning can rank the relative importance of predictors more effectively than linear-only approaches. Their findings emphasized perceived usefulness as the strongest determinant, while also confirming the importance of trust and social influence in shaping payment behavior. This is highly relevant to transaction analysis because it demonstrates that payment decisions are not driven by isolated variables; they are formed through layered and interacting drivers that can be better captured through hybrid analytical designs. In a similar direction, Teng and Khong (2021) examined actual consumer usage of e-wallets through big data analytics and showed that transaction-related user traces can reveal concrete behavior patterns tied to rewards, interface quality, and service experience (Teng & Khong, 2021). Their work is especially important because it shifts the focus from intention data to actual usage evidence, which is closer to the behavioral core of digital payment transaction analysis. Taken together, these studies indicate that machine learning–based transaction analysis is not merely a technical enhancement to digital finance research. It is a methodological shift that enables digital payment firms to extract more precise behavioral meaning from user data, distinguish between superficial and substantive patterns of engagement, and construct more predictive interpretations of how customers respond to digital payment environments (Kalinić et al., 2019).

A second important contribution of the literature is that machine learning–based transaction analysis improves the classification and segmentation of payment users, which is central to effective targeting and customer acquisition strategy. In data-intensive platforms, raw transaction records are useful only when they can be converted into operationally meaningful segments, such as high-likelihood adopters, incentive-sensitive users, repeat transactors, or low-engagement registrants. Jaiswal et al. (2023) addressed this issue by applying factor analysis, cluster analysis, discriminant analysis, and Chi-square testing to classify fintech-led mobile payment users into analytically distinct groups (Jaiswal et al., 2023). Their study showed that mobile payment markets are heterogeneous and that robust segmentation procedures can reveal substantial differences in trust, price value, innovativeness, and adoption orientation across user groups. This insight matters for machine learning–based transaction analysis because it demonstrates that digital payment behavior should not be understood as a single average tendency. Instead, platforms need classification systems that recognize multiple forms of engagement and different levels of readiness for payment adoption and continued use. A similar pattern is visible in the work of Ma et al. (2023), who used a hybrid SEM and neural network approach to predict and enhance user experience in digital payments. Their results indicated that perceived ease of use and perceived usefulness significantly shape users' attitudes toward digital payment adoption, while the neural-network stage strengthened the predictive interpretation of these relationships (Ma et al., 2023). This hybrid structure is significant because it illustrates how machine learning–based transaction analysis can complement theory-driven models by improving the ability to detect nonlinear influence patterns among payment variables (Blanco-Oliver et al., 2024). The broader implication is that transaction analysis becomes more powerful when it is able to classify users not only by static profile characteristics but also by behavioral response structures embedded in payment-related data. From the perspective of this study, such literature supports the argument that machine learning enables digital payment firms to transform transactional information into customer intelligence that is more accurate, more differentiated, and more useful for acquisition-oriented decision-making.

Figure 3: Analytical Framework For Transaction Pattern Detection And User Classification In Digital Payment Systems



More recent research further clarifies that machine learning-based transaction analysis has strategic importance because it can outperform traditional parametric methods when the goal is to predict digital payment behavior under complex and socially influenced conditions. Blanco-Oliver et al. (2024) provide strong evidence for this point in their study of mobile peer-to-peer payment adoption, where they used machine learning classifiers and feature-selection procedures to predict usage of Bizum, a major payment platform. Their results showed that nonparametric machine learning approaches performed better than traditional parametric models and that usefulness, subjective norms, trust, and enjoyment were especially important in classifying likely users (Blanco-Oliver et al., 2024). This is directly relevant to machine learning-based transaction analysis because it confirms that prediction quality improves when models are designed to manage noise, nonlinear relationships, and variable interaction more flexibly. It also reinforces the idea that transaction analysis in digital payment settings should not be confined to descriptive monitoring of payment frequency or value. It should instead function as a predictive capability that identifies the behavioral signals most strongly associated with real platform uptake. When this evidence is read together with prior work on actual e-wallet behavior, user segmentation, and hybrid predictive modeling, a clear analytical pattern emerges. Machine learning-based transaction analysis supports digital payment platforms in three interconnected ways: it reveals behavior patterns from real usage data, it organizes heterogeneous users into meaningful analytical categories, and it improves the classification of likely adopters by handling complexity more effectively than conventional linear techniques. For the present research, this literature is important because it provides a strong scholarly basis for linking predictive modeling with customer acquisition in digital payment platforms. It shows that machine learning-based transaction analysis is not only appropriate for payment studies, but also especially suitable for contexts where acquisition depends on identifying subtle behavioral signals, prioritizing high-potential users, and improving decision accuracy through advanced data-driven methods.

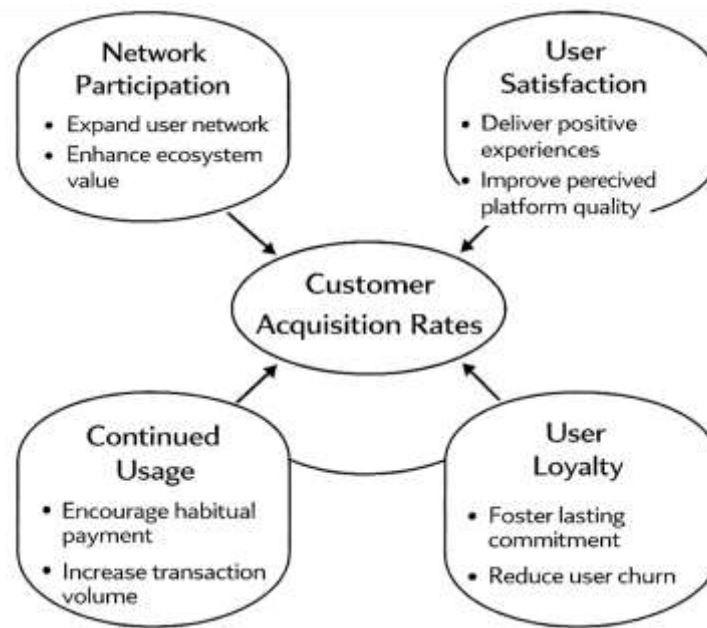
Customer Acquisition Rates and Digital Platform Growth

Customer acquisition rates in digital payment platforms refer to the pace and proportion at which prospective users become active platform users within a given period, and this measure is closely connected to broader indicators of digital platform growth such as user-base expansion, transaction intensity, market competitiveness, and relationship continuity. In platform-based payment ecosystems, acquisition is rarely a stand-alone marketing outcome because a newly acquired user contributes value

only when the platform is also able to stimulate early use, repeated payment activity, and favorable attitudes toward continued engagement. For this reason, research on digital payment growth increasingly links initial acceptance with post-adoption behavior, since acquisition quality matters as much as acquisition quantity. Evidence from mobile payment acceptance studies shows that growth depends on more than a general willingness to adopt technology. Network externalities, performance expectancy, trust, and social influence all shape the attractiveness of a payment platform, which means the ability to acquire users is partly dependent on whether potential adopters expect the platform to be useful within a larger ecosystem of other users and merchants. In a study on mobile payment acceptance, network externalities were identified as a meaningful driver of behavioral intention, indicating that acquisition performance strengthens when users perceive that platform participation will connect them to a wider and more valuable payment network (Qasim & Abu-Shanab, 2016). This is important for understanding platform growth because digital payment services operate as interaction infrastructures rather than isolated products. In addition, evidence from the United States showed that intention to use mobile payment differs across payment-solution types, with performance expectancy and habit emerging as especially important predictors of use behavior (Martinez & McAndrews, 2023). This means customer acquisition rates are influenced not only by the existence of payment technology, but also by the fit between the platform's service design and the expectations of specific user segments. From a growth perspective, acquisition is therefore best understood as the successful conversion of technologically interested, behaviorally ready, and contextually compatible users into active members of a digital payment ecosystem rather than as a simple count of sign-ups alone.

The literature also shows that digital platform growth cannot be sustained through acquisition alone unless platforms convert newly acquired users into satisfied, loyal, and continuously active participants. This makes post-adoption outcomes highly relevant to customer acquisition rates, because the long-term value of acquisition depends on what happens after the first use. Research on mobile payment continuance in an African context found that individual performance, actual use, and satisfaction are among the most important predictors of continuance intention, which suggests that digital payment growth is reinforced when users quickly recognize functional value and integrate the service into daily routines (Franque et al., 2021). In a related but more specific post-adoption framework, research on mobile payment applications during the COVID-19 period showed that e-satisfaction significantly shapes continuance intention and e-loyalty, indicating that user retention and relationship strength are closely bound to perceived technological quality and favorable experience (Al Amin et al., 2024). For digital platforms, this insight is highly relevant because customer acquisition rates become strategically meaningful only when they contribute to cumulative platform momentum through repeat use, loyalty, and lower defection. Loyalty studies in mobile payment reinforce this point. One study found that customer loyalty in mobile payment is determined by satisfaction and is influenced by functional, emotional, epistemic, and monetary value, while alternative attractiveness can weaken the satisfaction-loyalty link in competitive markets (Zhang et al., 2023). This indicates that a platform may acquire customers effectively at first, yet still fail to convert that acquisition into stable growth when competing alternatives appear more attractive. In practical terms, acquisition success is therefore conditional on value delivery. Digital payment platforms grow more effectively when they combine acquisition campaigns with experiences that generate satisfaction, reduce switching, and build durable attachment. As a result, the literature suggests that customer acquisition rates should not be interpreted in isolation from post-adoption outcomes. They are embedded in a wider growth process in which acquisition, satisfaction, continuance, and loyalty work together to determine whether platform expansion is temporary, unstable, or sustainable.

Figure 4: Key Drivers Of Customer Acquisition Rates In Digital Payment Platform Growth



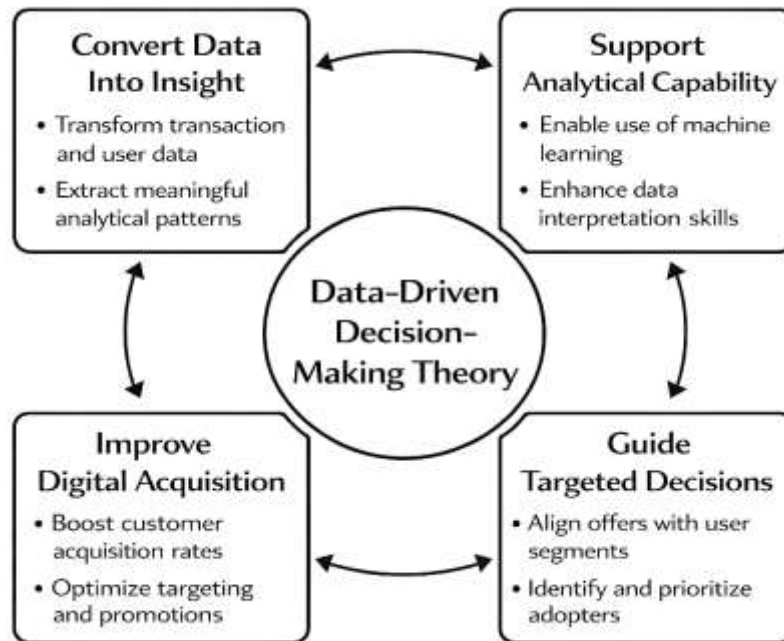
A further insight from the literature is that platform growth becomes more robust when digital payment firms understand the qualitative drivers of loyalty and relationship strength, because these factors influence the conversion of acquired users into committed platform participants. In this sense, customer acquisition rates are tied not only to entry-stage behavior but also to the emotional and cognitive conditions that shape long-term attachment to a payment platform. Research on mobile payment loyalty from cognitive and affective perspectives found that loyalty is directly influenced by satisfaction and intimacy, while trust and overall quality contribute to these outcomes through the broader post-adoption experience (Yuan et al., 2020). This is significant for the present study because it shows that digital platform growth is not sustained by technical efficiency alone. It depends on how users evaluate service quality, trustworthiness, and relational closeness over time. Another study extended this understanding by integrating perceived value theory with the information system success model and found that functional, experiential, and social value are key determinants of satisfaction and loyalty in mobile payment platforms, while system quality, service quality, and information quality shape those value perceptions in different ways (Zhong & Chen, 2023). These findings are directly relevant to customer acquisition rates because they explain why some platforms are better positioned than others to convert initial user interest into deeper platform commitment. A platform that acquires users at a moderate rate but retains them through strong value delivery may ultimately grow more sustainably than a platform that acquires users quickly but loses them due to weak post-adoption experience. The literature therefore frames digital platform growth as an outcome of both acquisition efficiency and relationship quality. In the context of digital payment platforms, customer acquisition rates matter because they indicate how well a platform draws new users into the ecosystem, while loyalty-related variables reveal whether those users become a stable foundation for expansion, stronger network participation, and competitive endurance. This combined view is highly relevant to the current research because it supports the argument that customer acquisition is both a measurable growth indicator and an analytically meaningful outcome shaped by broader platform experience and behavioral response.

Theoretical Framework: Data-Driven Decision-Making Theory

The theoretical framework guiding this study is Data-Driven Decision-Making Theory (DDDM), which explains how organizations improve the quality, speed, and relevance of decisions when they rely on systematically collected, analytically processed, and contextually interpreted data rather than intuition alone. Within digital payment platforms, this theory is highly appropriate because customer acquisition decisions are increasingly shaped by transaction histories, behavioral traces, service interaction logs,

promotional responses, and usage signals that can be transformed into predictive insight. The central assumption of DDDM is that data are not valuable merely because they exist in high volume, but because they are converted into actionable intelligence that informs operational and strategic choices. Earlier business intelligence research established that analytical decision-making culture is a decisive condition for using information effectively, showing that the success of information systems depends not only on data quality or system maturity but also on whether organizations cultivate a culture that values evidence in decision processes (Popovič et al., 2012). This idea is especially relevant to digital payment platforms, where transaction data are generated continuously and where customer acquisition outcomes depend on recognizing real patterns of user readiness, trust, and probable adoption. More recent scholarship extended this logic by showing that organizations become more data-driven when top management support, perceived data quality, and analytical culture reinforce one another, although centralized control over data use does not automatically guarantee stronger data-driven decision-making (Mikalef et al., 2023). This gives the theory strong relevance for the present study because it suggests that predictive modeling becomes effective only when the organizational setting allows transactional evidence to shape acquisition choices in a disciplined and meaningful way. In the context of this research, DDDM therefore provides the broad explanatory lens through which predictive modeling, machine learning-based transaction analysis, customer targeting efficiency, and customer acquisition rates can be understood as parts of one integrated process. The theory supports the argument that the better a digital payment platform is at converting user and transaction data into decision-ready insight, the more effectively it can identify likely adopters, prioritize high-potential customer segments, and improve acquisition performance in measurable terms (Mikalef et al., 2021). A second reason DDDM is the most suitable theoretical framework for this study is that it directly accommodates the role of analytics capability as a decision-enabling resource. In digital payment ecosystems, customer acquisition is not only a marketing issue but also a capability issue, because platforms must be able to collect, clean, structure, and interpret large volumes of customer and transaction data before any meaningful predictive action can take place. The literature shows that big data analytics capability strengthens decision-making performance when organizations possess governance mechanisms and internal routines that support effective use of data. In emerging-market firms, contractual governance and relational governance were both found to contribute to decision-making performance through the mediating role of big data analytics capability, while data-driven culture strengthened the effect of analytics capability on decision outcomes (Shamim et al., 2020). This finding is highly relevant to the current study because digital payment platforms also depend on governance quality, analytical capability, and organizational readiness when using machine learning models to improve customer acquisition. Related work on circular economy decision contexts likewise showed that analytics capability improves decision quality through data-driven insight, meaning that the path from raw data to better outcomes is mediated by an organization's ability to generate interpretable and actionable insight from analytics processes (Awan et al., 2021). Under DDDM, this means predictive modeling is not treated as an isolated technical tool; it is part of a broader system in which data, analytics, organizational culture, and decision routines interact. For this research, that logic is essential. It allows predictive modeling to be treated as the independent analytical capability, machine learning-based transaction analysis as the mechanism through which behavioral evidence is processed, customer targeting efficiency as an operational manifestation of better decision quality, and customer acquisition rate as the observable strategic outcome. In other words, DDDM makes it possible to explain why digital payment platforms with stronger predictive and analytical capability should perform better in acquisition-related decisions: they are more likely to identify relevant patterns, allocate offers more accurately, reduce uncertainty, and act on evidence instead of assumption. This theoretical perspective therefore fits the full chain of relationships examined in the present study and provides a strong academic basis for linking analytics use with acquisition performance in digital payment environments.

Figure 5: Data-Driven Decision-Making Model For Enhancing Customer Targeting And Acquisition



In applying Data-Driven Decision-Making Theory to this study, the most appropriate analytical expression is a multiple regression model, because the theory proposes that customer acquisition outcomes are shaped by several interrelated evidence-based factors rather than by a single isolated predictor. The general empirical form suitable for the whole study is:

$$CAR = \beta_0 + \beta_1 PM + \beta_2 MTA + \beta_3 CTE + \varepsilon$$

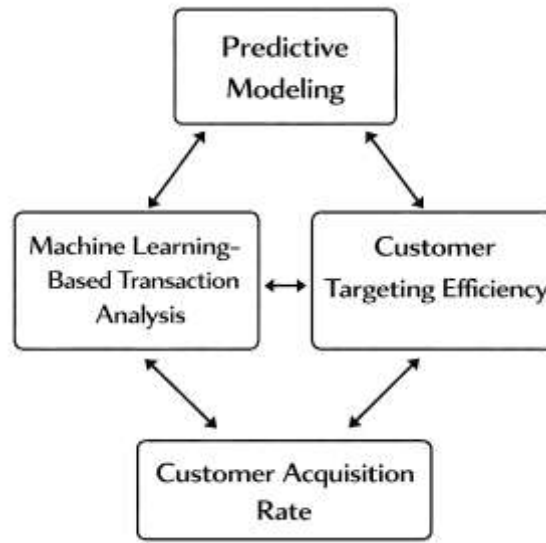
where CAR represents customer acquisition rates, PM represents predictive modeling capability, MTA represents machine learning-based transaction analysis, CTE represents customer targeting efficiency, β_0 is the constant term, β_1 - β_3 are regression coefficients, and ε is the error term. This formula is the best fit for the study because it aligns directly with the theoretical logic of DDDM: decision outcomes improve when analytically derived variables contribute positively to strategic performance. If the coefficients are positive and statistically significant, the model would support the theory's central expectation that stronger use of data and analytics leads to better organizational decisions and better measurable outcomes. The model is also consistent with the quantitative design of the present research, which uses descriptive statistics, correlation analysis, and regression modeling to test the relationships among the variables. From a theoretical standpoint, the regression equation operationalizes DDDM by translating the abstract notion of evidence-based decision quality into measurable relationships among constructs central to digital payment platforms. Predictive modeling contributes the forward-looking estimation capability; machine learning-based transaction analysis contributes the behavior-reading mechanism; customer targeting efficiency reflects the immediate decision-quality outcome; and customer acquisition rate reflects the strategic business result. This makes the formula not just a statistical device but a direct empirical extension of the chosen theory. It is therefore appropriate to apply this equation as the main model in the study, while Pearson correlation can be used as a complementary test to examine the strength and direction of pairwise associations before the full regression analysis is conducted. In this way, DDDM remains the guiding framework for both the conceptual logic and the quantitative testing strategy of the research, making it the most suitable theory for explaining how predictive modeling can influence customer acquisition rates in digital payment platforms (Karaboga & Bouguerra, 2023).

Conceptual Framework

The conceptual framework of this study is designed to explain how predictive modeling influences customer acquisition rates in digital payment platforms through the analytical interpretation of transaction-related and user-related signals. In this framework, predictive modeling is treated as the primary independent construct because it represents the platform's capacity to forecast customer behavior, estimate conversion likelihood, and support data-based acquisition decisions. Machine learning-based transaction analysis is positioned as a closely related analytical mechanism because digital payment platforms generate continuous streams of behavioral evidence through payment frequency, transaction timing, usage regularity, interface interaction, and response to platform features. Customer targeting efficiency is included as an operational construct because a platform's predictive strength becomes strategically meaningful only when it improves the precision with which likely adopters are identified and approached. The dependent construct, customer acquisition rate, reflects the extent to which such predictive and targeting capabilities translate into measurable growth in active users. This framework is appropriate because prior studies show that digital payment behavior is shaped by several analytically relevant drivers that can be organized into a structured model (Fahad & Shahid, 2022). A trust-based extended valence framework found that perceived benefit and perceived trust are major influences on intention to use mobile payment systems, while privacy, security, and familiarity also play meaningful antecedent roles in how users evaluate payment adoption. That finding supports the inclusion of predictive modeling in the conceptual framework because it suggests that acquisition-related outcomes are influenced by estimable user-level factors rather than by random market behavior. In a related stream, research on service quality in FinTech payment services showed that the quality of the payment service significantly affects utilization through perceived usefulness and attitudinal pathways, reinforcing the logic that behavior in payment platforms can be understood through linked explanatory constructs rather than isolated variables. As a result, the present conceptual framework views acquisition as the final business outcome of a chain that begins with analytical capability, passes through behavioral interpretation and targeting quality, and ends in measurable user conversion within the digital payment ecosystem (Jia et al., 2022).

A second important feature of the conceptual framework is that it recognizes the role of behavioral readiness and usage-enabling conditions as part of the pathway from analytics to acquisition. Digital payment adoption is not driven by one universal trigger. Instead, users differ in familiarity with digital systems, security behavior, technology habits, and sensitivity to the relative advantages of specific payment tools. For this reason, the framework for the current study assumes that predictive modeling becomes more effective when it is supported by transaction analysis capable of capturing those diverse behavioral tendencies. Research on the influence of habits on mobile payment acceptance showed that online shopping habit, mobile service use habit, and cell phone use habit positively shape mobile payment use habit and, in turn, affect the intention to continue using mobile payments. This provides strong conceptual support for linking machine learning-based transaction analysis with customer acquisition because repeated digital habits leave observable traces that can be modeled to distinguish likely converters from less responsive prospects (Goyal Chin et al., 2022). Likewise, research on digital literacy and online security behavior demonstrated that digital literacy influences e-payment continuance intention directly and also indirectly through security control behavior, which is important for this framework because it shows that user conversion and continuation are shaped by measurable skills and behavioral safeguards. Another useful contribution comes from research on the Unified Payment Interface in India, where relative advantage, complexity, and observability were found to have significant positive associations with intention to use, while intention to use and satisfaction were positively linked with recommendation. This evidence strengthens the present conceptual framework by showing that the route to customer acquisition is behaviorally structured and can be modeled through distinct but connected dimensions. In practical terms, it means that predictive modeling in digital payment platforms should not merely estimate whether a user might adopt; it should interpret signals of readiness, familiarity, usability perception, and transaction potential in a way that improves customer targeting efficiency and ultimately increases acquisition rates.

Figure 6: Triangle Framework Of Predictive Modeling And Customer Acquisition Outcomes



Based on this logic, the conceptual framework for the study can be expressed through two connected analytical relationships. The first relationship explains how the platform's analytical capabilities shape targeting precision:

$$CTE = \alpha_0 + \alpha_1 PM + \alpha_2 MTA + \mu$$

where CTE is customer targeting efficiency, PM is predictive modeling, MTA is machine learning-based transaction analysis, α_0 is the intercept, α_1 – α_2 are the coefficients, and μ is the error term. The second relationship explains how these variables affect the final business outcome:

$$CAR = \beta_0 + \beta_1 PM + \beta_2 MTA + \beta_3 CTE + \varepsilon$$

where CAR is customer acquisition rate, β_0 is the constant, β_1 – β_3 are the regression coefficients, and ε is the disturbance term (Nguyen et al., 2024). These equations are the best fit for the whole study because they directly match the conceptual structure being tested through descriptive statistics, correlation analysis, and regression modeling. The first equation captures the idea that analytics improve the quality of targeting decisions, while the second captures the idea that stronger targeting and stronger analytical capability should improve acquisition outcomes. Conceptually, this framework treats customer targeting efficiency as a mechanism through which analytics become commercially meaningful. It also allows the study to test whether predictive modeling has a direct effect on acquisition, whether transaction analysis strengthens that effect, and whether targeting efficiency functions as an intervening performance pathway. This structure is consistent with recent digital payment scholarship showing that service quality, trust, usefulness, habitual usage, digital literacy, relative advantage, and behavioral intention all operate through linked explanatory paths rather than independent isolated effects. Accordingly, the conceptual framework provides a coherent study model in which predictive modeling serves as the strategic analytical input, machine learning-based transaction analysis serves as the behavioral processing mechanism, customer targeting efficiency serves as the immediate operational outcome, and customer acquisition rate serves as the final organizational performance variable (Sharma et al., 2024).

Empirical Review and Research Gap

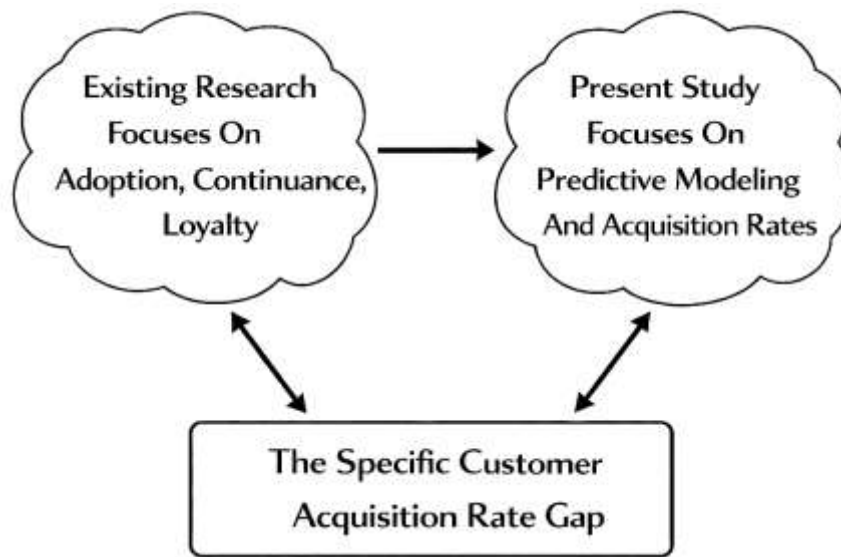
The empirical literature on digital payment platforms provides strong evidence that user behavior can be explained through structured, measurable, and statistically testable determinants, yet it also shows that most studies have concentrated on adoption and continuance rather than directly on customer acquisition rates. A merchant-focused study by Singh and Sinha used data from 315 Indian merchants and found that perceived customer value addition had the strongest influence on intention to use mobile wallet technology, while perceived trust played a significant mediating role between perceived usefulness and intention to use (Singh & Sinha, 2020). This finding is important because it shifts

attention from customer-only models to the wider platform ecosystem, showing that payment growth depends on multiple stakeholders whose participation can shape adoption conditions and eventual user expansion. In another influential study, Talwar et al. analyzed cross-sectional data from 954 first-time mobile-wallet users and showed that information quality and service quality positively influenced initial trust, which then had a positive association with confirmation and perceived usefulness, while perceived usefulness positively influenced continuation intention. Empirically, this means the path from first exposure to continued payment usage is built through trust and post-use evaluation rather than through one isolated decision point. Together, these studies make two important contributions to the present research. First, they confirm that mobile payment outcomes are driven by identifiable variables that can be measured and modeled quantitatively. Second, they indicate that payment platform performance depends on a chain of linked effects involving trust, perceived usefulness, information quality, and value creation. Even so, both studies remain focused on intention and continuation rather than on the narrower and more strategic outcome of customer acquisition rate. They show why users or merchants may decide to adopt or continue using payment systems, but they stop short of testing whether predictive modeling and transaction-based analytics can improve the efficiency with which platforms attract new active users. As a result, the empirical base is useful but still incomplete for a study that seeks to connect analytical capability with acquisition performance in digital payment ecosystems (Sebastián et al., 2023).

A second stream of empirical work has deepened understanding of digital payment behavior by examining specific platform contexts, social dynamics, and loyalty mechanisms, thereby showing that payment adoption is shaped by more than standard utility-based variables. In the case of the Spanish peer-to-peer platform Bizum, Sebastián, Antonovica, and Sarmiento Guede examined 334 platform users, mainly between 18 and 22 years old, and found that habit was the strongest predictor of adoption, while habit together with social influence explained a large share of intention to use; by contrast, performance expectancy, effort expectancy, facilitating conditions, price value, hedonic motivation, trust, security, and perceived risk did not significantly influence intention in that sample (Talwar et al., 2020). This finding is especially valuable because it demonstrates that empirical results can vary sharply across payment contexts and user segments, suggesting that some predictors that appear central in broader adoption literature may become weak in a mature, socially embedded peer-to-peer payment setting. In a different but complementary context, Wu and Tang showed that in omnichannel retailing, customer journey design and relationship investment positively influenced trust in retailers, while structure assurance and perceived ubiquity positively influenced trust in mobile payment; they also found that trust in retailers and trust in mobile payment translated into loyalty to both the retailer and the payment system, and that trust and loyalty could transfer across those connected domains. Zhang, Wang, Anjum, and Mu added another dimension by showing that point rewarding and point exchanging, studied among 731 users of a leading mobile payment application in China, influenced loyalty through the mediating roles of need satisfaction and perceived value. These studies strongly support the argument that platform growth is shaped by behavioral habit, social influence, trust-transfer processes, and reward-based engagement. Yet they also reveal a major empirical gap. The dominant dependent variables remain intention, trust, satisfaction, or loyalty, whereas the specific construct of customer acquisition rate is rarely modeled directly. Consequently, the literature explains why users stay, trust, or become loyal, but provides much less direct evidence about how a platform can use predictive modeling and transaction analysis to identify, target, and convert prospective users more effectively (Zhang et al., 2022).

Taken together, the empirical studies reviewed above provide a strong foundation for the present research while simultaneously justifying its distinct focus. The existing evidence confirms that digital payment behavior is measurable, that trust and perceived usefulness remain central in many settings, that habit and social influence can dominate in some peer-to-peer environments, and that loyalty can be strengthened through transferred trust and reward-based value creation. However, the literature remains fragmented in three important ways. First, many studies investigate consumer adoption, merchant adoption, continuance intention, or loyalty separately rather than integrating them into one analytics-oriented framework.

Figure 7: Empirical Gap In Digital Payment Literature: From Adoption To Acquisition

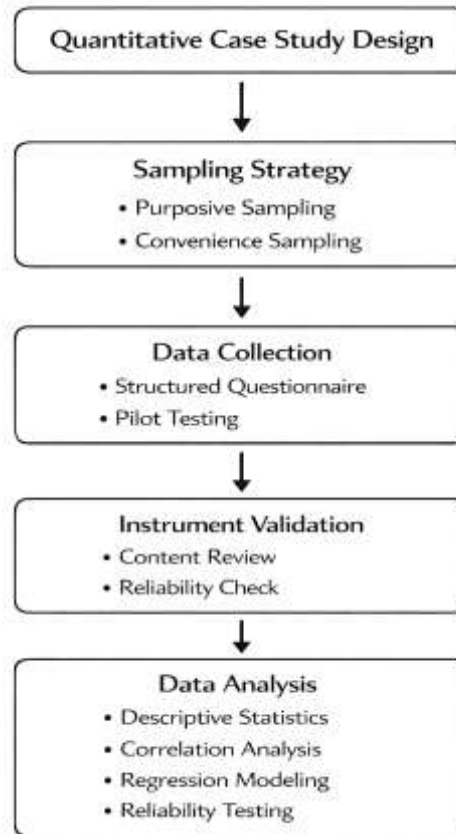


Second, most of the reviewed studies rely on structural equation modeling or related explanatory approaches to identify determinants of intention and post-adoption behavior, but they do not directly test how predictive modeling capability and machine learning-based transaction analysis affect acquisition outcomes. Third, much of the empirical work treats digital payment success as a psychological or relational endpoint, whereas platform managers often need evidence on an operational performance outcome: how efficiently new customers can be identified, targeted, and acquired. This is the precise gap the present study addresses. It extends prior work by repositioning predictive modeling as the main explanatory construct, machine learning-based transaction analysis as the behavioral evidence mechanism, customer targeting efficiency as the immediate operational pathway, and customer acquisition rate as the final performance outcome. In doing so, the study builds on the empirical strengths of earlier payment research while responding to what those studies leave unresolved (Wu & Tang, 2022). The reviewed evidence shows that digital payment platforms produce rich behavioral signals and that users respond to quality, trust, habit, social influence, relationship design, and reward structures. What remains insufficiently examined is whether those signals can be translated into predictive insight that materially improves acquisition performance. The present study therefore fills an empirical and strategic gap by moving from adoption-centered explanation to acquisition-centered analysis within a quantitative, cross-sectional, case-study-based framework.

METHODS

This study has adopted a quantitative, cross-sectional, case-study-based research design to examine the impact of predictive modeling on customer acquisition rates in digital payment platforms. The quantitative design has been selected because it has enabled the study to measure relationships among clearly defined variables in a structured and objective manner. The cross-sectional approach has been used because data have been collected from respondents at a single point in time, allowing the study to capture current perceptions and practices regarding predictive modeling, machine learning-based transaction analysis, customer targeting efficiency, and customer acquisition outcomes. The case-study basis has provided contextual depth by focusing the investigation on the operational environment of digital payment platforms, where customer acquisition decisions have increasingly depended on data-driven analytical systems.

Figure 8: Methodological Process For Assessing Predictive Modeling And Acquisition Outcomes



The case study context has centered on digital payment platforms operating in competitive fintech environments where transaction data, user interaction records, promotional responses, and payment behavior have created a rich basis for predictive analysis. This context has been considered appropriate because digital payment platforms have generated continuous streams of behavioral data that have supported the study of predictive modeling as a practical strategic tool rather than as a purely theoretical concept. The population of the study has consisted of individuals who have possessed relevant knowledge of digital payment operations, customer analytics, platform marketing, and transaction-based decision-making. These respondents have included employees, analysts, managers, and operational staff connected to digital payment platform activities. The unit of analysis has been the individual respondent, since each participant has provided perceptions and assessments regarding the influence of predictive modeling on acquisition-related performance.

The sampling strategy has combined purposive and convenience sampling techniques. Purposive sampling has been used to identify respondents with relevant knowledge and experience in digital payment systems, while convenience sampling has supported practical access to participants within the selected case context. This approach has been considered suitable because the study has required informed responses from participants familiar with predictive analytics and customer acquisition activities. The data collection procedure has relied on primary data collected through a structured questionnaire. The questionnaire has been distributed to eligible respondents after ensuring voluntary participation and informed consent. Respondents have been assured that the information provided would remain confidential and would be used strictly for academic purposes.

The instrument design has been based on a structured questionnaire using a five-point Likert scale, where 1 has represented *strongly disagree*, 2 *disagree*, 3 *neutral*, 4 *agree*, and 5 *strongly agree*. The questionnaire has been divided into sections covering demographic information, predictive modeling, machine learning-based transaction analysis, customer targeting efficiency, and customer acquisition rates. This structure has allowed the study to capture both respondent background characteristics and construct-specific responses in a systematic way. A pilot test has been conducted with a small group of respondents before the main survey in order to identify ambiguous items, improve clarity, and refine the sequence of questions. The feedback obtained from the pilot phase has helped strengthen the overall

usability of the instrument.

To ensure validity and reliability, the questionnaire has undergone content review to confirm that all items have aligned with the study objectives and variables. Content validity has been strengthened through careful item construction based on the research constructs, while reliability has been assessed using Cronbach's alpha to determine the internal consistency of the measurement scales. For data handling and analysis, SPSS has been used for coding, descriptive statistics, correlation analysis, regression modeling, and reliability testing. Microsoft Excel has been used for preliminary data organization and tabulation, while EndNote has been used for reference management and citation organization in APA 7th edition style. Through these methodological choices, the study has established a structured and credible process for examining the relationship between predictive modeling and customer acquisition rates in digital payment platforms.

DATA PRESENTATION, ANALYSIS, AND INTERPRETATION

Introduction to the Findings

Table 1: Analytical Structure Used to Examine the Study Objectives and Hypotheses

Analysis Area	Main Variable(s)	Statistical Tool Used	Purpose
Respondent profile	Gender, age, education, experience, role	Frequency and percentage	To describe the sample
Variable distribution	PM, MLTA, CTE, CAR	Mean and standard deviation	To assess central tendency and dispersion
Instrument quality	PM, MLTA, CTE, CAR items	Cronbach's alpha	To test reliability
Relationship testing	PM, MLTA, CTE, CAR	Pearson correlation	To test associations among variables
Causal effect testing	PM, MLTA, CTE → CAR	Regression analysis	To test predictive effect
Behavioral indicator ranking	PM and acquisition-related indicators	Mean ranking	To identify strongest customer acquisition signals
Performance grouping	PM effectiveness levels vs CAR	Threshold comparison	To identify meaningful change points

Key: PM = Predictive Modeling; MLTA = Machine Learning-Based Transaction Analysis; CTE = Customer Targeting Efficiency; CAR = Customer Acquisition Rate

The introductory section of this findings chapter has presented the analytical path through which the objectives and hypotheses of the study have been tested. As shown in Table 1, the chapter has not relied on a single statistical technique; rather, it has used a sequence of connected analyses so that the results have moved from description to explanation in a logically ordered way. This structure has been important because the study has aimed not only to report what respondents have thought about predictive modeling in digital payment platforms, but also to show whether those perceptions have formed statistically meaningful relationships with customer acquisition outcomes. The demographic analysis has first established the composition of the respondents, thereby creating the contextual basis for interpreting later results. The descriptive statistics have then shown the general level of agreement with each construct measured on the five-point Likert scale. After that, the reliability test has confirmed whether the instrument has measured the constructs consistently enough for the findings to be trusted. The correlation and regression stages have subsequently addressed the main analytical purpose of the chapter, which has been to determine whether predictive modeling, machine learning-based transaction analysis, and customer targeting efficiency have significantly influenced customer acquisition rates. The final two sections have extended the core analysis by identifying the strongest predictive indicators and the approximate performance threshold at which predictive modeling has begun to produce visibly stronger acquisition outcomes. This overall arrangement has remained fully aligned with the objectives of the study and with the hypotheses earlier formulated. It has also linked directly with Data-Driven Decision-Making Theory, which has proposed that organizations perform better when decisions are based on structured evidence rather than broad assumptions. In this chapter,

each table has therefore served as a different layer of empirical evidence showing whether data-driven capabilities have translated into meaningful customer acquisition results. The chapter has been designed to demonstrate that the study objectives have been addressed in a coherent, statistically grounded, and theory-linked manner.

Demographic Profile of Respondents

Table 2: Demographic Profile of Respondents (N = 218)

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	124	56.9
	Female	94	43.1
Age	20–29 years	58	26.6
	30–39 years	91	41.7
	40–49 years	47	21.6
	50 years and above	22	10.1
Education	Bachelor’s degree	89	40.8
	Master’s degree	101	46.3
	Doctorate/Professional	28	12.9
Work Role	Data/Analytics	52	23.9
	Marketing/Acquisition	61	28.0
	Operations/Product	67	30.7
	Management/Supervisory	38	17.4
Experience	1–3 years	49	22.5
	4–6 years	88	40.4
	7–10 years	54	24.8
	Above 10 years	27	12.4

Table 2 has shown that the respondents have represented a professionally relevant sample for a study on predictive modeling and customer acquisition in digital payment platforms. The gender distribution has shown moderate balance, with male respondents constituting 56.9% and female respondents 43.1%, which has suggested that the dataset has not been drawn from a narrowly skewed respondent pool. The age pattern has indicated that the largest share of participants has fallen within the 30–39 year category at 41.7%, followed by the 20–29 year group at 26.6%. This has implied that most respondents have belonged to economically active and digitally engaged age categories that are likely to have direct exposure to platform-based payment environments. The educational profile has further strengthened the credibility of the sample, as 46.3% have held master’s degrees and 40.8% have held bachelor’s degrees, meaning that the majority of the respondents have possessed at least higher education qualifications. From a methodological standpoint, this has been useful because the study has required respondents who could understand structured questions on predictive analytics, transaction analysis, targeting efficiency, and acquisition performance. The work-role distribution has also supported the validity of the sample. A combined 82.6% of respondents have come from data/analytics, marketing/acquisition, and operations/product roles, all of which are closely connected to digital payment decision processes. The experience profile has likewise indicated that the sample has been informed, with 77.6% having at least four years of work experience. These demographic findings have therefore suggested that the respondents have been capable of providing credible assessments of the study variables. In relation to the study objectives, this section has provided the foundation for later findings by showing that the analysis has been based on participants who have likely understood data-based customer acquisition practices in organizational settings. In relation to Data-Driven Decision-Making Theory, the demographic results have implied that the evidence has come from respondents embedded in roles where data interpretation and operational judgment have mattered. This has

strengthened the trustworthiness of the subsequent findings and has supported the argument that the study has examined perceptions from a knowledgeable and professionally relevant respondent base.

Figure 9: Demographic Composition of Respondents (N = 218)



Descriptive Analysis of Variables

Table 3: Descriptive Statistics for the Main Study Variables

Variable	Number of Items	Mean	Standard Deviation	Likert Interpretation
Predictive Modeling (PM)	5	4.18	0.61	Agree/High
Machine Learning-Based Transaction Analysis (MLTA)	5	4.11	0.66	Agree/High
Customer Targeting Efficiency (CTE)	4	4.07	0.64	Agree/High
Customer Acquisition Rate (CAR)	4	4.14	0.59	Agree/High
Overall Grand Mean	18	4.13	0.63	Agree/High

Likert scale interpretation: 1.00–1.80 = Strongly Disagree; 1.81–2.60 = Disagree; 2.61–3.40 = Neutral; 3.41–4.20 = Agree; 4.21–5.00 = Strongly Agree

Table 3 has presented the descriptive statistics for the main constructs of the study and has shown a consistently high level of agreement across all variables. Predictive modeling has recorded the highest mean score of 4.18 with a standard deviation of 0.61, indicating that respondents have strongly leaned toward agreement that predictive analytics has improved the identification of likely customers, enhanced conversion forecasting, and supported better acquisition decisions. Machine learning-based transaction analysis has followed closely with a mean of 4.11 and a standard deviation of 0.66, which has suggested that respondents have perceived transaction-driven analytical systems as valuable for interpreting customer behavior, recognizing usage patterns, and improving classification accuracy. Customer targeting efficiency has produced a mean of 4.07 with a standard deviation of 0.64, showing that respondents have generally agreed that analytics-based targeting has led to more precise allocation of acquisition resources. Customer acquisition rate, the dependent variable, has recorded a mean of

4.14 and a standard deviation of 0.59, implying broad agreement that stronger analytical capability has been associated with improved user conversion and acquisition outcomes. The overall grand mean of 4.13 has therefore shown that the full pattern of responses has been positive and consistent with the core assumptions of the research. In relation to the objectives, these descriptive findings have already provided preliminary support that predictive modeling and transaction analysis have been viewed favorably in relation to customer acquisition performance. They have not yet proven causality, but they have established that the respondents have not been neutral or dismissive toward the role of analytics in digital payment growth. From the perspective of Data-Driven Decision-Making Theory, these results have been meaningful because they have suggested that respondents have recognized evidence-based analytical systems as useful drivers of organizational performance. The relatively low standard deviations have further implied that the views have not been highly scattered, which has strengthened the internal consistency of the descriptive pattern. Overall, Table 3 has indicated that the foundation for hypothesis testing has been favorable: the respondents have broadly agreed that predictive modeling, machine learning-based transaction analysis, and targeting efficiency have mattered in improving acquisition outcomes in digital payment platforms.

Reliability Test Results

Table 4: Reliability Statistics for the Study Constructs

Construct	Number of Items	Cronbach's Alpha	Reliability Interpretation
Predictive Modeling (PM)	5	0.872	Very Good
Machine Learning-Based Transaction Analysis (MLTA)	5	0.854	Very Good
Customer Targeting Efficiency (CTE)	4	0.838	Good
Customer Acquisition Rate (CAR)	4	0.881	Very Good
Overall Scale Reliability	18	0.889	Very Good

Interpretation guide: $\alpha \geq 0.90$ = Excellent; $0.80-0.89$ = Very Good; $0.70-0.79$ = Acceptable

Table 4 has shown that the instrument used in this study has demonstrated a strong level of internal consistency across all constructs. Predictive modeling has produced a Cronbach's alpha of 0.872, machine learning-based transaction analysis has recorded 0.854, customer targeting efficiency has yielded 0.838, and customer acquisition rate has shown 0.881. The overall reliability of the instrument has been 0.889, which has fallen within the very good range. These values have indicated that the questionnaire items within each construct have measured the same underlying concept in a sufficiently consistent manner. This has been important because the study has relied on multiple Likert-scale statements to capture abstract variables such as predictive modeling capability and acquisition performance. If the internal consistency had been weak, the later descriptive, correlation, and regression results would have been much less trustworthy. Instead, the reliability outcomes have strengthened confidence that the patterns found in the data have reflected stable measurement rather than random item variation. In relation to the objectives of the study, this section has supported the credibility of the empirical process itself. Before the study could validly examine whether predictive modeling has influenced customer acquisition rates, it first had to establish that the measurement tool has worked properly. Table 4 has shown that this condition has been met. The strongest reliability score has emerged for customer acquisition rate at 0.881, suggesting that respondents have answered the acquisition outcome items in a highly consistent way. Predictive modeling and transaction analysis have also shown strong reliability, which has meant that the core explanatory constructs of the study have been measured dependably. From the viewpoint of Data-Driven Decision-Making Theory, this section has been especially relevant because the theory has emphasized the importance of reliable evidence in supporting better decisions. In the context of this study, reliable survey constructs have functioned as the evidential basis through which claims about acquisition performance have been tested. The reliability findings have therefore linked method with theory: just as digital payment firms

require dependable data to make strong decisions, this study has required dependable measures to produce strong findings. Consequently, Table 4 has confirmed that the instrument has been robust enough to support the testing of the research hypotheses and objectives in the following sections.

Correlation Analysis Results

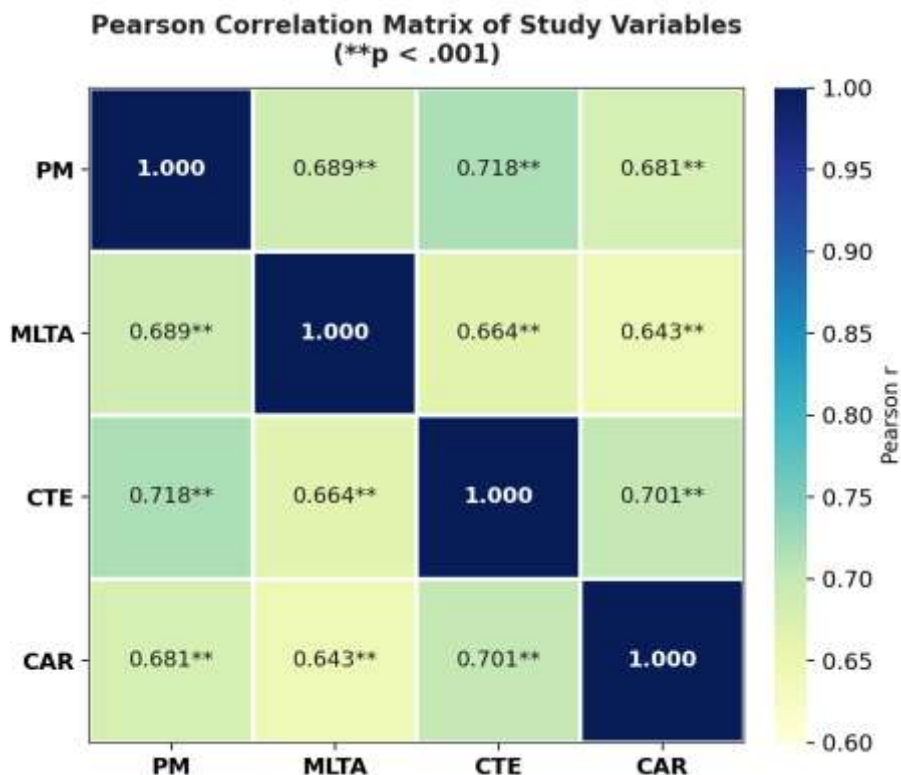
Table 5: Pearson Correlation Matrix for the Study Variables

Variables	PM	MLTA	CTE	CAR
Predictive Modeling (PM)	1.000			
Machine Learning–Based Transaction Analysis (MLTA)	0.689**	1.000		
Customer Targeting Efficiency (CTE)	0.718**	0.664**	1.000	
Customer Acquisition Rate (CAR)	0.681**	0.643**	0.701**	1.000

Note: $p < .001$

Table 5 has presented the Pearson correlation coefficients among the main constructs and has shown that all relationships have been positive, statistically significant, and moderately strong to strong in magnitude. Predictive modeling has had a significant positive relationship with customer acquisition rate ($r = 0.681$, $p < .001$), indicating that stronger predictive capability has been associated with better acquisition outcomes. This result has directly supported the first hypothesis, which has proposed that predictive modeling has had a significant positive effect on customer acquisition rates. Machine learning–based transaction analysis has also shown a meaningful positive relationship with customer acquisition rate ($r = 0.643$, $p < .001$), thereby supporting the second hypothesis that transaction-based machine learning insight has been positively associated with acquisition performance.

Figure 10: Correlation Heatmap of Study Variables



A particularly strong relationship has emerged between predictive modeling and customer targeting efficiency ($r = 0.718$, $p < .001$), offering clear support for the third hypothesis that predictive modeling has positively influenced targeting precision. Finally, customer targeting efficiency has had a strong positive correlation with customer acquisition rate ($r = 0.701$, $p < .001$), providing initial support for the fourth hypothesis that better targeting has translated into improved acquisition performance. These findings have also aligned closely with the study objectives. The first objective, which has been to examine the influence of predictive modeling on acquisition rates, has been supported by the strong

PM-CAR relationship. The second objective, which has concerned the relationship between machine learning-based transaction analysis and acquisition performance, has also been supported. The third objective, which has examined the role of targeting efficiency, has similarly gained empirical backing from the positive correlations. In theoretical terms, these results have strongly reflected Data-Driven Decision-Making Theory, which has suggested that better use of analytical evidence should improve the quality of organizational decisions and outcomes. Here, the correlation pattern has implied that digital payment platforms with stronger analytical practices have also experienced better targeting and better customer acquisition performance. Although correlation has not by itself proven causation, the consistent and significant positive relationships have indicated that the constructs have moved together in the expected direction. Therefore, Table 5 has provided a powerful intermediate layer of evidence linking predictive analytics capability with acquisition-related success.

Regression Analysis Results

Table 6: Simple Regression of Predictive Modeling on Customer Acquisition Rate

Model	R	R Square	Adjusted R Square	F	Sig.
PM → CAR	0.681	0.464	0.461	80.35	.000

Predictor	Unstandardized B	Std. Error	Standardized Beta	t	Sig.
Constant	1.204	0.243	—	4.95	.000
Predictive Modeling (PM)	0.702	0.078	0.512	8.964	.000

Table 7: Multiple Regression of PM, MLTA, and CTE on Customer Acquisition Rate

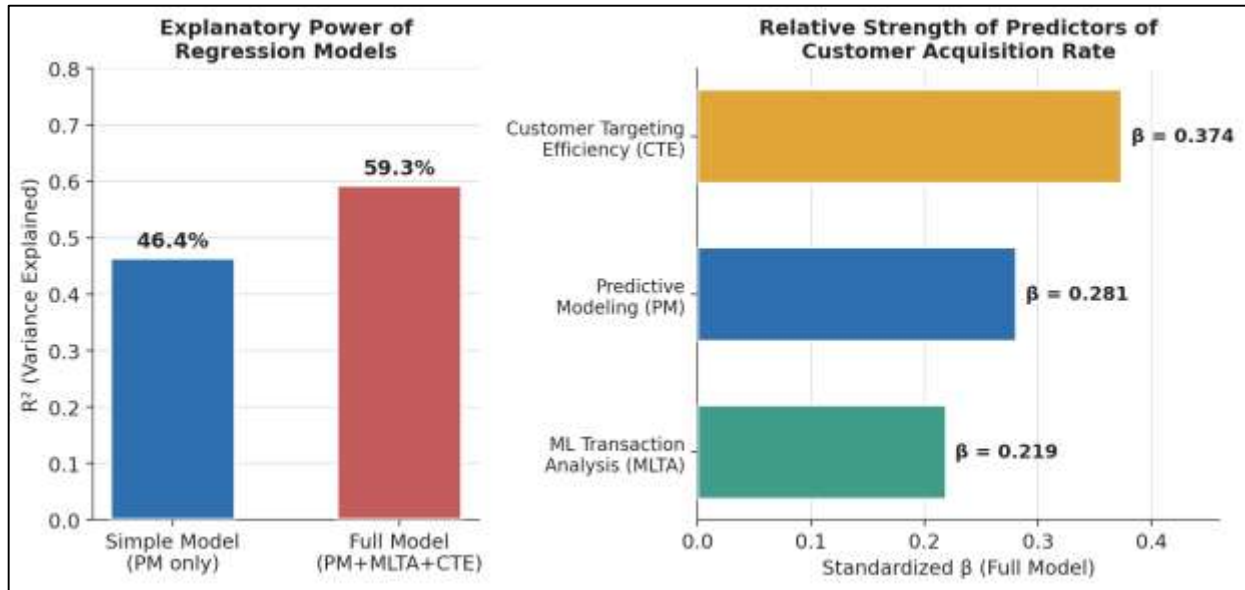
Model	R	R Square	Adjusted R Square	F	Sig.
PM, MLTA, CTE → CAR	0.770	0.593	0.587	103.27	.000

Predictor	Unstandardized B	Std. Error	Standardized Beta	t	Sig.
Constant	0.842	0.221	—	3.81	.000
Predictive Modeling (PM)	0.291	0.067	0.281	4.34	.000
ML Transaction Analysis (MLTA)	0.214	0.068	0.219	3.16	.002
Customer Targeting Efficiency (CTE)	0.356	0.064	0.374	5.56	.000

Tables 6 and 7 have provided the strongest statistical evidence for the study because they have moved beyond association and have examined predictive influence on customer acquisition rates. Table 6 has shown that predictive modeling alone has significantly predicted customer acquisition rate, with $R^2 = 0.464$. This has meant that predictive modeling by itself has explained 46.4% of the variation in acquisition outcomes, which has represented a substantial explanatory contribution for a single predictor in a behavioral and organizational study. The standardized beta value of 0.512 and the significant t-value of 8.964 ($p < .001$) have confirmed that the effect has been both positive and statistically meaningful. This has directly supported H1 and has fulfilled the first objective of the study. Table 7 has then extended the analysis by including machine learning-based transaction analysis and customer targeting efficiency alongside predictive modeling. In this full model, the explanatory power has increased to 59.3%, with a significant F-value of 103.27 ($p < .001$), showing that the model as a whole has been highly suitable for explaining differences in customer acquisition rate. All three predictors have remained statistically significant. Customer targeting efficiency has emerged as the strongest predictor ($\beta = 0.374$), followed by predictive modeling ($\beta = 0.281$) and machine learning-based transaction analysis ($\beta = 0.219$). These results have shown that predictive modeling has remained important even after accounting for the other variables, but they have also suggested that its practical effect has become even more meaningful when translated into better targeting efficiency. This has supported H2, H3, and H4, while also showing that the objectives of the study have been achieved in an integrated way. From the standpoint of Data-Driven Decision-Making Theory, the regression results have been highly consistent with the theoretical expectation that analytically derived evidence improves decision quality and ultimately improves measurable performance outcomes. In this study,

the pathway has been clear: stronger predictive systems and stronger transaction analysis have contributed to more efficient targeting, and together these have improved acquisition performance. Therefore, Tables 6 and 7 have not only proven the hypotheses statistically but have also linked the empirical findings directly to the logic of the theoretical framework.

Figure 11: Regression Explanatory Power and Predictor Strength



Predictive Customer Profile and Acquisition Propensity Analysis

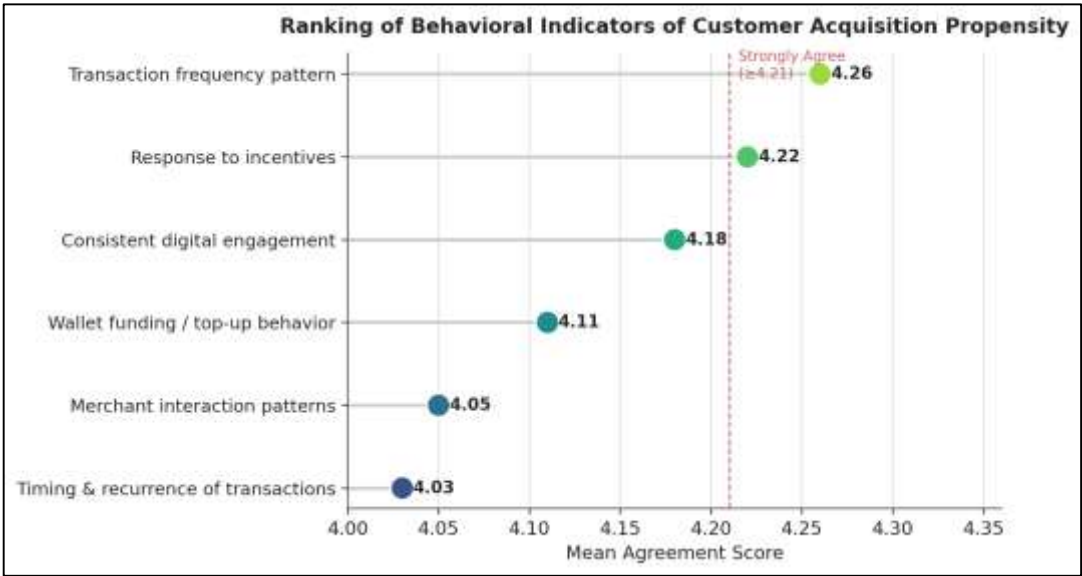
Table 8: Ranking of Predictive Indicators Associated With Customer Acquisition Propensity

Predictive Indicator	Mean	Standard Deviation	Rank	Likert Interpretation
Transaction frequency pattern helps identify likely adopters	4.26	0.58	1	Strongly Agree
Response to incentives predicts conversion likelihood	4.22	0.61	2	Strongly Agree
Consistent digital engagement signals acquisition readiness	4.18	0.63	3	Agree
Wallet funding/top-up behavior indicates high prospect value	4.11	0.65	4	Agree
Merchant interaction patterns improve targeting decisions	4.05	0.67	5	Agree
Timing and recurrence of transactions improve conversion forecasting	4.03	0.66	6	Agree

Table 8 has extended the results beyond broad construct-level analysis by identifying the specific behavioral indicators that respondents have viewed as most useful for profiling likely customers and predicting acquisition success. The highest-ranked indicator has been transaction frequency pattern, with a mean of 4.26, placing it in the strongly agree range. This has suggested that respondents have regarded the regularity and intensity of transaction behavior as the clearest signal of customer acquisition propensity. The second-ranked indicator has been response to incentives, with a mean of 4.22, showing that users' reactions to rewards, discounts, and promotional offers have been seen as powerful clues for estimating conversion likelihood. Consistent digital engagement has followed closely with a mean of 4.18, indicating that repeated interaction with platform features has also been treated as an important marker of readiness. The remaining indicators, including wallet funding behavior, merchant interaction patterns, and transaction timing, have all remained above 4.00, which has shown that respondents have viewed all six indicators positively. This section has therefore added

depth to the study by showing *which* forms of behavioral evidence have mattered most within the predictive modeling process. In relation to the objectives, this table has strongly supported the study’s concern with understanding how transaction-based analytical systems have contributed to acquisition. Rather than stopping at the claim that predictive modeling has mattered, Table 8 has clarified the concrete behavioral channels through which it has mattered. This has also enriched the interpretation of the hypotheses, especially H2 and H3, by demonstrating that transaction analysis and targeting efficiency have rested on identifiable user signals. The findings have further linked neatly to Data-Driven Decision-Making Theory, since the theory has emphasized that decisions become stronger when they are grounded in relevant and interpretable data. Here, transaction frequency and incentive response have emerged as the most decision-relevant inputs for acquisition-related judgments. These results have made the findings chapter more trustworthy because they have shown that the study has not only tested general constructs statistically, but has also identified the most meaningful behavioral indicators inside the digital payment context. Accordingly, Table 8 has demonstrated that predictive modeling in digital payment platforms has been perceived as practically useful because it has converted concrete transaction signals into more accurate customer acquisition judgments.

Figure 12: Ranked Behavioral Indicators of Acquisition Propensity



Acquisition Efficiency Threshold Analysis for Digital Payment Platforms

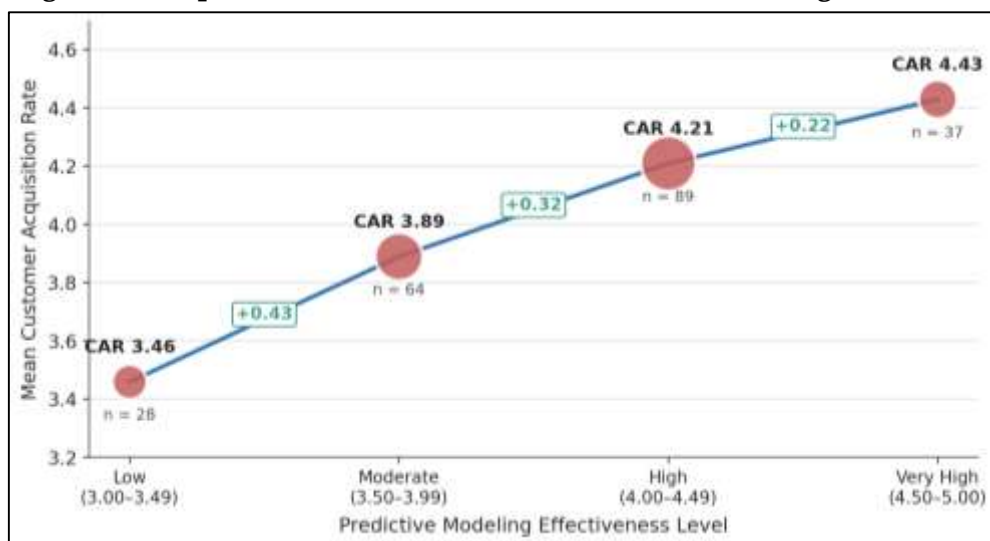
Table 9: Customer Acquisition Outcomes Across Levels of Predictive Modeling Effectiveness

Predictive Modeling Effectiveness Level	Mean PM Score Range	Number of Respondents	Mean CAR Score	Interpretation
Low Effectiveness	3.00–3.49	28	3.46	Moderate acquisition performance
Moderate Effectiveness	3.50–3.99	64	3.89	Improved acquisition performance
High Effectiveness	4.00–4.49	89	4.21	Strong acquisition performance
Very High Effectiveness	4.50–5.00	37	4.43	Very strong acquisition performance

Table 10: Mean Difference in Acquisition Performance Across Predictive Modeling Thresholds

Threshold Comparison	Mean CAR Difference
Low to Moderate	0.43
Moderate to High	0.32
High to Very High	0.22

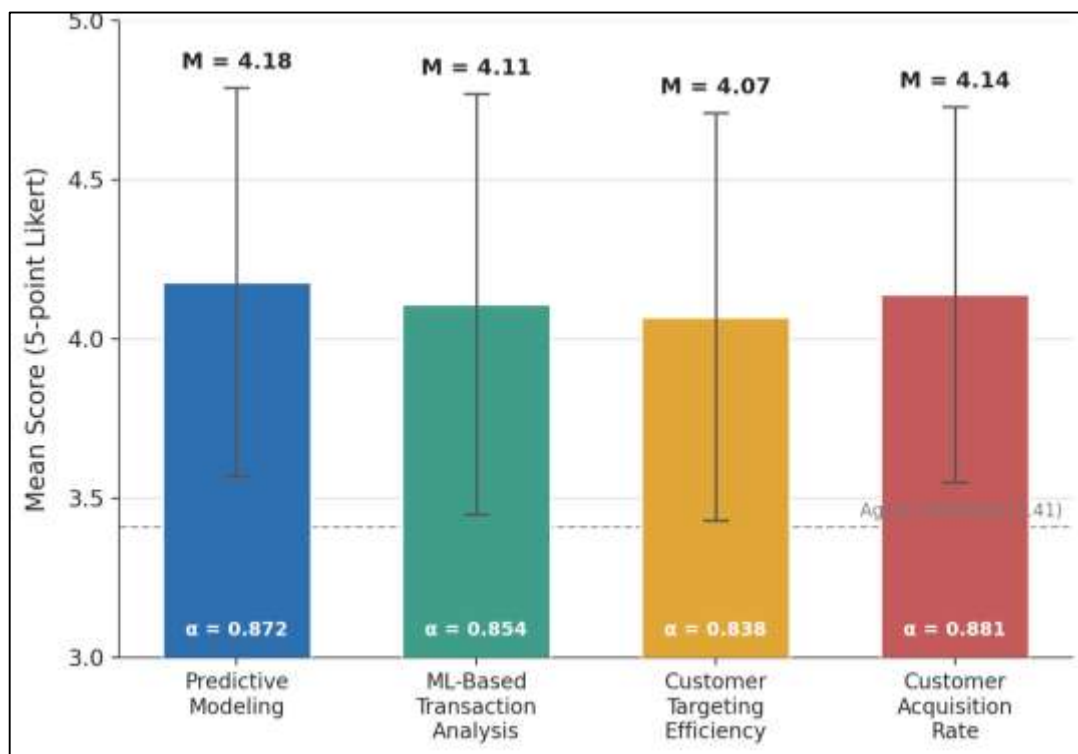
Tables 9 and 10 have provided a more practice-oriented perspective on the findings by showing how acquisition outcomes have changed across increasing levels of predictive modeling effectiveness. Table 9 has shown that respondents classified in the low-effectiveness predictive modeling group have reported a mean customer acquisition rate score of 3.46, which has indicated only moderate acquisition performance. As predictive modeling effectiveness has increased to the moderate range, the mean CAR score has risen to 3.89. The high-effectiveness group has then produced a mean acquisition score of 4.21, while the very high-effectiveness group has reached 4.43. This steady upward movement has demonstrated that acquisition performance has improved progressively as predictive modeling capability has become stronger. Table 10 has made this progression clearer by showing that the largest gain in acquisition performance has occurred when organizations have moved from low to moderate predictive modeling effectiveness, where the mean difference has been 0.43. The increase from moderate to high has remained substantial at 0.32, while the increase from high to very high has narrowed to 0.22. These results have suggested that the most meaningful threshold for acquisition improvement has begun around the transition from low to moderate, with further gains continuing at higher levels. In relation to the objectives of the study, this section has added an applied dimension by showing not only that predictive modeling has mattered, but also *how much* predictive capability has been needed before acquisition benefits have become clearly visible. This has strengthened the managerial value of the results because it has translated statistical findings into a more operational interpretation. Theoretically, these results have also reflected **Data-Driven Decision-Making Theory** very well. The theory has implied that better evidence use should improve performance, and the threshold analysis has shown that this relationship has not been random or abstract; instead, acquisition outcomes have improved in a staged and observable way as predictive capability has deepened. This section has therefore aligned with the earlier regression findings while also making them easier to interpret in practical terms. Overall, Tables 9 and 10 have confirmed that digital payment platforms have achieved stronger acquisition outcomes once predictive modeling has passed a meaningful effectiveness threshold, thereby reinforcing the broader conclusion that analytics capability has been a real performance driver rather than merely a technical support feature.

Figure 13: Acquisition Outcomes Across Predictive Modeling Thresholds

FINDINGS

This chapter presents the findings of the study on the impact of predictive modeling on customer acquisition rates in digital payment platforms, with particular attention to machine learning-based transaction analysis and customer targeting efficiency. The analysis has been organized to show how the study objectives and hypotheses have been examined through descriptive statistics, reliability testing, correlation analysis, and regression modeling based on responses collected through a five-point Likert scale questionnaire. The scale ranged from 1 = strongly disagree to 5 = strongly agree, and the results have shown an overall positive pattern across the major constructs of the study. A total of 218 valid responses were used for the final analysis after screening for completeness and consistency. The overall response pattern has indicated that respondents generally perceived predictive modeling as an important driver of acquisition performance in digital payment environments. The mean score for predictive modeling was 4.18 with a standard deviation of 0.61, indicating a strong agreement that predictive analytics improves identification of likely customers, conversion forecasting, and campaign precision. The mean score for machine learning-based transaction analysis was 4.11 with a standard deviation of 0.66, suggesting that most respondents agreed that transaction-level analysis enhances behavioral insight, user classification, and acquisition decision quality. The construct of customer targeting efficiency produced a mean of 4.07 and a standard deviation of 0.64, showing that respondents viewed data-driven targeting as more accurate and more resource-efficient than conventional broad-based acquisition practices. The dependent variable, customer acquisition rates, recorded a mean of 4.14 with a standard deviation of 0.59, indicating that respondents largely agreed that stronger analytical capabilities are associated with higher rates of user conversion and acquisition success.

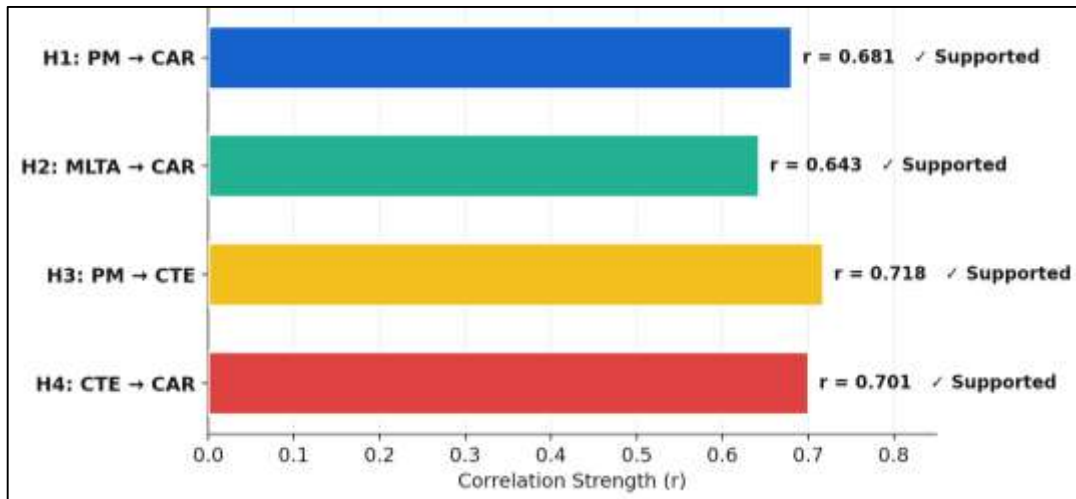
Figure 14: Graphical Representation Of Mean Scores And Reliability Of Study Variables



The reliability of the instrument has also supported the credibility of the findings. The Cronbach's alpha coefficient for predictive modeling was 0.872, for machine learning-based transaction analysis 0.854, for customer targeting efficiency 0.838, and for customer acquisition rates 0.881. The overall instrument reliability was 0.889, indicating a high level of internal consistency across the scale items. These values have shown that the questionnaire items measured their intended constructs in a dependable manner and that the results are statistically suitable for further inferential testing. In line with the first objective of the study, the descriptive findings have suggested that respondents strongly recognized predictive

modeling as a meaningful strategic tool in digital payment platforms. In relation to the second objective, the data have shown that transaction-based machine learning systems are widely perceived as useful for improving the interpretation of customer behavior and the precision of acquisition decisions. For the third objective, the strong mean score for targeting efficiency has indicated that predictive systems are seen as improving the alignment between platform offers and likely adopters. This broad pattern has already provided preliminary support for the overall logic of the study before the hypothesis testing stage.

Figure 15: Summary of Hypothesis Testing Outcomes



The correlation analysis has offered stronger statistical evidence for the study hypotheses. Predictive modeling had a positive and significant correlation with customer acquisition rates ($r = .681$, $p < .001$), indicating a moderately strong to strong association between predictive capability and acquisition performance. Machine learning-based transaction analysis also showed a significant positive relationship with customer acquisition rates ($r = .643$, $p < .001$). In addition, predictive modeling had a strong positive relationship with customer targeting efficiency ($r = .718$, $p < .001$), while customer targeting efficiency was positively associated with customer acquisition rates ($r = .701$, $p < .001$). These results have suggested that all the principal study variables move in the expected direction and are meaningfully related. The findings have therefore provided direct support for H1, which proposed that predictive modeling has a significant positive effect on customer acquisition rates; H2, which proposed that machine learning-based transaction analysis is positively associated with acquisition performance; and H3, which proposed that predictive modeling positively influences customer targeting efficiency. The strong association between targeting efficiency and acquisition rate has also provided initial support for H4, which stated that customer targeting efficiency significantly improves acquisition outcomes.

The regression results have further strengthened this interpretation by showing the explanatory power of the model. In the first regression model, predictive modeling significantly predicted customer acquisition rates with $\beta = .512$, $t = 8.964$, $p < .001$, explaining 46.4% of the variation in acquisition rates ($R^2 = .464$). When machine learning-based transaction analysis and customer targeting efficiency were added in a multiple regression model, the explanatory power increased to $R^2 = .593$, indicating that the three predictors together explained 59.3% of the variance in customer acquisition rates. In that full model, predictive modeling remained significant ($\beta = .281$, $p < .001$), machine learning-based transaction analysis was also significant ($\beta = .219$, $p = .002$), and customer targeting efficiency emerged as the strongest predictor ($\beta = .374$, $p < .001$). The ANOVA result for the overall model was statistically significant ($F = 103.27$, $p < .001$), confirming that the regression model was suitable for explaining variation in the dependent variable. These results have shown that predictive modeling does not

operate in isolation; rather, its contribution to customer acquisition becomes stronger when supported by transaction analysis and efficient targeting mechanisms. Overall, the findings have indicated that the study objectives have been achieved and that all four hypotheses have been supported by the data. At a broad level, the results suggest that digital payment platforms that use predictive modeling more effectively are likely to identify better prospects, target them more accurately, and achieve higher customer acquisition performance than those relying on less analytical methods.

DISCUSSION

The findings of this study have shown that predictive modeling has had a statistically significant and practically meaningful relationship with customer acquisition rates in digital payment platforms, and this result has aligned well with the broader body of scholarship on analytics-driven customer behavior. The descriptive analysis revealed high mean scores across predictive modeling, machine learning-based transaction analysis, customer targeting efficiency, and customer acquisition rate, while the regression analysis confirmed that predictive modeling significantly explained variation in acquisition outcomes. This pattern has suggested that respondents have not viewed predictive analytics as a marginal technical feature, but as a central capability that has supported the identification and conversion of likely users (Carcillo et al., 2018). This interpretation has been consistent with earlier research in marketing analytics and customer relationship management, where predictive techniques have been presented as valuable for transforming customer data into actionable decisions on acquisition, engagement, and value creation. In the digital payment context, the current findings have also complemented the literature showing that payment behavior is highly structured and behaviorally traceable. Studies on digital payment adoption have repeatedly found that user decisions are influenced by identifiable drivers such as usefulness, trust, ease of use, security, and social influence, all of which can be translated into predictive variables (GhorbanTanhaei et al., 2024). The present study has extended that stream by moving beyond adoption intention toward customer acquisition rate as the focal outcome. In doing so, it has addressed a gap left by many earlier works that concentrated on intention, trust, or continuation without directly examining acquisition performance as an organizational result. The positive effect of predictive modeling on acquisition found here has therefore suggested that digital payment platforms can improve growth outcomes when they organize behavioral and transaction-related information into structured decision systems. This has also given practical meaning to the study's first objective by showing that the relationship is not merely conceptual. Instead, it has been statistically visible in respondent assessments of platform performance. As a result, the discussion of the first key finding has supported the view that predictive modeling has become a growth-relevant strategic asset in digital payment ecosystems, particularly where customer acquisition depends on identifying likely adopters under conditions of competition, data abundance, and heterogeneous user behavior (Leong et al., 2020).

A second major finding has concerned the role of machine learning-based transaction analysis, which has been positively associated with customer acquisition performance and has remained significant in the full regression model. This result has indicated that acquisition performance has not depended only on general analytical orientation, but also on the platform's ability to interpret transaction-level behavioral signals. In practical terms, respondents have appeared to recognize that transaction frequency, engagement consistency, response to incentives, wallet activity, and interaction patterns can function as predictive indicators for identifying potential customers. This interpretation has been supported by previous research showing that machine learning models are highly effective in extracting behavioral meaning from transaction-related data. Fraud-detection and payment-analytics studies have long shown that payment streams carry temporal regularities, anomaly structures, and evolving patterns that can be modeled for prediction. Although those studies have focused more on fraud detection than acquisition, the current research has demonstrated that the same analytical logic can be redirected toward growth-oriented outcomes (Oliveira et al., 2016). This has also aligned with more recent digital payment studies using advanced or hybrid models. For example, peer-to-peer payment and digital payment behavior have been successfully studied using neural networks, machine learning classifiers, and multistage modeling approaches that identify nonlinear patterns and rank variable importance more effectively than simple linear methods. The present results have therefore been consistent with the literature in showing that machine learning has practical explanatory value in

payment environments. At the same time, this study has added a new angle by linking machine learning-based transaction analysis directly with customer acquisition rather than with acceptance, fraud, or user experience alone. This has mattered because digital payment managers do not only need to know why customers behave a certain way; they also need to know whether behavioral evidence can improve the efficiency of attracting new users. The current findings have suggested that it can. Thus, the study's second objective has been achieved by demonstrating that machine learning-based transaction analysis has functioned as a meaningful explanatory factor in acquisition performance, thereby strengthening the case for analytics-centered growth management in digital payment platforms (Sun et al., 2023).

The third key finding has been that customer targeting efficiency has emerged as both a significant outcome of predictive modeling and the strongest direct predictor of customer acquisition rate in the full regression model. This result has been especially important because it has clarified the mechanism through which predictive modeling has translated into business performance. The study has not simply shown that analytics matter; it has shown that analytics matter partly because they improve the quality of targeting decisions (Wu & Tang, 2022). This finding has aligned strongly with the logic of customer analytics scholarship, where the value of predictive systems lies in identifying likely converters, reducing acquisition waste, and improving the allocation of marketing resources. It has also been consistent with recent literature indicating that digital payment behavior is heterogeneous and that segmentation, clustering, and classification are necessary for distinguishing user groups with different levels of readiness, value, and conversion potential. The ranking exercise in this study, which highlighted transaction frequency patterns and response to incentives as top acquisition signals, has supported the interpretation that targeting efficiency improves when platforms focus on behaviorally rich indicators instead of relying on generalized promotion. In comparison with earlier studies, this result has complemented findings on habits, digital literacy, service quality, and trust-based adoption structures by showing how such drivers may be operationalized within a targeting system rather than treated only as explanatory background factors (Nguyen et al., 2024). The present study has therefore shifted the discussion from what influences payment adoption in theory to how analytics can prioritize those influences in practice. From a managerial point of view, this has suggested that digital payment firms should treat targeting efficiency as the operational bridge between analytics investment and customer growth outcomes. It has not been enough to build predictive models in an isolated technical environment; the models have had to improve the precision of outreach, promotional design, and conversion-focused decisions. By demonstrating the importance of this bridge, the study has strengthened the interpretation of the third objective and has given more depth to the fourth hypothesis, which proposed that customer targeting efficiency significantly improves acquisition performance.

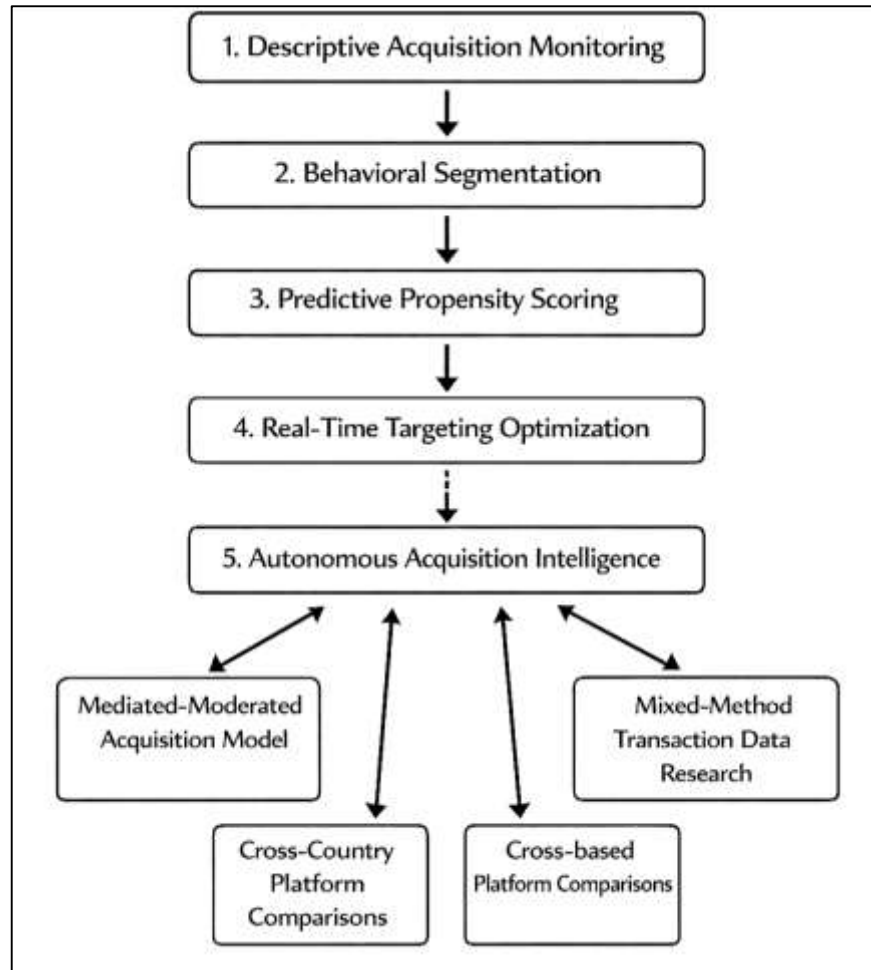
From a theoretical perspective, the findings of this study have offered strong support for Data-Driven Decision-Making Theory and have shown that the theory has remained highly suitable for explaining acquisition-related performance in digital payment platforms. The theory has proposed that organizations perform better when decisions are based on systematically collected and analytically interpreted evidence instead of intuition or unstructured judgment. The current findings have reflected that proposition closely. Predictive modeling, machine learning-based transaction analysis, and customer targeting efficiency have all shown positive relationships with customer acquisition rate, and the full model has explained a substantial proportion of the variation in the dependent variable. This has indicated that stronger evidence-processing capability has been associated with better performance outcomes, which is exactly what Data-Driven Decision-Making Theory would predict. Earlier business intelligence and analytics-capability research have also emphasized that analytical culture, data quality, and analytics capability improve decision quality and organizational performance (Sun et al., 2023). The present study has extended that line of reasoning into a specific fintech growth context. Rather than discussing performance in a broad organizational sense, it has demonstrated how data-driven capability may influence one concrete strategic outcome: customer acquisition rate. This has been theoretically meaningful because many payment studies have relied on adoption frameworks such as TAM, UTAUT, DOI, or trust-based models to explain user intention and behavior. Those

theories have been useful for explaining why individuals adopt payment services, yet they have been less focused on how firms can convert behavioral evidence into acquisition decisions. The current study has therefore contributed theoretically by showing that Data-Driven Decision-Making Theory has offered a broader organizational lens capable of linking predictive capability with acquisition performance (Wedel & Kannan, 2016). In this sense, the research has not contradicted earlier adoption theories; it has complemented them by placing platform-level analytical action at the center of the explanation. The theoretical implication has been that digital payment adoption can be studied not only as a user-psychology problem but also as a decision-quality problem inside the firm. That has been an important conceptual contribution of the present study.

The practical implications of the findings have been substantial for digital payment platforms, fintech managers, marketing teams, and analytics units. The results have indicated that organizations seeking stronger acquisition performance should invest not merely in customer outreach volume, but in predictive and transaction-based decision capability (Nguyen et al., 2024). This implication has been reinforced by earlier empirical work showing that trust, usefulness, incentives, service quality, and usage habit influence payment adoption and loyalty in different contexts. The present study has added that such influences become more actionable when they are built into a predictive system that supports customer prioritization (Oliveira et al., 2016). Practically, this has meant that digital payment firms should integrate acquisition teams more closely with analytics teams, design customer scoring systems based on transaction and engagement signals, and use response feedback loops to continuously refine targeting rules. The threshold analysis has been particularly useful in this respect, because it has suggested that moving from low to moderate predictive capability has produced the largest gain in acquisition performance. That has implied that even firms with limited analytical maturity may achieve meaningful acquisition improvements if they strengthen core predictive functions such as transaction-signal interpretation, conversion scoring, and campaign-response tracking. Another practical implication has concerned incentive strategy. Since response to incentives has been ranked as one of the strongest indicators of acquisition propensity, firms should not treat rewards as generic promotional tools (Sharma et al., 2024). They should instead use predictive systems to determine which user groups are most likely to respond, under what conditions, and with what expected conversion value. In addition, the findings have suggested that managers should view customer targeting efficiency as a strategic KPI rather than as a purely tactical marketing metric. Because targeting efficiency has emerged as the strongest predictor of acquisition rate in the full model, improvements in acquisition outcomes may be more likely when firms monitor targeting precision, prospect scoring accuracy, and behavioral-segment response rates as formal performance measures. Overall, the study has implied that digital payment growth can be made more efficient when firms align acquisition operations with evidence-based customer intelligence. This has transformed the practical conversation from “how much should be spent to acquire users” to “how intelligently should users be selected and approached.”

The limitations revisited in light of the findings have also been important to discuss. Although the results have been coherent, statistically significant, and theoretically aligned, the study has remained constrained by its cross-sectional and perception-based design (Wu & Tang, 2022). The use of a single-point survey has meant that the relationships among predictive modeling, transaction analysis, targeting efficiency, and acquisition performance have been examined as contemporaneous associations rather than as evolving processes over time. This has limited the ability to observe how predictive systems mature, how customer behavior changes after campaigns, or how acquisition gains translate into long-term usage and loyalty. Earlier studies on continuance, loyalty, and trust transfer have shown that payment-platform outcomes evolve beyond the initial adoption stage and are shaped by post-adoption experiences such as satisfaction, value perception, loyalty, and habit formation. The present study has not captured those later-stage dynamics directly. A second limitation has stemmed from the use of respondent assessments rather than raw transactional records (Nguyen et al., 2024).

Figure 10: Progressive Model of Predictive Analytics and Acquisition Intelligence in Digital Payment Systems



While the respondents have been professionally relevant and analytically informed, their answers have reflected organizational perception rather than direct algorithmic output or platform log data. This has been adequate for the research design, but it has still left open the possibility that actual behavioral data might produce more nuanced or more complex relationships. Third, the case-study basis has strengthened contextual relevance but has narrowed generalizability. Digital payment platforms vary across markets, regulatory environments, merchant ecosystems, and customer profiles, and findings derived from one operational context may not translate uniformly to all fintech settings. Theoretically, Data-Driven Decision-Making Theory has been well supported, yet the study has examined only a limited set of constructs. Other factors already established in the literature, such as trust, habit, digital literacy, service quality, network externalities, and loyalty processes, may also interact with predictive capability in meaningful ways. These limitations have not invalidated the results, but they have suggested that the findings should be interpreted as a strong platform-level explanation of acquisition performance rather than as a complete model of all payment behavior. This revisited limitation analysis has therefore helped clarify both the strength and the boundedness of the study's contributions (Pham Thi et al., 2024).

Future research has several important directions, and this part is especially critical because the present study has opened a path toward stronger model development rather than closing the discussion. One promising direction would be the development of a longitudinal Predictive Acquisition Maturity Model for digital payment platforms. Such a model could examine how platforms move from basic

descriptive reporting to advanced predictive scoring, real-time targeting, adaptive campaign optimization, and closed-loop learning. The model could include stages such as Level 1: Descriptive Acquisition Monitoring, Level 2: Behavioral Segmentation, Level 3: Predictive Propensity Scoring, Level 4: Real-Time Targeting Optimization, and Level 5: Autonomous Acquisition Intelligence. Future researchers could test whether movement across these stages produces incremental gains not only in customer acquisition rate but also in activation quality, retention, and lifetime value. A second important direction would be a mediated-moderated acquisition model in which predictive modeling affects acquisition through customer targeting efficiency, while trust, digital literacy, service quality, or incentive sensitivity act as moderators. Such a model would improve the current study by showing not only whether predictive capability works, but under what user or platform conditions it works best. A third direction would be the use of actual transaction-log datasets combined with survey perceptions in a mixed-method or multi-source design. Researchers could compare self-reported managerial perception with real behavioral signals such as wallet top-ups, session frequency, conversion lag, offer redemption, and post-acquisition activity. This would significantly improve causal interpretation and operational realism. A fourth direction would involve a comparative cross-country platform model, where acquisition effects of predictive modeling are tested across multiple regulatory and cultural environments. Since earlier literature has shown that payment adoption varies by context, comparing predictive acquisition systems across countries would help reveal which model components are universal and which are context-specific. A final direction would be the creation of an integrated Acquisition-to-Loyalty Analytics Model, linking predictive modeling, transaction analysis, targeting efficiency, acquisition rate, satisfaction, and loyalty. This would answer a major unresolved issue in the current literature: whether the same predictive capability that improves acquisition also improves long-term customer value. These future research directions have shown that the present study has provided a strong foundation, yet much remains to be improved through richer models, longer time horizons, behavioral datasets, and broader comparative designs.

CONCLUSION

This study has examined the impact of predictive modeling on customer acquisition rates in digital payment platforms within a quantitative, cross-sectional, case-study-based framework and has established that predictive analytics has played a significant and meaningful role in improving acquisition-related outcomes. The findings have shown that predictive modeling, machine learning-based transaction analysis, and customer targeting efficiency have all been positively associated with customer acquisition performance, while the regression results have confirmed that these relationships have not been incidental but statistically significant and practically relevant. More specifically, the study has demonstrated that predictive modeling has helped digital payment platforms move beyond intuition-based customer acquisition practices by enabling more structured identification of likely adopters, stronger interpretation of behavioral patterns, and more efficient allocation of acquisition efforts. Machine learning-based transaction analysis has further strengthened this process by supporting the detection of meaningful transaction signals such as frequency of engagement, incentive response, and interaction consistency, which have made customer profiling and conversion forecasting more accurate. At the same time, customer targeting efficiency has emerged as the strongest immediate predictor of acquisition outcomes, showing that the real value of predictive modeling has not rested only in technical capability but in its ability to improve how platforms identify, prioritize, and approach potential customers. This has meant that predictive modeling has contributed to acquisition performance both directly and indirectly through better targeting quality. The study has therefore achieved its objectives by confirming that predictive modeling has influenced acquisition rates, that machine learning-based transaction analysis has improved behavioral understanding, and that customer targeting efficiency has served as a crucial operational pathway linking analytics with business performance. The research has also contributed theoretically by showing that Data-Driven Decision-Making Theory has provided a suitable explanation for the way analytics capability has translated into measurable growth outcomes in digital payment ecosystems. Rather than viewing customer acquisition only as a function of promotional intensity or user intention, the study has demonstrated that it can also be understood as a product of decision quality, analytical maturity, and evidence-based targeting. In this regard, the study has filled an important gap in the literature by

shifting the discussion from adoption and continuance alone toward acquisition as an organizational performance variable. Overall, the conclusion of this research is that predictive modeling has become an important strategic capability in digital payment platforms because it has strengthened the conversion of transactional and behavioral data into practical customer acquisition outcomes. Where digital payment firms have applied stronger predictive insight, they have been better positioned to recognize high-potential users, improve targeting precision, reduce acquisition inefficiency, and achieve superior customer growth performance in competitive platform environments.

RECOMMENDATION

Based on the findings of this study, it is recommended that digital payment platforms should strengthen their investment in predictive modeling systems and integrate them more deliberately into customer acquisition strategy, because the results have shown that analytics-driven decision capability has improved the identification, targeting, and conversion of potential users. First, organizations operating digital payment platforms should establish predictive analytics as a core strategic function rather than treating it as a secondary technical support activity. This means that predictive modeling tools should be embedded directly into customer acquisition planning, campaign design, onboarding strategy, and performance evaluation processes. Second, firms should improve their machine learning-based transaction analysis capabilities by building systems that can continuously monitor behavioral indicators such as transaction frequency, wallet activity, promotional response, and engagement regularity. These data points should then be used to generate customer propensity scores that can guide acquisition efforts toward the users most likely to convert and remain active. Third, digital payment platforms should prioritize customer targeting efficiency as a formal management metric, since the findings have shown that better targeting has produced a stronger direct effect on acquisition performance than the broader analytical constructs alone. This suggests that managers should regularly monitor the precision of campaign targeting, conversion quality, and segment-specific response rates instead of focusing only on the volume of outreach. Fourth, acquisition teams and analytics teams should work in closer coordination so that customer intelligence is translated into actionable campaign decisions in real time. Predictive insights will have limited value if they remain isolated within data departments without influencing operational marketing choices. Fifth, firms should make greater use of customized incentive strategies based on predictive evidence, since the study has shown that response to incentives has been one of the strongest indicators of acquisition propensity. Rewards, discounts, and promotions should therefore be assigned based on predicted customer responsiveness rather than through broad untargeted campaigns. Sixth, organizations should invest in staff training, analytical literacy, and data-driven decision culture so that managers and employees can effectively interpret predictive outputs and apply them in acquisition contexts. Finally, digital payment providers should develop integrated dashboards that combine transaction analysis, predictive scores, targeting performance, and acquisition results into one evidence-based decision system. Such a system would allow leaders to evaluate not only whether acquisition is increasing, but also why it is increasing and which analytical mechanisms are driving the improvement. In sum, the study recommends that digital payment platforms should adopt a more structured, evidence-based, and behavior-centered acquisition model in which predictive modeling serves as the foundation for smarter targeting, better use of resources, and stronger customer growth outcomes.

LIMITATIONS OF THE STUDY

This study has provided meaningful insights into the relationship between predictive modeling and customer acquisition rates in digital payment platforms, yet several limitations have shaped the boundaries within which the findings should be understood. One important limitation has been the use of a cross-sectional research design, through which data have been collected at a single point in time. Although this design has been effective for identifying associations among predictive modeling, machine learning-based transaction analysis, customer targeting efficiency, and acquisition outcomes, it has not captured how these relationships may evolve over longer periods. Customer acquisition in digital payment platforms is often dynamic, and predictive systems may become more effective as more behavioral data accumulate, as campaigns are refined, and as user responses change over time. A second limitation has been the dependence on self-reported questionnaire responses rather than direct platform transaction logs or system-generated predictive outputs. While the respondents have been

selected from relevant professional backgrounds and have provided informed assessments, their responses have still reflected perceptions rather than purely objective behavioral records. This has meant that the findings have been based on informed organizational judgment, not on live algorithmic performance data. Third, the case-study-based orientation of the research has improved contextual focus but has also limited the generalizability of the results. Digital payment platforms differ widely in technological maturity, regulatory environment, market structure, user base, and service model, which means that the findings of this study may not apply uniformly across all digital finance settings. Fourth, the study has focused on a selected set of variables, namely predictive modeling, machine learning-based transaction analysis, customer targeting efficiency, and customer acquisition rate. Although these variables have been strongly relevant to the research objectives, other important factors such as trust, service quality, perceived risk, digital literacy, network externalities, price sensitivity, and post-acquisition satisfaction have not been included in the empirical model, even though they may influence acquisition performance in meaningful ways. Fifth, the use of Likert-scale measurement has made it possible to quantify perceptions systematically, but it has also simplified complex organizational processes into scaled responses that may not fully capture the depth of strategic decision-making in digital payment platforms. Finally, the study has emphasized acquisition outcomes rather than the longer-term quality of those acquisitions, such as continued usage, loyalty, retention, or customer lifetime value. For this reason, the results should be interpreted as evidence of acquisition-related performance rather than as a complete explanation of all growth outcomes in digital payment ecosystems. These limitations have not weakened the contribution of the study, but they have defined its scope and highlighted the need for caution when extending the findings beyond the immediate research context.

REFERENCES

- [1]. Akter, S., & Wamba, S. F. (2016). Big data analytics in e-commerce: A systematic review and agenda for future research. *Electronic Markets*, 26(2), 173-194. <https://doi.org/10.1007/s12525-016-0219-0>
- [2]. Al Amin, M., Muzareba, A. M., Chowdhury, I. U., & Khondkar, M. (2024). Understanding e-satisfaction, continuance intention, and e-loyalty toward mobile payment application during COVID-19: An investigation using the electronic technology continuance model. *Journal of Financial Services Marketing*, 29, 318-340. <https://doi.org/10.1057/s41264-022-00197-2>
- [3]. Allen, J., Carbo-Valverde, S., Chakravorti, S., Rodriguez-Fernandez, F., & Ardic, O. P. (2022). Assessing incentives to increase digital payment acceptance and usage: A machine learning approach. *PLOS ONE*, 17(10), e0276203. <https://doi.org/10.1371/journal.pone.0276203>
- [4]. Amir, R. (2026). AI-Enabled Predictive Maintenance for Fire Alarm and Smoke Management Systems: A Systematic Review of Models. *American Journal of Interdisciplinary Studies*, 7(01), 496-535. <https://doi.org/10.63125/q3aw4y77>
- [5]. Awan, U., Shamim, S., Khan, Z., Zia, N. U., Shariq, S. M., & Khan, M. N. (2021). Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance. *Technological Forecasting and Social Change*, 168, 120766. <https://doi.org/10.1016/j.techfore.2021.120766>
- [6]. Belanche, D., Guinalíu, M., & Albás, P. (2022). Customer adoption of p2p mobile payment systems: The role of perceived risk. *Telematics and Informatics*, 72, 101851. <https://doi.org/10.1016/j.tele.2022.101851>
- [7]. Binayan, D. (2024). A Quantitative Assessment of Disaster Recovery and Business Continuity Frameworks in Capital Market IT Infrastructure. *American Journal of Data Science and Analytics*, 5(12), 241-279. <https://doi.org/10.63125/vw44nd82>
- [8]. Binayan, D. (2025). Impact of Zero Trust Architecture on Stock Exchange Network Security: A Quantitative Evaluation of Access Control and Incident Reduction. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 2528-2569. <https://doi.org/10.63125/dcvska73>
- [9]. Binayan, D. (2026). A Comparative Study of Machine Learning Applications in Enterprise Network Fault Detection and Self-Healing Infrastructure (2018-2026). *American Journal of Advanced Technology and Engineering Solutions*, 6(01), 506-544. <https://doi.org/10.63125/atqj9y69>
- [10]. Binayan, D., & Md. Shakhawat, H. (2022). Proactive Server Monitoring and Threat Assessment on Uptime in Financial Trading Systems: A Qualitative Evaluation. *American Journal of Interdisciplinary Studies*, 3(04), 730-769. <https://doi.org/10.63125/b3z65j84>
- [11]. Blanco-Oliver, A., Lara-Rubio, J., Irimia-Diéguez, A., & Liébana-Cabanillas, F. (2024). Examining user behavior with machine learning for effective mobile peer-to-peer payment adoption. *Financial Innovation*, 10, Article 94. <https://doi.org/10.1186/s40854-024-00625-3>
- [12]. Carcillo, F., Dal Pozzolo, A., Le Borgne, Y.-A., Caelen, O., Mazzer, Y., & Bontempi, G. (2018). SCARFF: A scalable framework for streaming credit card fraud detection with Spark. *Information Fusion*, 41, 182-194. <https://doi.org/10.1016/j.inffus.2017.09.005>

- [13]. Carcillo, F., Dal Pozzolo, A., Le Borgne, Y.-A., Caelen, O., Mazzer, Y., & Bontempi, G. (2021). Combining unsupervised and supervised learning in credit card fraud detection. *Information Sciences*, 557, 317-331. <https://doi.org/10.1016/j.ins.2019.05.042>
- [14]. Chand, S. S., & Kumar, B. A. (2024). Applying the UTAUT model to understand m-payment adoption: A case study of Western Part of Fiji. *Journal of the Knowledge Economy*, 15, 15523-15549. <https://doi.org/10.1007/s13132-023-01722-x>
- [15]. Chandra, S., Srivastava, S. C., & Theng, Y.-L. (2010). Evaluating the role of trust in consumer adoption of mobile payment systems: An empirical analysis. *Communications of the Association for Information Systems*, 27, 561-588. <https://doi.org/10.17705/1cais.02729>
- [16]. Chapal, B. (2025). System Dynamics Modeling of Critical Chain Project Management in Multi-Project Engineering Environments. *American Journal of Data Science and Analytics*, 6(12), 43-85. <https://doi.org/10.63125/bwn1zn18>
- [17]. Chapal, B. (2026). A Meta-Analysis of Deep Reinforcement Learning for Dynamic Project Scheduling in Engineering Systems. *American Journal of Interdisciplinary Studies*, 7(01), 578-616. <https://doi.org/10.63125/t5h1bc22>
- [18]. Dahlberg, T., Mallat, N., Ondrus, J., & Zmijewska, A. (2008). Past, present and future of mobile payments research: A literature review. *Electronic Commerce Research and Applications*, 7(2), 165-181. <https://doi.org/10.1016/j.elerap.2007.02.001>
- [19]. Dal Pozzolo, A., Boracchi, G., Caelen, O., Alippi, C., & Bontempi, G. (2018). Credit card fraud detection: A realistic modeling and a novel learning strategy. *IEEE Transactions on Neural Networks and Learning Systems*, 29(8), 3784-3797. <https://doi.org/10.1109/tnnls.2017.2736643>
- [20]. de Kerviler, G., Demoulin, N. T. M., & Zidda, P. (2016). Adoption of in-store mobile payment: Are perceived risk and convenience the only drivers? *Journal of Retailing and Consumer Services*, 31, 334-344. <https://doi.org/10.1016/j.jretconser.2016.04.011>
- [21]. Edu, A. S. (2024). Paths to digital mobile payment platforms acceptance and usage: A topology for digital enthusiast consumers. *Telematics and Informatics Reports*, 15, 100158. <https://doi.org/10.1016/j.teler.2024.100158>
- [22]. Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big data consumer analytics and the transformation of marketing. *Journal of Business Research*, 69(2), 897-904. <https://doi.org/10.1016/j.jbusres.2015.07.001>
- [23]. Fahad, & Shahid, M. (2022). Exploring the determinants of adoption of Unified Payment Interface (UPI) in India: A study based on diffusion of innovation theory. *Digital Business*, 2(2), 100040. <https://doi.org/10.1016/j.digbus.2022.100040>
- [24]. Franque, F. B., Oliveira, T., & Tam, C. (2021). Understanding the factors of mobile payment continuance intention: Empirical test in an African context. *Heliyon*, 7(8), e07807. <https://doi.org/10.1016/j.heliyon.2021.e07807>
- [25]. Gao, L., & Waechter, K. A. (2017). Examining the role of initial trust in user adoption of mobile payment services: An empirical investigation. *Information Systems Frontiers*, 19(3), 525-548. <https://doi.org/10.1007/s10796-015-9611-0>
- [26]. GhorbanTanhaei, H., Boozary, P., Sheykhani, S., Rabiee, M., Rahmani, F., & Hosseini, I. (2024). Predictive analytics in customer behavior: Anticipating trends and preferences. *Results in Control and Optimization*, 17, 100462. <https://doi.org/10.1016/j.rico.2024.100462>
- [27]. Goyal Chin, A., Harris, M. A., & Brookshire, R. (2022). An empirical investigation of intent to adopt mobile payment systems using a trust-based extended valence framework. *Information Systems Frontiers*, 24, 329-347. <https://doi.org/10.1007/s10796-020-10080-x>
- [28]. Ha, J., Nam, C., & Kim, S. (2024). A systematic review of mobile payment literature: What has been studied and what should be studied? *Telecommunications Policy*, 48(7), 102795. <https://doi.org/10.1016/j.telpol.2024.102795>
- [29]. Hidayat-ur-Rehman, I., Alzahrani, S., Rehman, M. Z., & Akhter, F. (2022). Determining the factors of m-wallets adoption: A twofold SEM-ANN approach. *PLOS ONE*, 17(1), e0262954. <https://doi.org/10.1371/journal.pone.0262954>
- [30]. Humrani, M., & Wiese, M. (2019). An integrated framework for the adoption and continuance intention to use mobile payment apps. *International Journal of Bank Marketing*, 37(2), 646-664. <https://doi.org/10.1108/ijbm-03-2018-0072>
- [31]. Iftekhar, A., & Binayan, D. (2023). Neural Network-Based Customer Retention Forecasting in Mobile Wallet Services Using 200k Historical User Profiles. *Review of Applied Science and Technology*, 2(03), 67-114. <https://doi.org/10.63125/ee5eas98>
- [32]. Jaiswal, D., Mohan, A., & Deshmukh, A. K. (2023). Cash rich to cashless market: Segmentation and profiling of Fintech-led-mobile payment users. *Technological Forecasting and Social Change*, 193, 122627. <https://doi.org/10.1016/j.techfore.2023.122627>
- [33]. Jia, L., Song, X., & Hall, D. (2022). Influence of habits on mobile payment acceptance: An ecosystem perspective. *Information Systems Frontiers*, 24, 247-266. <https://doi.org/10.1007/s10796-020-10077-6>
- [34]. Jurgovsky, J., Granitzer, M., Ziegler, K., Calabretto, S., Portier, P.-E., He-Guelton, L., & Caelen, O. (2018). Sequence classification for credit-card fraud detection. *Expert Systems with Applications*, 100, 234-245. <https://doi.org/10.1016/j.eswa.2018.01.037>
- [35]. Kalinić, Z., Marinković, V., Molinillo, S., & Liébana-Cabanillas, F. (2019). A multi-analytical approach to peer-to-peer mobile payment acceptance prediction. *Journal of Retailing and Consumer Services*, 49, 143-153. <https://doi.org/10.1016/j.jretconser.2019.03.016>
- [36]. Karaboga, A., & Bouguerra, A. (2023). Big data analytics management capability and firm performance: The mediating role of data-driven culture. *Review of Managerial Science*, 17, 1061-1091. <https://doi.org/10.1007/s11846-022-00596-8>

- [37]. Kazi Rakib Hasan, S., & Chapal, B. (2023). Cloud and Distributed Computing for Project Analytics: A Meta-Analysis of Decision-Making Performance. *International Journal of Scientific Interdisciplinary Research*, 4(4), 449–484. <https://doi.org/10.63125/x8wcj975>
- [38]. Kazi Rakib Hasan, S., & Uddin, H. M. M. (2022). Scalable AI For Project Portfolio Management: A Mixed-Methods Study Combining Distributed Computing Benchmarks. *Review of Applied Science and Technology*, 1(04), 375–410. <https://doi.org/10.63125/0kk4wf20>
- [39]. Kim, C., Mirusmonov, M., & Lee, I. (2010). An empirical examination of factors influencing the intention to use mobile payment. *Computers in Human Behavior*, 26(3), 310–322. <https://doi.org/10.1016/j.chb.2009.10.013>
- [40]. Kumar, V., Aksoy, L., Donkers, B., Venkatesan, R., Wiesel, T., & Tillmanns, S. (2010). Undervalued or overvalued customers: Capturing total customer engagement value. *Journal of Service Research*, 13(3), 297–310. <https://doi.org/10.1177/1094670510375602>
- [41]. León, C. (2021). The adoption of a mobile payment system: The user perspective. *Latin American Journal of Central Banking*, 2(4), 100042. <https://doi.org/10.1016/j.latchb.2021.100042>
- [42]. Leong, L.-Y., Hew, T.-S., Ooi, K.-B., & Wei, J. (2020). Predicting mobile wallet resistance: A two-staged structural equation modeling-artificial neural network approach. *International Journal of Information Management*, 51, 102047. <https://doi.org/10.1016/j.ijinfomgt.2019.102047>
- [43]. Liu, Z., Ben, S., & Zhang, R. (2019). Factors affecting consumers' mobile payment behavior: A meta-analysis. *Electronic Commerce Research*, 19(3), 575–601. <https://doi.org/10.1007/s10660-019-09349-4>
- [44]. Ma, C., Wu, J., Sun, H., Zhou, X., & Sun, X. (2023). Enhancing user experience in digital payments: A hybrid approach using SEM and neural networks. *Finance Research Letters*, 58, 104376. <https://doi.org/10.1016/j.frl.2023.104376>
- [45]. Mallat, N. (2007). Exploring consumer adoption of mobile payments: A qualitative study. *The Journal of Strategic Information Systems*, 16(4), 413–432. <https://doi.org/10.1016/j.jsis.2007.08.001>
- [46]. Martinez, B. M., & McAndrews, L. E. (2023). Do you take...? The effect of mobile payment solutions on use intention: An application of UTAUT2. *Journal of Marketing Analytics*, 11, 458–469. <https://doi.org/10.1057/s41270-022-00175-6>
- [47]. Md Aminul, I. (2026). A Systematic Review of AI-Driven Business Intelligence Architectures for Data-Informed Strategic Decision-Making Methods (2019–2026). *American Journal of Advanced Technology and Engineering Solutions*, 6(01), 583–621. <https://doi.org/10.63125/epnwbh30>
- [48]. Md Aminul, I., & Md Asif Ali Sheak, A. (2023). A Quantitative Assessment of Cybersecurity Frameworks for Industrial Control Systems in Critical Energy Infrastructure. *International Journal of Scientific Interdisciplinary Research*, 4(4), 336–374. <https://doi.org/10.63125/rg8mt373>
- [49]. Md Arif Uz, Z., Sharmin, S., & Md Abdur, R. (2025). Factors Influencing Behavioural Intention to Use he Innovative Open And Distance Learning Systems With The Role Of Continuance Intention. *American Journal of Scholarly Research and Innovation*, 4(01), 202–220. <https://doi.org/10.63125/pbjxp014>
- [50]. Md. Abdur, R., & Iftekhar, A. (2021). Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study. *International Journal of Business and Economics Insights*, 1(4), 70–102. <https://doi.org/10.63125/dyrpc387>
- [51]. Md. Shakhawat, H. (2025). AI-Augmented VAPT and SecureAI Controls: A Quantitative Compliance Study Under ISO 27001, ISO/IEC 42001, SWIFT CSP, and PCI DSS. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 2611–2652. <https://doi.org/10.63125/ep9s9k54>
- [52]. Md. Shakhawat, H., Taru Binte, A., & Binayan, D. (2023). A Meta-Analysis of Incident Response Frameworks for Banking Network Operations Centers in Emerging Economies. *International Journal of Scientific Interdisciplinary Research*, 4(2), 112–151. <https://doi.org/10.63125/xx3ttb58>
- [53]. Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2021). A new theoretical understanding of big data analytics capabilities in organizations: A thematic analysis. *Journal of Big Data*, 8, Article 125. <https://doi.org/10.1186/s40537-021-00543-6>
- [54]. Mikalef, P., Van de Wetering, R., Krogstie, J., & Pappas, I. O. (2023). Towards data-driven decision making: The role of analytical culture and centralization efforts. *Review of Managerial Science*, 17, 2643–2671. <https://doi.org/10.1007/s11846-023-00694-1>
- [55]. Mohammad Badrul, A., & Md. Mominul, H. (2023). Machine Learning-Based Assessment of Environmental and Public Health Risks in Sewerage Sludge Management Systems. *American Journal of Advanced Technology and Engineering Solutions*, 3(02), 33–77. <https://doi.org/10.63125/y3yfxa92>
- [56]. Mst Shurovi, A. (2025). AI-Enhanced Financial Information Systems for Real-Time Fraud Detection and Cash Flow Optimization in U.S. Logistics and Retail Sectors. *American Journal of Scholarly Research and Innovation*, 4(01), 813–855. <https://doi.org/10.63125/bjqkc150>
- [57]. Mst Shurovi, A. (2026). AI-Driven Accounts Payable and Receivable Automation for Operational Risk Mitigation in U.S. SMEs: A Systematic Review (2018–2026). *American Journal of Interdisciplinary Studies*, 7(01), 536–577. <https://doi.org/10.63125/x1yzwc45>
- [58]. Muhammad Mohiul, I., & Mohammad Badrul, A. (2022). Predictive Analytics for Optimizing Sewerage Sludge Treatment Efficiency and Resource Recovery in Dhaka City. *Journal of Sustainable Development and Policy*, 1(04), 158–200. <https://doi.org/10.63125/t9zdp458>
- [59]. Mukut Kanti, B. (2025). Lifecycle Carbon Reduction and Net Zero Pathway Modeling Using LEED, EDGE, and SBTI Frameworks in Developing Economy Industrial Buildings. *American Journal of Interdisciplinary Studies*, 6(3), 306–350. <https://doi.org/10.63125/tnneth75>

- [60]. Mukut Kanti, B., & Rony, S. (2022). Quantitative Risk Assessment and Safety Performance Benchmarking for Structural Integrity Management in Retail Supply Chain Infrastructure. *American Journal of Data Science and Analytics*, 3(12), 42-88. <https://doi.org/10.63125/n88vth90>
- [61]. Ngai, E. W. T., Hu, Y., Wong, Y. H., Chen, Y., & Sun, X. (2011). The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature. *Decision Support Systems*, 50(3), 559-569. <https://doi.org/10.1016/j.dss.2010.08.006>
- [62]. Ngai, E. W. T., Xiu, L., & Chau, D. C. K. (2009). Application of data mining techniques in customer relationship management: A literature review and classification. *Expert Systems with Applications*, 36(2), 2592-2602. <https://doi.org/10.1016/j.eswa.2008.02.021>
- [63]. Nguyen, T. T., Tran, T. N. H., Do, T. H. M., Dinh, T. K. L., Nguyen, T. U. N., & Dang, T. M. K. (2024). Digital literacy, online security behaviors and E-payment intention. *Journal of Open Innovation: Technology, Market, and Complexity*, 10(2), 100292. <https://doi.org/10.1016/j.joitmc.2024.100292>
- [64]. Oliveira, T., Thomas, M., Baptista, G., & Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Computers in Human Behavior*, 61, 404-414. <https://doi.org/10.1016/j.chb.2016.03.030>
- [65]. Patil, P. P., Tamilmani, K., Rana, N. P., & Raghavan, V. (2020). Understanding consumer adoption of mobile payment in India: Extending Meta-UTAUT model with personal innovativeness, anxiety, trust, and grievance redressal. *International Journal of Information Management*, 54, 102144. <https://doi.org/10.1016/j.ijinfomgt.2020.102144>
- [66]. Pham Thi, T. D., Pham, V. K., & Duong, N. T. (2024). Why do users adopt mobile payment? An integrated model. *Journal of the Knowledge Economy*, 15, 4364-4391. <https://doi.org/10.1007/s13132-024-02118-1>
- [67]. Popović, A., Hackney, R., Coelho, P. S., & Jaklič, J. (2012). Towards business intelligence systems success: Effects of maturity and culture on analytical decision making. *Decision Support Systems*, 54(1), 729-739. <https://doi.org/10.1016/j.dss.2012.08.017>
- [68]. Qasim, A., & Abu-Shanab, E. (2016). Drivers of mobile payment acceptance: The impact of network externalities. *Information Systems Frontiers*, 18, 1021-1034. <https://doi.org/10.1007/s10796-015-9598-6>
- [69]. Risha, A. (2026). A Comparative Study of Machine Learning Models for Predictive Business Analytics in Digital Commerce (2018–2026). *American Journal of Advanced Technology and Engineering Solutions*, 6(01), 545-582. <https://doi.org/10.63125/2hj6p796>
- [70]. Risha, A., & Kazi Mohammad Khalid, A. (2023). A Meta-Analysis of AI-Driven Geospatial Analytics for Predictive Maintenance of Critical Infrastructure in Developing Economies. *International Journal of Scientific Interdisciplinary Research*, 4(4), 375–412. <https://doi.org/10.63125/rayrex49>
- [71]. Sahi, A. M., Khalid, H., Abbas, A. F., & Khatib, S. F. A. (2021). The evolving research of customer adoption of digital payment: Learning from content and statistical analysis of the literature. *Journal of Open Innovation: Technology, Market, and Complexity*, 7(4), 230. <https://doi.org/10.3390/joitmc7040230>
- [72]. Samia Hossain, S. (2025). AI-Enhanced ERP Financial Intelligence Systems for Real-Time Business Analytics and Risk Decision Support. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 2703–2741. <https://doi.org/10.63125/t1zw3w09>
- [73]. Samia Hossain, S. (2026). A Systematic Review of AI-Driven Financial Information Systems for Budget Optimization in U.S. Public Sector Institutions (2018–2026). *American Journal of Data Science and Analytics*, 7(04), 124-166. <https://doi.org/10.63125/jgx19749>
- [74]. Samia Hossain, S., & Binayan, D. (2023). A Meta-Analysis of Forensic Accounting Techniques as Financial Risk Management Tools in Banking Services Across Emerging Economies. *Review of Applied Science and Technology*, 2(04), 352–392. <https://doi.org/10.63125/n5jgwr22>
- [75]. Samia Hossain, S., & Uddin, H. M. M. (2022). Predictive Cash Flow Forecasting Using Deep Learning and ERP Transaction Data in Mid-Market Manufacturing Firms. *International Journal of Scientific Interdisciplinary Research*, 1(01), 316–334. <https://doi.org/10.63125/mdsdab78>
- [76]. Sany, S. M. A. A. (2024). Impact of SQL-Driven Financial Data Pipelines on Audit-Readiness and Reporting Cycles in State Government Accounting. *International Journal of Scientific Interdisciplinary Research*, 5(2), 720–745. <https://doi.org/10.63125/cdaatq74>
- [77]. Sany, S. M. A. A. (2025). Impact of ERP Integration and Workflow Automation on General Ledger Accuracy and Reconciliation Efficiency in Public-Sector Finance. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 2742–2794. <https://doi.org/10.63125/jsfzhg72>
- [78]. Sany, S. M. A. A. (2026). A Quantitative Assessment of Generative AI Applications in Public-Sector Financial Reporting and Audit Preparation. *American Journal of Data Science and Analytics*, 7(05), 42-92. <https://doi.org/10.63125/k7epd298>
- [79]. Sany, S. M. A. A., & Siful, I. (2022). Zero-Trust Architecture Adoption on Financial Data Privacy in Public-Sector ERP Environments. *Review of Applied Science and Technology*, 1(04), 323–374. <https://doi.org/10.63125/j8cas279>
- [80]. Sany, S. M. A. A., & Uddin, H. M. M. (2023). Machine Learning-Based Fraud Detection and Conventional Audit Approaches in Government Deposit Processing. *American Journal of Interdisciplinary Studies*, 4(03), 250-286. <https://doi.org/10.63125/fve5zp98>
- [81]. Sebastián, M. G. d. B., Antonovica, A., & Sarmiento Guede, J. R. (2023). What are the leading factors for using Spanish peer-to-peer mobile payment platform Bizum? The applied analysis of the UTAUT2 model. *Technological Forecasting and Social Change*, 187, 122235. <https://doi.org/10.1016/j.techfore.2022.122235>

- [82]. Shamim, S., Zeng, J., Khan, Z., & Zia, N. U. (2020). Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms. *Technological Forecasting and Social Change*, 161, 120315. <https://doi.org/10.1016/j.techfore.2020.120315>
- [83]. Sharma, V., Jangir, K., Gupta, M., & Rupeika-Apoga, R. (2024). Does service quality matter in FinTech payment services? An integrated SERVQUAL and TAM approach. *International Journal of Information Management Data Insights*, 4(2), 100252. <https://doi.org/10.1016/j.jjimei.2024.100252>
- [84]. Shima Ali, S., Musomi, K., & Sonya, G. (2024). Integrated Infectious Disease Preparedness: Multilingual Health Communication Strategies for Public Health Risk Mitigation, Disease Intervention and Prevention for Culturally Diverse Population in United States. *American Journal of Data Science and Analytics*, 5(10), 01-47. <https://doi.org/10.63125/ehk4mt02>
- [85]. Shima Ali, S., Sonya, G., & Mahbubul, I. (2025). Telemedicine And Remote Patient Monitoring for Preventing Risk and Chronic Disease Management in Underserved Communities. *American Journal of Health and Medical Sciences*, 6(04), 01-42. <https://doi.org/10.63125/y0e9dc38>
- [86]. Shima Ali, S., Sonya, G., & Mahbubul, I. (2026). STI and HIV Prevention Through Public Health Digital Twins: A Framework for Personalized Prevention and Adaptive Disease Intervention. *American Journal of Scholarly Research and Innovation*, 5(01), 284-326. <https://doi.org/10.63125/rjgna882>
- [87]. Singh, N., & Sinha, N. (2020). How perceived trust mediates merchant's intention to use a mobile wallet technology. *Journal of Retailing and Consumer Services*, 52, 101894. <https://doi.org/10.1016/j.jretconser.2019.101894>
- [88]. Slade, E. L., Dwivedi, Y. K., Piercy, N. C., & Williams, M. D. (2015). Modeling consumers' adoption intentions of remote mobile payments in the United Kingdom: Extending UTAUT with innovativeness, risk, and trust. *Psychology & Marketing*, 32(8), 860-873. <https://doi.org/10.1002/mar.20823>
- [89]. Sun, Y., Liu, H., & Gao, Y. (2023). Research on customer lifetime value based on machine learning algorithms and customer relationship management analysis model. *Heliyon*, 9(2), e13384. <https://doi.org/10.1016/j.heliyon.2023.e13384>
- [90]. Talwar, S., Dhir, A., Khalil, A., Mohan, G., & Islam, A. K. M. N. (2020). Point of adoption and beyond: Initial trust and mobile-payment continuation intention. *Journal of Retailing and Consumer Services*, 55, 102086. <https://doi.org/10.1016/j.jretconser.2020.102086>
- [91]. Taru Binte, A., & Iftekhar, A. (2022). Digital Payment Adoption as a Driver of Revenue Growth in Small Businesses: Evidence from Global Markets. *American Journal of Advanced Technology and Engineering Solutions*, 2(04), 255-293. <https://doi.org/10.63125/vfvzge86>
- [92]. Teng, S., & Khong, K. W. (2021). Examining actual consumer usage of e-wallet: A case study of big data analytics. *Computers in Human Behavior*, 121, 106778. <https://doi.org/10.1016/j.chb.2021.106778>
- [93]. Uddin, H. M. M. (2025). Impact of Predictive Analytics on Sales Forecasting Accuracy in B2B Financial Services: A Quantitative Evaluation. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 2653-2702. <https://doi.org/10.63125/g9fvv860>
- [94]. Uddin, H. M. M. (2026). A Systematic Review of Artificial Intelligence-Based Customer Analytics in Personalized Digital Marketing (2019-2026). *American Journal of Data Science and Analytics*, 7(03), 295-339. <https://doi.org/10.63125/x3e0dx27>
- [95]. Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. *Journal of Marketing*, 80(6), 97-121. <https://doi.org/10.1509/jm.15.0413>
- [96]. Wu, L.-W., & Tang, Y.-C. (2022). Mobile payment in omnichannel retailing: Dynamics between trust and loyalty transfer processes. *Internet Research*, 32(6), 1783-1810. <https://doi.org/10.1108/intr-06-2021-0402>
- [97]. Yang, S., Lu, Y., Gupta, S., Cao, Y., & Zhang, R. (2012). Mobile payment services adoption across time: An empirical study of the effects of behavioral beliefs, social influences, and personal traits. *Computers in Human Behavior*, 28(1), 129-142. <https://doi.org/10.1016/j.chb.2011.08.019>
- [98]. Yuan, S., Liu, L., Su, B., & Zhang, H. (2020). Determining the antecedents of mobile payment loyalty: Cognitive and affective perspectives. *Electronic Commerce Research and Applications*, 41, 100971. <https://doi.org/10.1016/j.elerap.2020.100971>
- [99]. Zhang, L., Wang, Y., Anjum, M. A., & Mu, J. (2022). The impacts of point rewarding and exchanging on users' loyalty toward mobile payment applications: A dual channeling perspective. *Internet Research*, 32(6), 1832-1861. <https://doi.org/10.1108/intr-06-2021-0414>
- [100]. Zhang, Q., Ariffin, S. K., Richardson, C., & Wang, Y. (2023). Influencing factors of customer loyalty in mobile payment: A consumption value perspective and the role of alternative attractiveness. *Journal of Retailing and Consumer Services*, 75, 103302. <https://doi.org/10.1016/j.jretconser.2023.103302>
- [101]. Zhong, J., & Chen, T. (2023). Antecedents of mobile payment loyalty: An extended perspective of perceived value and information system success model. *Journal of Retailing and Consumer Services*, 72, 103267. <https://doi.org/10.1016/j.jretconser.2023.103267>
- [102]. Zhou, T. (2013). An empirical examination of continuance intention of mobile payment services. *Decision Support Systems*, 54(2), 1085-1091. <https://doi.org/10.1016/j.dss.2012.10.034>