Journal of
Theoretical and Applied Electronic Commerce Research

MDPI

Article

Predicting Mobile Payment Behavior Through Explainable Machine Learning and Application Usage Analysis

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Abstract: In the increasingly competitive mobile ecosystem, understanding user behavior is essential to improve targeted sales and the effectiveness of advertising. With the widespread adoption of smartphones and the increasing variety of mobile applications, predicting user behavior has become more complex. This study presents a comprehensive framework for predicting mobile payment behavior by integrating demographic, situational, and behavioral factors, focusing on patterns in mobile application usage. To address the complexity of the data, we use a combination of machine-learning models, including extreme gradient boosting, light gradient boosting machine, and CatBoost, along with Shapley additive explanations (SHAP) to improve interpretability. An analysis of extensive panel data from Korean Android users reveals that incorporating application usage behavior in such models considerably improves the accuracy of mobile payment predictions. The study identifies key predictors of payment behavior, indicated by high Shapley values, such as using social networking services (e.g., KakaoTalk and Instagram), media applications (e.g., YouTube), and financial and membership applications (e.g., Toss and OK Cashbag). Moreover, the results of the SHAP force analysis reveal the individual session-level drivers of mobile purchases. These findings advance the literature on mobile payment prediction and offer practical insights for improving targeted marketing strategies by identifying key behavioral drivers of mobile transactions.

Keywords: mobile payment; regression; classification; targeting; explainable machine learning; social network service

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Received: 10 March 2025
Revised: 27 May 2025
Accepted: 28 May 2025
Published: 30 May 2025

Citation: Lee, M.; Choi, I.; Kim, W.-C. Predicting Mobile Payment Behavior Through Explainable Machine Learning and Application Usage Analysis. *J. Theor. Appl. Electron. Commer. Res.* **2025**, *20*, 117. https://doi.org/10.3390/jtaer20020117

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1. Introduction

The advent of technological advancements has broadened the capabilities of mobile devices, enabling a wide range of mobile financial services including bill payments, account transfers, person-to-person transactions, offline payments at retail stores, and mobile payments for purchasing goods and services, along with additional features such as location-based services, mobile marketing, ticketing, discount applications, and virtual coupons [1]. With an expanding e-commerce market and the increased ubiquity of mobile devices, shopping via these devices has become a part of everyday life, leading to mobile payments becoming the preferred transaction method for many consumers [2]. Thus, understanding and predicting users' mobile payment behavior has become essential for businesses seeking to increase customer engagement, enhance service personalization, and increase revenue through targeted marketing strategies. However, despite the importance of mobile payments, few studies have systematically examined the direct predictors of

mobile shopping payment behaviors, especially the relationship between application usage and payment activities. This limitation is primarily attributable to limited data.

While previous studies have examined the antecedents of online shopping payments [3,4] and explored the factors influencing consumers' intention to adopt mobile payments [5–8], few directly investigate the predictors of mobile shopping payments and their connection to application usage behavior by analyzing proprietary mobile device usage data. Cheng and Fu [3] analyzed key factors affecting online shopping behaviors, emphasizing variables such as convenience and perceived risk; however, they did not specifically address mobile environments. Likewise, Yu and Wu [8] applied the theory of reasoned action to understand Internet shopping behavior, focusing on attitudinal and normative influences, but their analysis did not extend to mobile devices. Research on the adoption of mobile payments has further advanced with the study by Hongxia et al. [5], who identified drivers and barriers specific to the Chinese mobile payment market, highlighting technological and contextual factors. Meanwhile, Liébana-Cabanillas et al. [6] used a hybrid structural equation modeling and neural network approach to predict mobile payment acceptance; this approach provided a more sophisticated analytical framework but focused on acceptance rather than actual payment behavior. Similarly, Mahran and Enaba [7] investigated the factors affecting consumers' intentions to use mobile payment services, emphasizing the importance of trust and perceived ease of use; however, their study mainly captured behavioral intentions rather than actual usage patterns. Motivated by this research gap, this study aims to address the following questions:

(1) Can diverse mobile application usage behavior variables improve the accuracy of predicting mobile payment behavior?
(2) Which mobile applications most significantly influence consumers' mobile payment behavior?
(3) How do hedonic motivations (e.g., YouTube use) and social connectivity (e.g., social networking service use) relate to mobile payment usage?

To address these questions, we propose a comprehensive predictive framework that integrates demographic, situational, and behavioral factors, focusing on application usage behavior. We use nonlinear machine-learning (ML) models—extreme gradient boosting (XGBoost), light gradient boosting machine (LightGBM), and category boosting (CatBoost)—combined with SHAP to improve the predictive accuracy of the framework while providing a transparent interpretation of the model outputs. Our empirical analysis is based on proprietary panel data from a leading consumer research firm in South Korea, consisting of detailed application usage logs and demographic data from 500 Android users. This dataset allows us to capture complex, real-world mobile usage patterns and analyze their impact on payment activities.

We analyzed the data to evaluate the predictive power of various factors in a mobile payment prediction model. The average daily smartphone usage worldwide is 3 h 43 min [9], which includes frequent engagement with mobile applications and transitions between the applications. To effectively capture the complexity of application usage behavior, we applied XGBoost, LightGBM, and CatBoost. Additionally, we incorporated the SHAP to clarify the key factors driving each model's predictive performance. These methods effectively overcome the limitations of traditional logistic regression, such as its inability to capture complex nonlinear relationships and variable interactions and its poor performance when applied to sparse or high-dimensional data.

We observed an increase in the model's overall predictive power after including consumer application usage data, notably driven by YouTube usage history, which had a greater impact on the model's predictive performance than data from other applications, followed by SNSs such as KakaoTalk—Korea's most popular messaging application—and Instagram. The findings suggest that a substantial portion of mobile payments are affected by the connectivity of social platforms, particularly in user networks. Additionally, financial management applications such as Toss and OK Cashbag demonstrated a relatively strong influence on mobile payment behavior, attributable to common consumer behavior patterns of checking account balances or accumulating points before making mobile payments.

By identifying and quantifying the key drivers of mobile payment behavior, this study contributes to the literature in several ways. First, it deepens the understanding of behavioral predictors in mobile commerce. Second, it highlights the practical value of employing explainable ML models in consumer behavior research. Third, it provides actionable insights for businesses seeking to optimize marketing strategies and payment service designs. By accurately predicting users' mobile payment behavior, the proposed model can improve the efficiency of various marketing efforts and reveal new revenue opportunities, such as in-application advertisements, native ads, and cross-selling.

2. Literature Review and Hypotheses Development

2.1. Determinants of Mobile Payment Behavior

This section reviews the literature on the predictors of mobile payments, focusing on demographic, situational, and behavioral factors, to establish a theoretical foundation for the study. In addition, we examine how SNS use and media consumption behaviors, particularly YouTube usage, impact mobile payment behavior. This review identifies research gaps and provides the basis for developing our hypotheses.

To explore the determinants of mobile payment behavior among mobile device users, our proposed framework integrates demographic, situational, and behavioral factors [10–13]. Users' attitudes and motivations toward mobile payments correlate with demographic characteristics such as gender, age, and geographical location [8,14]. Bigne et al. [14] observed that younger consumers as well as those frequently engaging in Internet shopping are more likely to engage in mobile buying behavior, underscoring the importance of digital literacy and experience. Likewise, Wang et al. [13] revealed that mobile shopping often leads to an increased frequency of impulse purchases, with younger and urban consumers being particularly responsive, suggesting that demographic and behavioral factors are key factors for adopting mobile payment behavior. Moreover, users' attitudes toward mobile payments are strongly influenced by a range of psychological and environmental situational factors. Contextual factors, such as users' emotional state, physical surroundings, and social environment, affect their mobile usage experience and purchasing behavior [15,16]. Korhonen et al. [15] emphasized that users' experiences with mobile devices vary depending on contextual aspects such as location and social setting, whereas Li et al. [16] highlighted how emotional and sensory experiences in mobile commerce environments enhance consumer engagement. Additionally, Pal et al. [17] demonstrated that convenience and perceived barriers in local contexts can encourage or hinder the adoption of mobile payments, especially in developing countries. Regarding environmental factors, situational conditions such as the day of the week, time of day, and current weather influence mobile payment behavior. For example, De La Rosa and Tully [18] found that the timing of payments (e.g., frequency in a pay cycle) affects consumers' spending levels and their perceptions of financial well-being. Meanwhile, Murray et al. [19] reported that pleasant weather conditions encourage increased consumer spending, and Sandqvist and

Siliverstovs [20] demonstrated that unusual weather patterns (e.g., extreme cold or heat) negatively affect overall spending.

Behavioral factors, particularly previous mobile usage behavior, also play an important role in shaping mobile payment decisions. A user's device usage history and application interaction patterns are important behavioral predictors of mobile payment behavior [21–23]. Dinner et al. [21] found that active engagement with branded mobile applications considerably increases the likelihood of purchases, emphasizing the mediating role of sustained application usage between application adoption and purchasing behavior. Similarly, Huang et al. [22] performed a large-scale, cross-platform study, finding that consumers' browsing and interaction patterns in mobile shopping applications can be used to predict their purchase decisions. This finding indicates that subtle usage signals, such as dwell time and revisit frequency, are key indicators. Zeng et al. [23] further highlighted that when integrated with recommendation system data, user behavior patterns during peak shopping periods, such as shopping festivals, can effectively predict purchase outcomes. The duration of application usage is also a key factor in predicting mobile user behavior [12,24]. Liao et al. [24] demonstrated that analyzing historical application usage sequences allows for accurately predicting future application engagement, implying that usage duration and frequency and application transition patterns collectively provide strong predictive signals. Shin et al. [12] expanded these findings by demonstrating that application usage patterns are not random but can be modeled to predict future behavior, stressing contextual factors such as the time of day and user habits. Engaging with mobile applications can serve as an informational cue encouraging continued application usage and, in some instances, directly triggers mobile payment initiation in an application. For example, interacting with review applications, SNSs, or product comparison tools may guide users toward purchase decisions through mobile payments. Based on this discussion, we propose the following hypothesis:

H1: *The inclusion of mobile application usage variables significantly improves the performance of mobile payment prediction models.*

Despite these findings, few studies systematically combine demographic, situational, and behavioral factors into a single predictive framework. Furthermore, although the predictive value of users' general application usage has been recognized, there has been limited focus on the specific influence of SNSs and media consumption platforms, such as YouTube, as direct drivers of payment behavior. This gap represents a critical area that this study aims to address.

2.2. Impact of SNSs on Users' Mobile Payment Behavior

In this section, we examine how engaging with SNSs influences mobile payment behavior and build a theoretical foundation on the social support theory. While few studies directly explore the impact of SNS usage on mobile payment behavior, we interpret this relationship through the perspective of the social support theory. "Social support" refers to an individual's perception of receiving physical and psychological assistance, responses, and care from other members in a group or organization [25]. In the context of an SNS, the provision of social support has been recognized as crucial for fostering interpersonal connections and enhancing well-being in organizational settings [26]. In an SNS, individuals perceive other contributors as demonstrating care and helpfulness by providing valuable life- or product-related information [27]. Frequent exchanges of supportive information among users strengthen their bonds of friendship and trust, thereby increasing the likelihood of engaging in commercial activities, such as mobile payments [28]. Despite this potential, previous research has not sufficiently

investigated the direct relationship between SNS use and mobile payment behavior, revealing a clear gap that this study seeks to address. Based on this discussion, we propose the following hypothesis:

H2: *The usage time of SNSs is a key determinant of mobile users' purchasing behavior.*

2.3. Impact of YouTube Viewing on Mobile Users' Payment Behavior

Along with the examination of the use of SNSs on mobile payment behavior, we consider media psychology theories and explore YouTube usage to clarify the role of hedonic influences on payment decisions. Media psychology is a key field studying how individuals perceive, interpret, respond to, and engage with different types of media [29,30]. Many psychological studies on media align with the well-established "media effects" paradigm, suggesting that specific media can directly shape individuals' attitudes, emotions, and behaviors [31]. From a media psychology perspective, video-based social media platforms such as YouTube may induce more immediate psychological changes in mobile consumers [32] than other forms of media. As the leading video-sharing platform in the world, YouTube serves as a curator and a distributor of videos by collecting, endorsing, and delivering content to its users [33]. It provides various tools such as search functionality, social engagement, real-time compilations of trending videos, and automated recommendations [34]. Social media messages can stimulate the consumption of targeted products [35,36]. Over the past decade, YouTube has developed into a key marketing platform used by social media influencers for product promotion [32]. When using video-based social networking applications, consumers engage in a sequential viewing process while making a series of decisions where each choice follows the previous one. For example, a user may choose to watch a music video, a video related to food or beauty product promotions, or a gaming video; this choice influences the content that the platform then presents to the user. Due to this sequential structure, earlier decisions or viewing experiences can influence subsequent preferences in a consumption sequence [37,38]. As a video-based SNS offers hedonic experiences characterized by enjoyment, fun, and excitement [39,40], consumers are likely to pursue a hedonic goal when watching videos. Thus, they may engage in mobile transactions to enhance their enjoyment while using mobile devices [41]. However, despite these indications, few empirical studies have directly connected YouTube usage patterns with mobile payment behavior, revealing a considerable gap that our research aims to address. Based on this discussion, we propose the following hypothesis:

H3: *The usage time of YouTube is a key determinant of mobile users' purchasing behavior.*

Figure 1 presents the conceptual framework for these factors. As previously discussed, the inclusion of behavioral variables is based on the literature on informational cues and signaling effects in the mobile device usage context. Our model encompasses the influence of SNS apps, grounded in the social support theory, and the role of YouTube usage, which is informed by media psychology and effects theory.

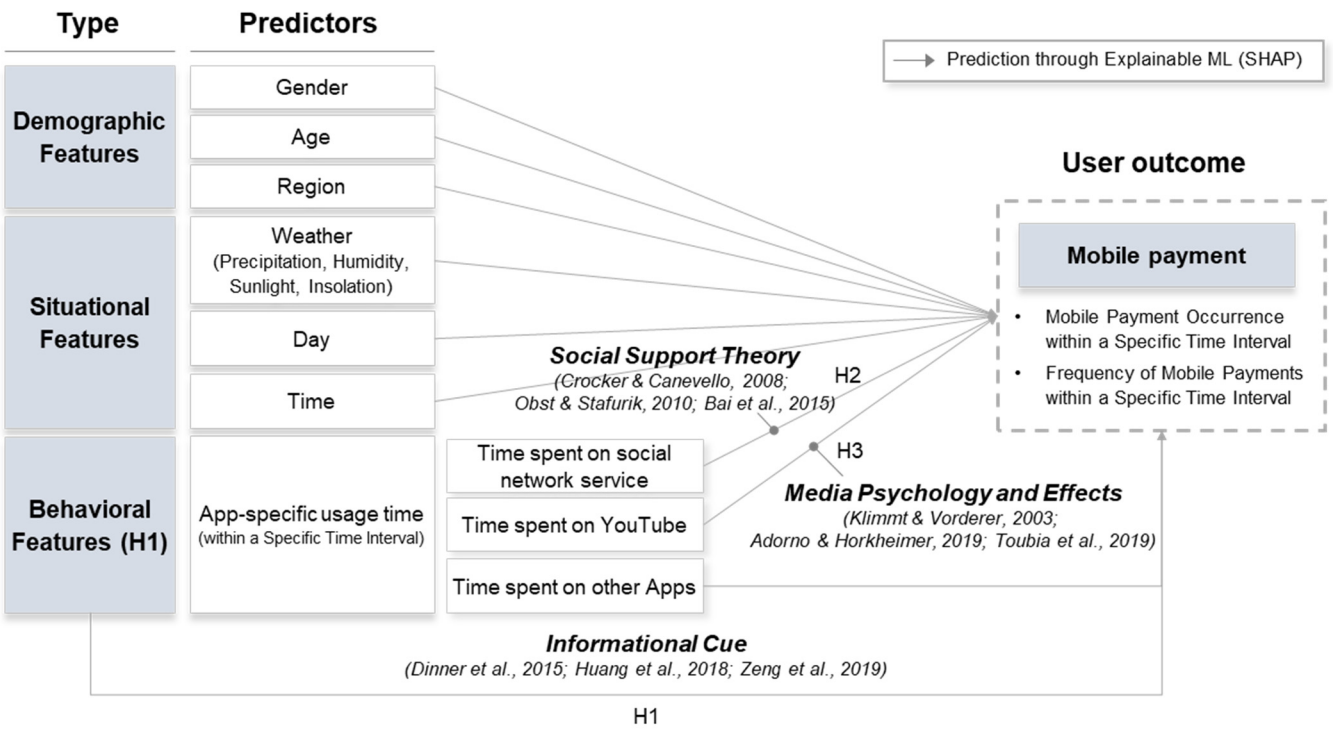


Figure 1. Conceptual framework of the study (Referred from [21–23,25–27,29–31]).

3. Method

3.1. Data and Samples

We obtained data on mobile application usage history from a major marketing research firm in South Korea. The dataset captures device usage behaviors, such as application launches, collected from a random sample of 500 Android smartphone users drawn from a master panel designed to represent the national population in terms of region, gender, age, occupation, education level, and income distribution. The observation period spanned from 1 October 2019 to 15 December 2019. The dataset consisted of 8,434,077 observations, each representing a single application launch. We analyzed usage data of 776 applications, excluding those below the 10th percentile in usage frequency. The demographic information covered gender, age, and geographic region of device use. To incorporate situational factors, we gathered temperature, humidity, precipitation, sunlight, and insolation data at various times of day from the Korea Meteorological Administration's website. We then organized all observations into panel data indexed by user and time of day, linking them with the demographic and weather information. Accordingly, except for some demographic variables derived from surveys (e.g., gender and region), all independent and target variables are quantitative and based on user-level observational and collected data. For feature engineering, we used categorical variables, including gender, region, and day, directly in CatBoost, which supports categorical inputs. Meanwhile, for XGBoost and LightGBM, we applied label encoding to convert the categorical variables into numerical forms. Continuous variables, such as time of day, were treated as numeric features without additional encoding. As all application usage features denoted usage time in seconds as continuous numeric variables, no label encoding was required. We scaled the continuous variables using StandardScaler before inputting them into XGBoost and LightGBM, whereas CatBoost processed them directly. This preprocessing step ensured model compatibility and improved reproducibility.

To identify mobile payment activity, we coded whether users activated specific mobile payment applications or commerce-linked payment applications, such as 11pay (for the shopping mall 11th Street), Coupay (for the shopping mall Coupang), Paynow, and K-pay, on their smartphones at particular times of day. This method allowed for more accurate identification of users' purchase intentions compared with simply tracking the use of shopping applications. Additionally, we created variables indicating the applications users were using at the chosen time and for how long, measured in seconds. In the classification analysis, the dependent variable was whether a payment application was launched at a specific time of day; in the regression analysis, the dependent variable was the frequency of payment application launches at the specified time. Table 1 presents a description of the variables employed in the proposed model.

Table 1. Description of the variables.

Variable	Variable Type	Operational Definition (Measurement)
		Target Variables
Mobile payment occurrence	Binary	Whether a mobile payment occurred within a specific time interval during the day
Mobile payment frequency	Numerical	Number of mobile payments made within a specific time interval during the day
		Demographic Features
Gender	Categorical	Gender of the smartphone user
Age	Numerical	Age of the smartphone user, measured in years
Region	Categorical	Residential region of the smartphone user
		Situational Features
Weather	Numerical	Weather at the time of observation, including precipitation, humidity, sunlight, and insolation variables
Day	Categorical	Day of the week on which the observation was made
Time	Numerical	Specific time of day when the observation was made
		Behavioral Features
Time spent on SNSs	Numerical	Total time (in seconds) spent using applications categorized as SNSs during a specific time interval
Time spent on YouTube	Numerical	Total time (in seconds) spent using the YouTube application during a specific time interval
Time spent on other applications	Numerical	Total time (in seconds) spent using other apps (excluding SNSs and YouTube) during a specific time interval

3.2. Predictive Algorithms and Explainable ML Techniques

ML, a subfield of artificial intelligence (AI), refers to computational methods allowing systems to improve their performance by learning from sample data (training data) or prior experience. It enables the performance of prediction and decision-making tasks without explicitly programmed instructions. This study examines how mobile application usage behavior can help predict mobile payments by combining SHAP, an explainable ML technique, with established classification and regression models—XGBoost, LightGBM, and CatBoost. These models were chosen because of their ability to efficiently manage structured, high-dimensional behavioral data while balancing predictive accuracy, computational efficiency, and interpretability. Compared with deep-learning models, which typically require very large datasets and tend to produce black-box results, gradient-boosting models are better suited for situations with moderate sample sizes where model transparency is essential for practical applications.

We aimed to validate the performance of well-established ML methods, acknowledging that while they may not always deliver cutting-edge performance, they provide a balance of predictability, interpretability, and practical applicability across various settings. To avoid overfitting and ensure that the models generalize well, we applied a fivefold

cross-validation strategy during training and evaluation. The dataset was randomly split into five equal parts, with four parts used for training and one part used for validation. This process was repeated five times, ensuring that each part served once as the validation set and that the performance metrics were averaged over all iterations. This systematic cross-validation approach reduced the likelihood of overfitting to particular data subsets and yielded more reliable estimates of the models' predictive performance for unseen data. We applied this uniform validation framework across all models (XGBoost, LightGBM, and CatBoost), ensuring a fair comparison between the algorithms. This rigorous approach reinforces the validity of our findings, particularly the demonstration of improved predictive performance resulting from the inclusion of application usage features.

To enhance interpretability, we incorporated SHAP, which offers consistent and theoretically sound measures of feature importance at the global and local levels. This integrated methodological approach, which combines robust gradient-boosting models with SHAP-based interpretation, ensures that our results are statistically predictive and actionable in real-world digital commerce applications. This approach bridges the gap between predictive accuracy and explanatory insight, effectively addressing a key challenge in behavioral analytics research.

All analyses were conducted on a workstation equipped with an AMD Ryzen 5 7500F (Advanced Micro Devices, Inc., Santa Clara, CA, USA) 6-Core Processor (3.70 GHz) and 64 GB of RAM operating on a 64-bit Windows system. The computational environment was based on Python 3.11.9. SHAP values were computed using the Python SHAP package.

3.2.1. XGBoost

XGBoost is an ensemble learning algorithm based on the principle of gradient boosting [42,43]. It builds a strong predictive model by sequentially adding weak learners—usually decision trees—that correct residual errors of preceding models. Known for its scalability, regularization-based robustness against overfitting, and high computational efficiency, XGBoost is well-suited for managing large, complex behavioral datasets. The predicted outcome for a sample i is the sum of the predictions from K trees:

$$\hat{y}_{\mathrm{i}} = \sum_{\mathrm{k}=1}^{\mathrm{K}} f_k(x_{\mathrm{i}}),\ f_{\mathrm{k}} \in \mathcal{F}, \tag{1}$$

where $\mathcal{F}$ denotes the functional space of all possible classification and regression trees, and f_{k} represents the prediction from the k-th tree using variables x_{i} described in Table 1. The target variables are mobile payment behavior variables and the predictors include demographic, situational, and behavioral features. The mathematical formulation of the objective function used during training was presented by Chen and Guestrin [42] (for details, refer to Appendix A.1). In particular, the regularization term in this approach is essential for preventing overfitting, particularly when modeling complex and high-dimensional behavioral interactions, such as those observed in mobile application usage data.

3.2.2. LightGBM

LightGBM, developed by Ke et al. [44], is a gradient boosting framework designed to improve training speed and reduce memory consumption without sacrificing predictive accuracy, and it has been widely used in various areas [45]. It introduces two key innovative functions—gradient-based one-sided sampling, which selects a subset of data points with large gradients to focus on harder-to-predict samples, and exclusive feature bundling, which combines mutually exclusive features to reduce dimensionality. LightGBM's unique feature is its leaf-wise tree growth strategy. Unlike traditional boosting methods that grow trees level by level, LightGBM expands the leaf with the greatest loss reduction, resulting in

trees that are deeper and more accurate. A full mathematical description of the LightGBM prediction function is provided in Appendix A.2.

3.2.3. CatBoost

CatBoost, introduced by Prokhorenkova et al. [46], is a gradient boosting algorithm designed specifically for datasets with numerous categorical features. A key innovation of CatBoost is its use of "ordered boosting" and "ordered target statistics"; these techniques reduce prediction bias and prevent target leakage—an issue commonly encountered in traditional categorical encoding methods. CatBoost iteratively updates its prediction function as follows:

$$F^{t}(x) = F^{t-1}(x) + \alpha h^{t}(x), \quad (2)$$

where $F^{t}(x)$ is a predictive outcome of the input variable x at iteration t; $h^{t}(x)$ is the base learner selected at iteration t; and α denotes the learning rate. The mathematical formulation of the expected loss during training and encoding of categorical variables using smooth target statistics was presented by Prokhorenkova et al. [46] (for details, refer to Appendix A.3).

3.2.4. SHAP

ML has great potential to facilitate the prediction of shopping payments based on mobile application usage behavior, mainly due to its ability to handle complex, nonlinear relationships in user data. However, the need for researchers to explain their predictions often hinders the adoption of ML. To address this challenge, Lundberg and Lee introduced the SHAP method for interpreting predictions across various ML algorithms [47]. SHAP helps users understand complex model predictions, increases transparency, and builds trust by clearly explaining how specific predictions are generated [48].

The basis of this concept, the Shapley value, was originally developed by the American economist Lloyd Shapley and is based on game theory [49]. It has gained prominence as an AI technique to explain predictions for specific inputs by assessing the contribution of each feature. Through game theory, the average Shapley values can be determined by averaging the conditional expected values for each data column as follows:

$$\Phi_{i} = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(M-|S|-1)!}{M!} [f_{x}(S \cup \{i\}) - f_{x}(S)], \quad (3)$$

where N denotes the set of all input features; M is the total number of features; and S refers to any subset of features that does not include i. The marginal contribution of feature i is averaged over all possible permutations.

Although directly calculating Shapley values is computationally expensive, TreeSHAP—an optimized algorithm introduced by Lundberg et al. [50]—facilitates the efficient and exact calculation of SHAP values for tree-based models such as XGBoost, LightGBM, and CatBoost. By reducing the computational complexity from exponential to polynomial time, TreeSHAP makes interpreting complex models feasible, even with large datasets. We calculated the SHAP values for each feature across all observations and used the mean absolute SHAP (MAS) values to evaluate the global importance of each feature as follows:

$$I_{j} = \frac{1}{N} \sum_{i=1}^{N} \left| \phi_{j}^{(i)} \right| \quad (4)$$

3.2.5. Performance Metrics of the Classification Problem

We also assessed the correspondence between the predicted and the actual values using a confusion matrix derived from the classification results. Generally, a confusion matrix is used to verify the accuracy of predicted values against actual outcomes. We

applied a confusion matrix to analyze the extent of users' engagement with mobile payment applications. Figure 2 depicts the confusion matrix and Table 2 summarizes the evaluation metrics based on the matrix.

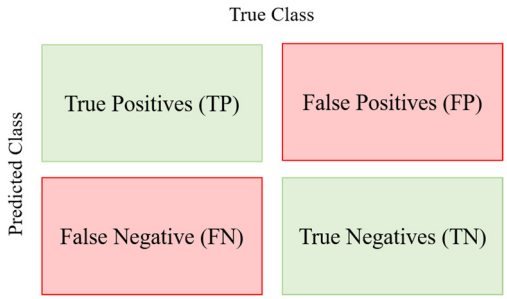


Figure 2. Confusion matrix.

Table 2. Performance metrics of the classification models.

Metric	Definition
Accuracy	$\frac{TP+TN}{P+N}$
Balanced Accuracy	$\frac{TP/P+TN/N}{2}$
Cohen's Kappa Coefficient	$\frac{2\times(TP\times TN-FN\times FP)}{(TP+FP)\times(FP+TN)+(TP+FN)\times(FN+TN)}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F1 Score	$\frac{2TP}{2TP+FP+FN}$
F-Beta Score	$\frac{(1+\beta^2)\times Precision\times Recall}{\beta^2\times Precision+Recall}$, where β represents the ratio of recall importance to precision importance.
Hamming Loss	$\frac{1}{n_{samples}*n_{labels}}\sum_{i=0}^{n_{samples}-1}\sum_{j=0}^{n_{labels}-1}1\left(\hat{y}_{i,j}\neq y_{i,j}\right)$, where $\hat{y}_{i,j}$ is the predicted value for the *j*-th label of a given sample i; $y_{i,j}$ is the corresponding true value; $n_{samples}$ is the number of samples; n_{labels} is the number of labels, which equals 2 in this study; and 1(●) is the indicator function.

4. Results

Table 3 presents the performance comparison of the prediction models. Incorporating users' application usage behavior variables in the mobile payment prediction model (Table 3 (2)) resulted in considerably higher predictive power compared to when these variables were not included (Table 3 (1)). Prediction models that did not include users' application usage data revealed only moderate performance, with an accuracy rate of approximately 50%. However, when behavioral variables were included, all the models demonstrated a substantial improvement, reaching up to 86.9% accuracy.

Table 3. Performance comparison of the mobile transaction prediction models.

	Accuracy	Balanced Accuracy	F1 Score	F-Beta Score (0.5)	F-Beta Score (2)	Jaccard Score	Cohen-Kappa Score	Precision	Recall	Hamming Loss
(1) When users' application usage information is not incorporated										
XGBoost	0.507344	0.507333	0.507021	0.507142	0.507131	0.351023	0.014666	0.507188	0.532718	0.492656
LightGBM	0.513009	0.51299	0.512016	0.512415	0.512355	0.364284	0.025981	0.512129	0.557886	0.486991
CatBoost	0.522661	0.522656	0.522592	0.522621	0.522614	0.358974	0.045312	0.522345	0.534396	0.477339
(2) When users' application usage history information is incorporated										
XGBoost	0.826479	0.826406	0.821066	0.843314	0.818323	0.742448	0.652908	0.742448	1.000000	0.173521
LightGBM	0.779689	0.779602	0.769629	0.799069	0.767564	0.69172	0.559302	0.697454	0.988255	0.220311
CatBoost	0.869282	0.869228	0.866995	0.880469	0.864773	0.792817	0.738536	0.792817	1.000000	0.130718

Tables 4 and 5 present the classification and regression analysis results, respectively, for mobile payment adoption among smartphone users, using the previously mentioned machine-learning models. The top 10 predictive factors, ranked by their MAS values, are presented in these tables. The results demonstrate how detailed components—comprising the demographic, situational, and behavioral factors that serve as predictors of mobile payment usage—contribute to the models' predictive performance, as demonstrated through their MAS. SNSs such as KakaoTalk (Rank 1; MAS = 0.109212 when using XGBoost) ranked among the top three, thus supporting H2; YouTube (Rank 4; MAS = 0.076053 when using XGBoost) also achieved a high position in the top five, thus supporting H3 (Table 4). Instagram (Rank 10; MAS = 0.034390 when using XGBoost) also secured a spot among the top ten. These findings are consistent with previous research emphasizing that hedonic motivations and social connectivity can drive purchase behavior [30,39,40,51]. We infer that mobile payment usage is strongly influenced not only by direct financial need but also by entertainment and social engagement behaviors. Thus, increased usage time of social media applications (e.g., KakaoTalk) and video platforms (e.g., YouTube) is associated with a higher likelihood of mobile payment behavior.

Table 4. MAS values in the classification models.

Rank	XGBoost		LightGBM		CatBoost	
	App	MAS	App	MAS	App	MAS
1	KakaoTalk	0.109212	KakaoTalk	0.133905	KakaoTalk	0.142688
2	Age	0.093692	Age	0.126247	SMS/MMS	0.106602
3	SMS/MMS	0.080585	SMS/MMS	0.106662	YouTube	0.097857
4	YouTube	0.076053	Google Play Store	0.094762	Google Play Store	0.092699
5	Google Play Store	0.075813	YouTube	0.093545	Gallery	0.079983
6	Gallery	0.060954	Gallery	0.079825	NAVER	0.071494
7	NAVER	0.056387	NAVER	0.074961	Internet (Google Chrome)	0.057376
8	Internet (Google Chrome)	0.044601	Sunlight	0.061104	Age	0.056742
9	Internet (Android Browser)	0.040527	Internet (Google Chrome)	0.060246	Internet (Android Browser)	0.049429
10	Instagram	0.034390	Internet (Android Browser)	0.055109	Instagram	0.044512

Table 5. MAS values in the regression model.

Rank	XGBoost		LightGBM		CatBoost	
	App	MAS	App	MAS	App	MAS
1	KakaoTalk	0.167031	KakaoTalk	0.187107	KakaoTalk	0.200396
2	SMS/MMS	0.131609	SMS/MMS	0.159697	SMS/MMS	0.161679
3	YouTube	0.107573	Gallery	0.126637	YouTube	0.132160
4	Gallery	0.107385	YouTube	0.123747	Gallery	0.130083
5	Age	0.094372	Age	0.117732	Google Play Store	0.123630
6	NAVER	0.082575	NAVER	0.102833	NAVER	0.099726
7	Google Chrome	0.072698	Google Chrome	0.09045	Google Chrome	0.088613
8	Instagram	0.053221	Instagram	0.071258	Internet (Android Browser)	0.072147
9	Toss	0.049509	OK Cashbag	0.068063	Instagram	0.066184
10	OK Cashbag	0.049188	Toss	0.066205	OK Cashbag	0.063808

In addition to SNSs, the use of gallery applications, web browsers, such as Google Chrome (Rank 8; MAS = 0.044601 when using XGBoost), and search portal applications, such as Naver (Rank 7; MAS = 0.056387 when using XGBoost), is associated with an information exploration process that precedes mobile payments. This pattern reflects users' tendency to search for product information or compare options before completing a transaction, which is consistent with prior findings by Huang et al. [22], who noted that browsing behaviors predict purchase outcomes. Table 5 presents the predictive strength of financial management applications such as Toss (Rank 9; MAS = 0.049509 when using XGBoost) and loyalty-based membership applications such as OK Cashbag (Rank 10; MAS = 0.049188 when using XGBoost). Both types of applications rank among the top ten factors affecting mobile payment behavior. These results indicate that consumers often check account balances or manage rewards and loyalty points before making mobile payments, aligning with the behavioral patterns reported by Zeng et al. [23]. Thus, increased usage time of financial management and loyalty-based membership applications is associated with a higher likelihood of engaging in mobile payment behavior.

Additionally, in the classification model (Table 4), the demographic factor of age ranked 2nd while the regional variable ranked 14th. Meanwhile, in the regression model, age ranked 5th while the regional variable ranked 17th. These results indicate that, alongside behavioral factors, demographic factors contribute to predicting mobile payment usage. The findings are consistent with those of Bigne et al. [14] and Wang et al. [13], who emphasized that younger, more digitally savvy consumers tend to exhibit higher engagement in mobile commerce. Younger users tend to show a higher propensity to engage in mobile payment behavior. Furthermore, the high ranking of the sunlight variable implies that people are more likely to make purchases during the day rather than after sunset. Figure 3 depicts the total number of application launches per hour for all users. The data support the finding that sunlight is a strong predictor of mobile purchase behavior. Peaks in payment activity were observed at around midday and immediately after regular working hours. This finding implies that time may contribute to predicting purchase behavior. This situational factor supports previous findings by De La Rosa and Tully [18], who noted that temporal variables considerably influence consumer spending behavior. Overall, the results validate the exploratory hypotheses, indicating that behavioral factors, hedonic media usage, social engagement, and situational conditions contribute considerably to mobile payment behavior.

One of the distinctive advantages of the SHAP method is its ability to provide local explanations at the user or session level. To verify whether the factors discussed earlier have an impact at the session level, we examined the SHAP force plots, as illustrated in Figure 4. In these plots, the red and blue arrows represent the contributions of individual

variables to the predicted outcome; the red arrows indicate positive effects and the blue arrows indicate negative effects. The point where the arrows converge corresponds to the final predicted value for a specific observation, indicated by a gray marker. Additionally, the *y*-axis includes a second gray marker representing the overall mean of the dependent variable across all observations, serving as a baseline prediction. Sequential deviations from this baseline to the final prediction reflect the cumulative impact of individual variables, which either increase or decrease the predicted outcome.

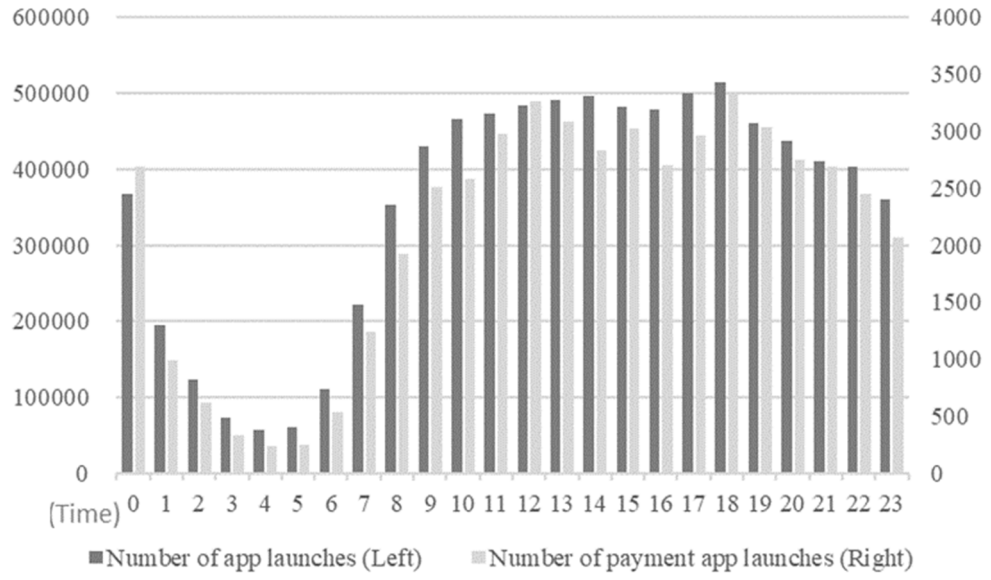
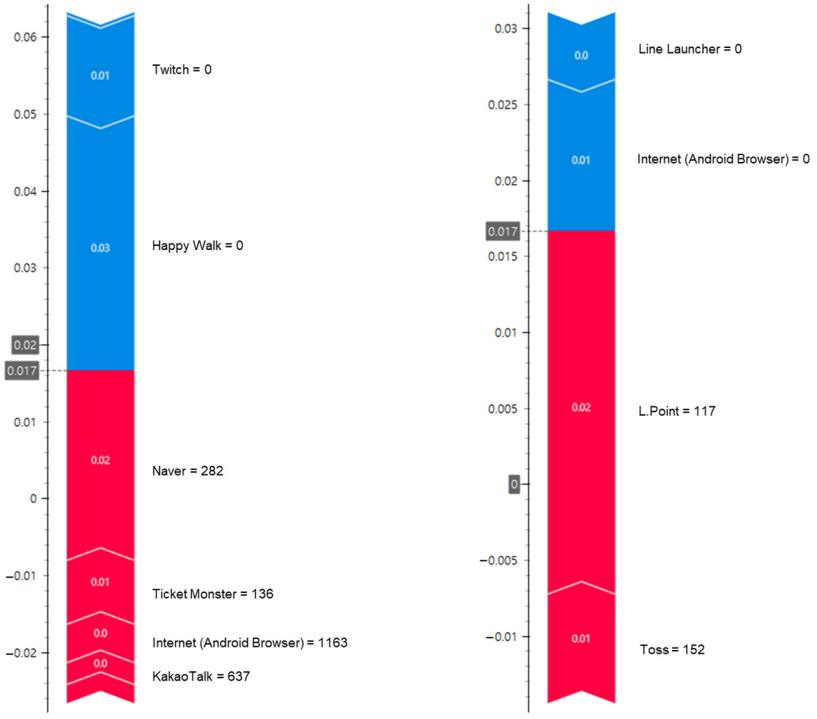


Figure 3. Frequency of application launches at different times.



Note: the red arrows indicate positive effects and the blue arrows indicate negative effects.

Figure 4. Interpretation of the two predictions.

5. Discussion

We investigated the determinants of mobile payment behavior using explainable ML methods. In addition to demographic and situational factors that are widely discussed in the literature, this study identified behavioral factors predicting mobile payment behavior. Given the complexity of the mobile application usage patterns studied, we used nonlinear ML-based regression and classification methods. Furthermore, we employed the SHAP method, an explainable ML approach, to assess the contribution of each factor to the predictive performance. Thus, we derived several key implications for mobile payment prediction.

5.1. Theoretical Implications

We employed an integrated framework related to mobile payment behavior to identify its determinants and presented empirical evidence of the psychological influence of SNSs and YouTube on mobile payments, grounded in the social support and media psychology theories. This novel approach employs explainable ML techniques to reveal application- and session-level influences, which have been difficult to identify due to the complexity of mobile usage behavior. By applying a novel ML approach within the context of mobile commerce, we find the following.

First, incorporating application-specific usage time, a behavioral variable, into ML models significantly improved the models' accuracy, thereby providing empirical support for H1. This finding highlights the critical role of mobile application usage behavior in predicting payment actions, which surpasses the predictive power of traditional demographic and situational variables. These results are consistent with those of previous studies that emphasize the importance of informational cues derived from mobile usage patterns. Specifically, mobile users are often exposed to motivational or triggering cues through their interactions with various applications. Thus, integrating application usage data into predictive models enables a more accurate understanding and prediction of users' mobile payment behavior.

Second, we assessed the contributions of individual mobile application usage to the prediction of mobile payment behavior. Consistent with prior research, we found that SNS applications usage significantly influenced mobile payment decisions (KakaoTalk: MAS = 0.109212; Instagram: MAS = 0.034390), thereby providing empirical support for H2. This finding is consistent with the social support theory, which posits that mobile users acquire valuable life- and product-related information through SNS platforms, thereby influencing commercial behaviors such as mobile transactions. Moreover, YouTube usage was found to be a significant predictor of mobile payment behavior (MAS = 0.076053), supporting H3. This result aligns with theoretical perspectives from media psychology suggesting that video-based social media platforms such as YouTube elicit immediate psychological responses in users by activating their hedonic motivations, ultimately encouraging payment behavior.

Third, we identified financial management applications (Toss) and loyalty-based membership apps (OK Cashbag) as significant predictors of mobile payment behavior (Toss: MAS = 0.049509; OK Cashbag: MAS = 0.049188). These findings may reflect common consumer behaviors, such as checking account balances prior to making payments or using accumulated membership points to facilitate transactions.

Fourth, we conducted a session-level SHAP force plot analysis, confirming that the direction of the influence of each factor on mobile payment behavior is consistent with established theoretical frameworks. The left panel of Figure 4 indicates that users who spend more time on social networking apps (i.e., KakaoTalk) and information seeking (i.e., Naver and web browsers) are more likely to engage in mobile payments than otherwise.

The right panel indicates that users who spend more time on financial management apps (i.e., Toss) and loyalty apps (i.e., L.Point) are more likely to engage in mobile payments than otherwise. Although these results are based on individual session-level observations, they complement the aggregate-level findings by confirming the directionality of the influence on payment behavior. Thus, the session-level SHAP analysis further supports H2 and H3 by explaining the roles of SNSs and hedonic media, as well as financial-related applications, in promoting mobile payment behavior.

5.2. Managerial Implications

This study offers several important managerial implications for stakeholders in the mobile commerce ecosystem. First, the validation of H1 demonstrates that including mobile application usage behaviors, particularly application-specific and session-level patterns, significantly enhances the performance of ML-based mobile payment prediction models. These behavioral signals support more accurate and personalized user targeting. Therefore, mobile commerce platforms and digital marketers should integrate fine-grained application usage data into their predictive analytics systems to enable real-time, automated targeting and dynamic promotional strategies. Using explainable AI techniques, such as SHAP force plots, facilitates the design of interpretable, individualized marketing interventions.

Second, the positive relationship between SNS application usage and mobile payment behavior suggests practical opportunities for collaboration. Mobile commerce firms and financial institutions should partner with SNSs to deliver context-driven, peer-influenced marketing campaigns. Embedding payment features and promotional offers within SNS environments, such as KakaoTalk or Instagram, can effectively leverage users' socially receptive states to increase conversion rates.

Third, the positive influence of video-based, hedonic platforms such as YouTube on mobile payment behavior suggests that emotionally engaging media contexts should be utilized strategically. Application developers and advertisers should design payment-enabled video ads, in-application promotions, or context-aware coupons timed to peak entertainment engagement, thereby triggering impulsive purchases and enhancing hedonic consumption.

Fourth, companies can improve their marketing efficiency by prioritizing applications with a high predictive value, identified through Shapley values, instead of attempting to analyze all available application usage data. This selective, theory-driven targeting approach allows for more focused resource allocation, streamlined data analytics processes, and reduced operational costs.

In summary, these insights contribute to a deeper understanding of behavioral signals in mobile commerce and provide a strategic framework for developing more predictive, efficient, and personalized digital engagement solutions.

5.3. Limitations and Future Research

This study offers an understanding of mobile payment usage patterns through interpretable ML approaches. However, it has several limitations. First, this study does not establish causality regarding mobile payments. While explainable ML methods can assess the predictive contribution of individual factors, they cannot account for all phenomena. Capturing causality in complex application usage patterns is a challenging task that should be addressed in future research. Second, we focused on Android OS users due to data limitations, restricting the generalizability of our findings to others, including iOS users, who represent a considerable portion of mobile users. Additionally, our analysis relies on data from 2019, which may not fully reflect present-day user behaviors. This limitation should be addressed in future research. Third, more advanced ML models for predicting

mobile payments should be considered in future studies. Recently, accurate prediction models based on deep learning have emerged, and their validation in this context should be pursued. Fourth, this study used random fivefold cross-validation techniques without considering the chronological order. While robust, this approach does not fully evaluate a model's ability to generalize over time. Future research should incorporate time-based validation (e.g., training during earlier months and testing in later months) to improve time-based generalizability. Fifth, performing user-segment-level analyses based on demographic clusters (e.g., by age, region, or application-usage patterns) presents a promising direction for future research. While we focus on identifying generalizable factors determining mobile-payment behavior across a broad user population, future research can build on our findings by exploring how predictive factors vary for different user segments. Such analyses would offer more nuanced insights and support the development of targeted marketing and service strategies.

6. Conclusions

This study clarifies the informational value, theoretical interpretation, and practical applicability of mobile application usage behavior, which has not yet been fully explored in the context of mobile commerce. With the emergence and proliferation of new technologies such as AI, the mobile commerce environment is becoming increasingly complex. Therefore, analyzing the behavioral determinants of mobile payment is more important than ever. We employed explainable ML techniques to handle the data's complexity and identify key behavioral determinants for mobile payment usage behavior. Based on the results, we derived actionable implications on user targeting by linking the findings to psychological theories.

Integrating application usage information into automated mobile user targeting systems enables more precise delivery of advertisements and promotional offers. In particular, focusing on applications with higher MAS values would allow for more efficient targeting compared with models that incorporate undifferentiated app usage data. Meanwhile, product recommendations and cross-selling strategies closely linked to social networks can achieve higher conversion rates than traditional website-based online sales. Embedding purchasing functions within SNSs enhances the effectiveness of branded content. Furthermore, consistent with the social support theory, the influence of celebrities on social networking platforms can be leveraged to convert potential consumers into buyers. The advertising impact can be maximized by displaying ads at peak viewership moments on YouTube videos or embedding purchase cues directly into the content. Notably, combining the word-of-mouth influence of SNS platforms with the hedonic consumption effects of YouTube content offers a promising direction for cross-platform marketing. In this context, user-level application usage data serves as a critical signal for designing integrated strategies. Ultimately, this study is a foundational work that integrates explainable AI with behavioral science to design transparent, personalized, and theory-driven digital commerce strategies and sheds light on new avenues for future mobile commerce research. While the analysis is based on Android users in South Korea during a specific period (late 2019), which may limit the immediate generalizability of the findings, this context may provide a valuable foundation for comparative studies across different platforms, regions, and timeframes in future research.

Author Contributions: Conceptualization, M.L. and I.C.; methodology, M.L. and I.C.; software, M.L. and I.C.; validation, M.L. and I.C.; formal analysis, M.L. and I.C.; investigation, M.L.; resources, M.L.; data curation, M.L.; writing—original draft preparation, M.L.; writing—review and editing, M.L., I.C. and W.-C.K.; visualization, M.L.; supervision, M.L. and W.-C.K.; project administration, M.L.; funding acquisition, M.L. All authors have read and agreed to the published version of the manuscript.

Funding: This paper was supported by Konkuk University in 2024.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The authors do not have permission to share data.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Appendix A.1. Details of eXtreme Gradient Boosting (XGBoost)

XGBoost is an ensemble learning method grounded in the framework of gradient boosting [6,13]. It constructs a powerful predictive model by iteratively incorporating weak base learners—typically decision trees—that aim to minimize the residual errors made by previous iterations. Renowned for its scalability, computational efficiency, and regularization mechanisms that help mitigate overfitting, XGBoost is particularly effective for handling large-scale, high-dimensional behavioral data. Mathematically, the prediction for a given instance i is expressed as the aggregated output of K individual decision trees:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in \mathcal{F}, \tag{A1}$$

where $\mathcal{F}$ denotes the functional space of all possible classification and regression trees and f_k represents the prediction from the k-th tree using variables x_i described in Table 1. The target variables are mobile-payment behavioral variables, while the predictors include demographic, situational, and behavioral features.

The objective function optimized during training is:

$$Z = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k) \tag{A2}$$

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda w^2. \tag{A3}$$

Here, $l(\hat{y}_i, y_i)$ is a differentiable convex loss function that quantifies the difference between the predicted and true outcomes; γ penalizes the number of leaves T in each tree to control the model's complexity; and λ is a regularization parameter applied to the leaf weights w. This regularization approach is necessary in order to prevent overfitting, particularly when modeling complex, high-dimensional behavioral interactions such as those found in mobile-application-usage data.

Appendix A.2. Details of Light Gradient-Boosting Machine

LightGBM, developed by Ke et al. [20], is a gradient-boosting framework designed to improve a model's training speed and reduce memory consumption without sacrificing predictive accuracy [48]. It introduces two key innovative functions: Gradient-Based One-Side Sampling, which selects a subset of data points with large gradients to focus on harder-to-predict samples, and Exclusive Feature Bundling, which combines mutually exclusive features to reduce dimensionality. A unique feature of LightGBM is its leaf-wise tree growth strategy. Unlike traditional boosting methods that grow trees level by level, LightGBM expands the leaf with the greatest loss reduction, resulting in trees that are deeper and potentially more accurate.

The prediction function for LightGBM can be represented as

$$Y_t = \sum_{t=1}^{T} f_t(x_i), \tag{A4}$$

where $f_t(x_i)$ represents the tree constructed at iteration t using variables x_i described in Table 1. The target variables represent mobile-payment behavioral variables, while the predictors include demographic, situational, and behavioral features. LightGBM offers advantages over other frameworks such as faster training speed, superior performance on large datasets, and reduced memory usage. In this study, LightGBM is evaluated against XGBoost, providing a valuable benchmark for comparing the framework's efficiency and scalability in modeling mobile-payment behaviors.

Appendix A.3. Details of Category Boosting (CatBoost)

CatBoost, introduced by Prokhorenkova et al. [37], is a gradient-boosting algorithm specifically designed for datasets with numerous categorical features. A key innovation of CatBoost is its use of "ordered boosting" and "ordered target statistics", techniques that reduce prediction bias and prevent target leakage—an issue commonly encountered in traditional categorical encoding methods. CatBoost updates its prediction function iteratively as follows:

$$F^t(x) = F^{t-1}(x) + \alpha h^t(x), \tag{A5}$$

where $F^t(x)$ is a predictive outcome of the input variable x at iteration t, α denotes the learning rate and $h^t(x)$ is the base learner selected at iteration t, by minimizing the expected loss as follows:

$$h^t(x) = \underset{h \in H}{\operatorname{argmin}} E\left[L\left(y, F^{t-1}(x) + h(x)\right)\right] \tag{A6}$$

Categorical variables are encoded using smooth target statistics, calculated as follows:

$$\hat{x}_{ik} = \frac{\sum_{j=1}^{n}\left(x_i^j = k\right) y_j + ap}{\sum_{j=1}^{n} 1_{x_i^j = k} + a}, \tag{A7}$$

where a is a smoothing parameter and p is a prior mean. This method uses only the historical information available up to a specific point, avoiding the influence of future data and thereby reducing overfitting and prediction shift.

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