

Predicting Digital Transactions in Thailand Using Satellite Data and Machine Learning Methods

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ABSTRACT

The digital economy in Thailand has experienced significant growth over the past decade. With the adoption of financial technology, monitoring this rapid expansion poses challenges for policymakers, particularly in predicting the trajectory of such growth given data compilation constraints. This paper aims to predict digital transactions in Thailand by utilizing alternative economic data, such as satellite imagery, and applying machine learning approaches to support more proactive policymaking strategies. Monthly data from 2018 to 2024, sourced from the Bank of Thailand and NASA satellite imagery, is employed. Key variables include internet banking, mobile banking, PromptPay usage, population density, GDP per capita, nighttime light intensity, daytime surface temperature, and nighttime surface temperature. The study compares the predictive performance of various machine learning algorithms, including artificial neural networks, Random Forests, and support vector machines. The dataset is split into training and testing subsets at a 70:30 ratio for validating the prediction. The results highlight the potential of satellite data in prediction, particularly the significant influence of nighttime light intensity and daytime surface temperature on digital transactions. Additionally, the Random Forest outperforms other algorithms due to its ability to capture complex associations, even in the presence of non-linear and irregular patterns.

Keywords: digital transactions, satellite data, machine learning, Thailand

INTRODUCTION

The rapid evolution of digital technology has fundamentally reshaped financial systems, accelerating the shift toward cashless economies worldwide. In Thailand, this transformation is reflected in the growing adoption of digital payments, e-commerce, and mobile banking, supported by significant improvements in digital infrastructure and financial innovation (Chaiyasoonthorn, 2019; Puwirat & Tripopsakul, 2019). Despite this progress, digital financial inclusion remains uneven, as mobile banking accounts and electronic payment usage still cover only a fraction of total financial activities, particularly in rural and low-income regions (Puriwat & Tripopsakul, 2017; Mahphoth et al., 2020; Kitipacharadechatron & Phasuk, 2025).

Predicting digital transaction behavior in such a dynamic environment presents unique challenges. Rapid technological change, evolving fraud patterns, and the complex interplay of user attitudes, perceived risks, and behavioral intentions complicate forecasting models (Abbassi et al., 2024; Alghofaili et al., 2020; Namahoot & Boonchieng, 2023). Moreover, traditional statistical and machine learning models often struggle to capture nonlinear interactions or adapt to shifting behavioral and economic conditions (Chaveesuk et al., 2021; Susanto et al., 2022). While prior studies have examined determinants of adoption and usage across Asian markets (Chen et al., 2019; Boonsiritomachai & Sud-on, 2022; Robkob & Pankham, 2023), few have explored the spatial dimension of digital economic activity or the use of non-traditional data sources for prediction.

Recent advances in satellite remote sensing offer a promising opportunity to bridge this gap. Satellite-derived indicators such as nighttime light intensity and urban expansion serve as high-frequency, spatially explicit proxies for economic activity that can complement conventional financial data. Integrating these geospatial variables with machine learning algorithms enables deeper insights into the spatial

heterogeneity and temporal evolution of digital financial behavior.

Building on this premise, the present study develops a comparative machine learning framework to predict digital transaction activity in Thailand using satellite-based economic proxies. Specifically, it evaluates the predictive performance of multiple algorithms and identifies the most influential geospatial features associated with digital transaction intensity. By integrating remote sensing, behavioral insights, and computational modeling, this study contributes to the emerging literature on digital economy analytics and provides policy-relevant evidence to guide Thailand's transition toward an inclusive and data-driven digital economy (Meedach & Lekcharoen, 2023).

LITERATURE REVIEW

The Role of Satellite Data in Economic Studies

The use of satellite data in investigating economic phenomena began around the early 2000s (Donaldson & Storeygard, 2016). This shift was driven by two key factors: the limited accessibility of conventional data in certain areas and the advent of big data in economic research. Consequently, economists sought innovative ways to address data limitations while simultaneously leveraging these advancements.

A critical step in utilizing satellite data was the establishment of new assumptions to validate the robustness of geospatial proxies in representing economic phenomena. A review of the literature reveals that various geospatial-based indices have been applied to analyze economic issues, such as poverty (Doll et al., 2006; Lehnert et al., 2023), household expenditure (Puttanapong & Lim, 2024), economic growth (Prasertsoong & Puttanapong, 2022), and agriculture and environmental concerns (Filewod & Kant, 2021). The details and implications of these indices are summarized in Table 1.

Table 1
Implications of Satellites

Index	Satellite	Implication
Nighttime Light Index	VIIRS	The nighttime light index is used to derive economic activities and socio-economic status. The underlying hypothesis is that brighter areas often indicate economic density, infrastructure development, industrial expansion, and economic growth. Empirical findings confirm its ability to capture these phenomena (Prasertsoong & Puttanapong, 2022; Dasgupta, 2022).
Daytime Surface Temperature	MODIS	This index captures climate change effects and economic status. Higher temperatures might indicate industrial concentration, drought effects on crops, or public health concerns. Studies confirm its significant relationship with these economic phenomena as indicating industrial progression and infrastructural development, particularly socioeconomic change (Dissanayake et al., 2019; Puttanapong & Lim, 2024).
Nighttime Surface Temperature	MODIS	This index reflects nighttime industrial activities, as many industries operate at night to reduce electricity costs. Empirical evidence shows a positive relationship between nighttime temperatures and economic growth (Dissanayake et al., 2019; Puttanapong & Lim, 2024).
Rainfall	CHIRPS	The rainfall index is critical for studying economic growth, especially in agriculture, natural resources, and disaster management. But the results obtained are varied across the cases studied. It mostly predicted crop yields, energy production (e.g., hydropower), and flood risks, indicating economic vulnerability (Barrios et al., 2010; Damania et al., 2020; Puttanapong & Lim, 2024).
Leaf Area Index (LAI)	MODIS	LAI is used to assess crop yield, forest productivity, and ecological health. Darker areas on satellite imagery indicate healthier forests, contributing to economic phenomena, especially agricultural income (Orlando et al., 2016; Puttanapong & Lim, 2024).

Table 1 (Continued)

Index	Satellite	Implication
Normalized Difference Water Index (NDWI)	MODIS	NDWI is used to monitor environmental resources and crop health by detecting water bodies. Darker areas represent water clusters, indicating agricultural and aquaculture wealth while signalling flood risks. Empirical evidence supports its effectiveness (Li et al., 2015; Chen et al., 2022; Puttanapong & Lim, 2024).
Normalized Difference Vegetation Index (NDVI)	MODIS	NDVI measures vegetation health, biomass, and photosynthetic activity, while LAI focuses on plant density and capacity. Both indices are critical for capturing economic growth in agricultural sectors as well as the socioeconomic status (Li et al., 2015; Chen et al., 2022; Puttanapong & Lim, 2024).
Normalized Difference Drought Index (NDDI)	MODIS	NDDI provides comprehensive drought assessments and helps predict crop yields by evaluating vegetation health and productivity, linking drought conditions to economic outcomes (Li et al., 2015; Chen et al., 2022; Puttanapong & Lim, 2024).
Normalized Difference Urban Index (NDUI)	MODIS	NDUI measures urbanization, economic development, and associated social impacts. Empirical studies confirm its strong correlation with economic growth (Libório et al., 2022; Prasertsoong & Puttanapong, 2022).
Pollution Index	Sentinel-5P	Pollution indices are crucial for analysing the relationship between economic growth and environmental quality. Sentinel-5P provides near-real-time data on pollutants (e.g., NO2, SO2, CO2, ozone, aerosols), enabling precise policy formulation. Empirical studies show significant contributions of pollution to economic activities (Levy & Yagil, 2011; Shi & Wu, 2020).

These indices demonstrated the significant potential of satellite data to quantify and analyze diverse economic phenomena. The use of these proxies, supported by robust empirical findings, paves the way for more accurate and innovative economic research (Donaldson & Storeygard, 2016).

The Development of Digital Economy Predictions

Traditional macroeconomic forecasting has long depended on national accounts and survey-based indicators such as GDP, trade, and inflation. These methods, while robust, suffer

from low temporal frequency and limited spatial granularity. As economies digitalize and spatial disparities widen, researchers have increasingly turned to satellite-based data to capture real-time signals of economic activity.

Early evidence highlighted the predictive power of nighttime light (NTL) imagery as a proxy for regional output. Galimberti (2020) demonstrated that satellite-derived luminosity could serve as a location-based indicator for GDP growth, enhancing traditional economic forecasting frameworks despite regional heterogeneity. Similarly, Nie & Oksol (2018) found that high-frequency NTL data substantially improved export-growth forecasts compared to models using quarterly foreign GDP, underscoring the timeliness and reliability of satellite observations.

At subnational scales, Millán López & González Olivares (2024) confirmed that changes in NTL intensity accurately mirrored variations in GDP and local economic dynamism across Mexican municipalities. These foundational studies established luminosity as a reliable macroeconomic proxy, bridging the temporal gap between traditional statistics and rapidly evolving economic conditions.

Expanding the concept beyond luminosity, Ying et al. (2019) analyzed anthropogenic bare-ground gain (ABGG) derived from Landsat imagery as a leading indicator of GDP growth. Their findings revealed that annual built-up expansion strongly correlates with economic activity, positioning land-cover transitions as another robust predictor for macroeconomic performance.

Similarly, Juergens et al. (2021) employed very-high-resolution (VHR) Worldview imagery and k-Nearest Neighbor (kNN) classification to detect new construction areas as early signs of investment and urban expansion, proving the potential of spatial analytics for short-term economic forecasting (Mardi et al., 2023; Lu et al., 2022). These works mark a conceptual shift: Economic prediction is no longer confined to aggregated time-series but extends to geospatially explicit, remotely sensed indicators that capture the physical manifestations of growth and transformation.

Besides, these works highlight how methodologies have evolved from linear econometric frameworks to sophisticated

machine learning (ML) and deep learning (DL) architectures that extract complex spatial and temporal relationships from satellite imagery (Bansal et al., 2020; Khachiyan et al., 2022). This is revealing a clear pattern: The integration of geospatial data and ML/DL models enhances both predictive accuracy and spatial interpretability, moving toward real-time, high-resolution economic forecasting applicable across national and subnational scales (Abbate et al., 2024).

Despite major progress among these studies, the literature reveals persistent cross-domain integration gaps that limit the applicability of satellite-based forecasting to digital-economy outcomes. Therefore, this study aims to fuse multi-sensor satellite inputs and advanced ML techniques to directly forecast digital transaction patterns. This approach not only addresses temporal and spatial data gaps but also expands the methodological toolkit to include predictive modeling of Thailand's evolving digital economy, thus bridging the remaining cross-domain divide between remote sensing and financial digitalization. It, thereby, offers a new empirical approach for monitoring digital financial behavior in Thailand, especially in areas where conventional financial data may be limited. It also provides policy-relevant evidence for identifying provinces with strong digital financial activity and areas that may require further support for digital financial inclusion.

METHODOLOGY

In predicting digital transactions per the purpose of this paper, the investigation proceeded as follows:

Data Sources

This paper utilizes a monthly dataset spanning 2017 to 2024, comprising a total of 84 records from two primary data sources: (1) Statistical data from the Bank of Thailand, which includes detailed information on digital transactions such as mobile banking transactions, internet banking transactions, and PromptPay transactions, as well as conventional economic information such

as gross domestic product (GDP) per capita; and (2) Satellite imagery from NASA providing alternative economic indicators such as the nighttime light index, daytime temperature index, and nighttime temperature index. These indices are widely used to represent economic activities, as documented in the works of Puttanapong et al. (2022)

The Target Variables and Explanatory Variables

Toward the investigation, this paper uses all digital transaction data as target variables. These indicators include both the number of transactions and the monetary value of transactions, allowing for an analysis of usage behavior and the extent of digital economic circulation. Additionally, such indicators will be transformed into per capita ratios, which allow this study to compare its findings across

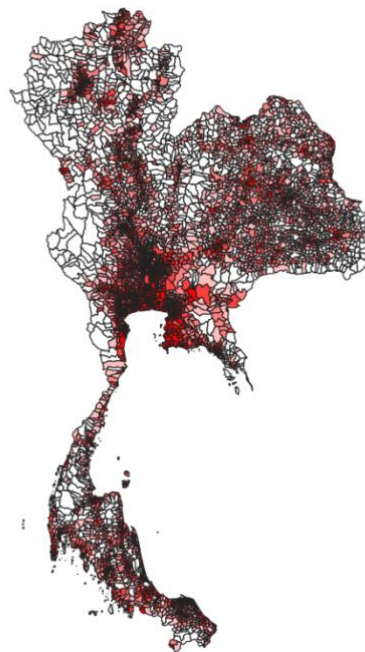
indicators and eliminate the urbanization effect hidden within the variables.

In addition, to address the limitations of observed data in Thailand, this study includes three main satellite-derived variables. First, nighttime light is commonly used to evaluate the socio-economic status of specific areas, as nighttime illumination reflects economic concentration and activity. Distribution of nighttime lights in Thailand is shown in Figure 1.

Further, daytime surface temperature captures economic conditions during the day, as areas with high economic concentration are likely to exhibit elevated temperatures. Nighttime surface temperature measures economic activity during nighttime conditions. An illustration of the former in the Thai case is shown in Figure 2 and in for the latter in Figure 3. Lastly, gross domestic product (GDP) per capita is incorporated into this investigation to represent the scale of economic activity.

Figure 1

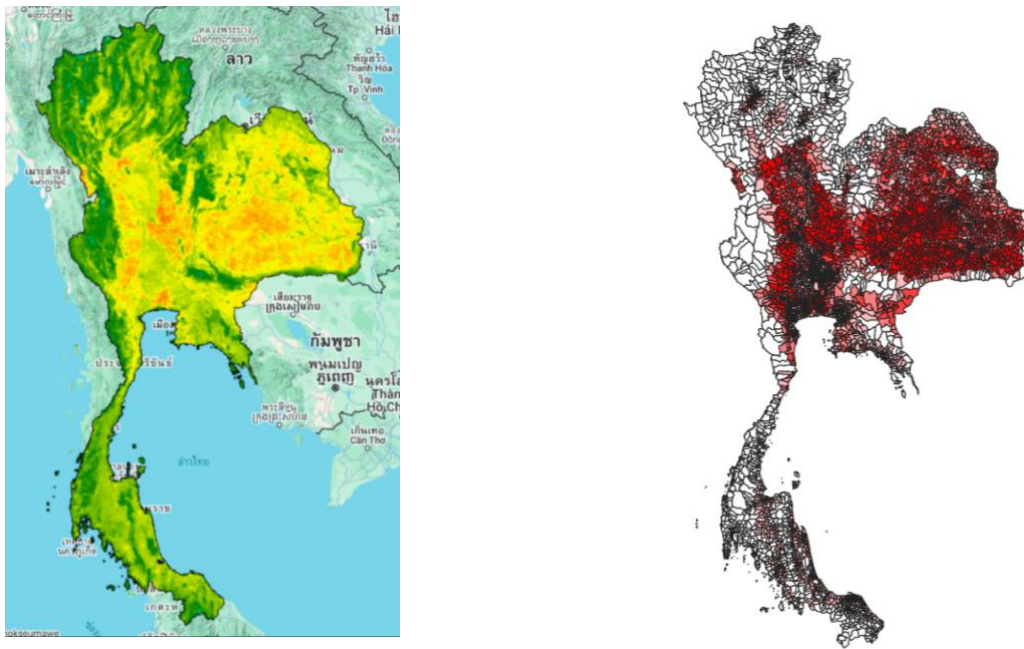
Spatial Distribution of Nighttime Light



Note. Adapted from *NTL Map of Thailand*, by Google Earth Engine, 2024. Google Earth Engine. (<https://code.earthengine.google.com/55177eb3193c563ab43e90d0ff721a4e>) Copyright 2024 by Google LLC.

Figure 2

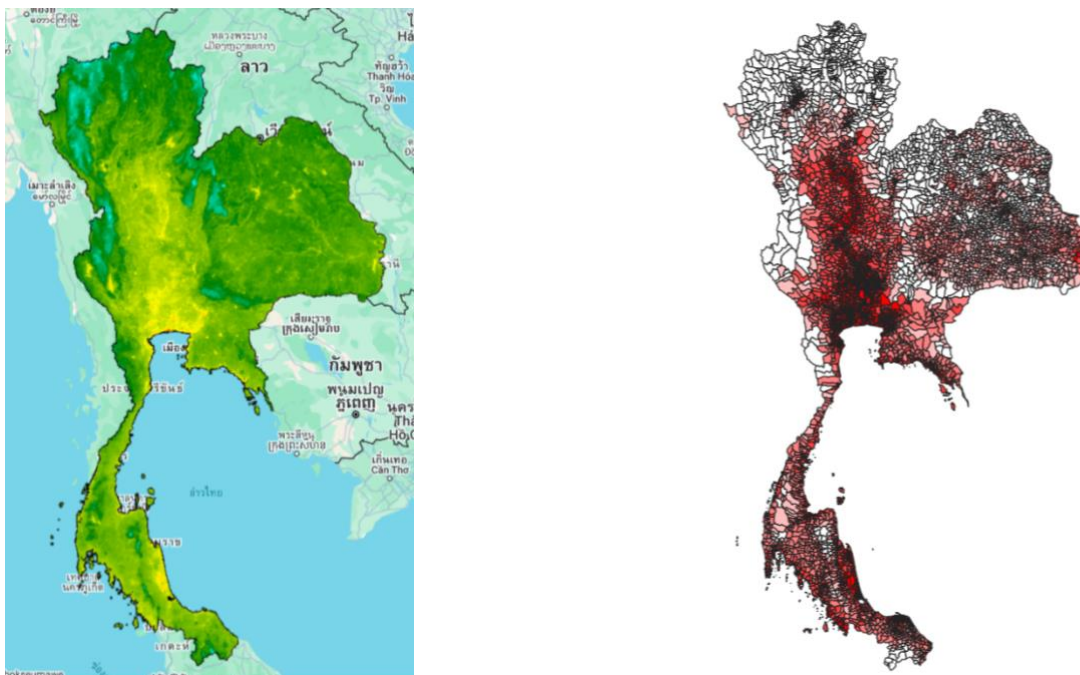
Spatial Distribution of Daytime Land-Surface Temperature



Note. Adapted from *DLST Map of Thailand*, by Google Earth Engine, 2024. Google Earth Engine. (<https://code.earthengine.google.com/54eb4a62f6ae9ec07a0d70f70530ed10>). Copyright 2024 by Google LLC.

Figure 3

Spatial Distribution of Nighttime Land-Surface Temperature



Note. Adapted from *NLST Map of Thailand*, by Google Earth Engine, 2024. Google Earth Engine. (<https://code.earthengine.google.com/a22709c995b5a68b85027675bacbc424>). Copyright 2024 by Google LLC.

Analysis Procedures

After retrieving all datasets, two steps were required for data preparation and cleaning. First, the dataset was analyzed through the descriptive statistics for summarizing overall information and characteristics of its distribution. The data was then normalized to a range of 0 to 1 to smooth variations within the dataset.

Following these preparations, machine learning algorithms were applied to predict digital transactions using three methods: Artificial Neural Network (ANN), Random Forest (RF), and Support Vector Machine (SVM). The algorithms were compared to identify the most suitable for prediction. Each method offered unique strengths. For example, ANN performs well with larger datasets and optimized layers, RF excels with granular data, and SVM is effective even with high-dimensional data. To evaluate the predictive power of the algorithms used in this investigation, metrics such as Root Mean Squared Error (RMSE), R-squared, and SHAP Value were utilized to quantify prediction errors, explain the underlying phenomena, and determine the relative contribution and directional influence of satellite-derived and socioeconomic predictors across algorithms. These can be computed as follows:

The Root Mean Squared Error – RMSE

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^T (Y_t - \hat{Y}_t)^2} \quad (1)$$

where Y_t stands for the actual value of each digital transaction and $\hat{Y}_t$ stands for the predicted value of a digital transaction. In machine learning sciences, RMSE is often used for measuring

predictive performance, where a low value indicates outstanding performance.

The R-squared - R^2

$$R^2 = 1 - \frac{\sum_{t=1}^T (Y_t - \hat{Y}_t)^2}{\sum_{t=1}^T (Y_t - \bar{Y})^2} \quad (2)$$

where Y_t stands for the actual value of each digital transaction and $\hat{Y}_t$ stands for the predicted value of a digital transaction. This index was employed for reflexing the proportion of variance that is explained, in other words, it demonstrates the explanatory fit of the models.

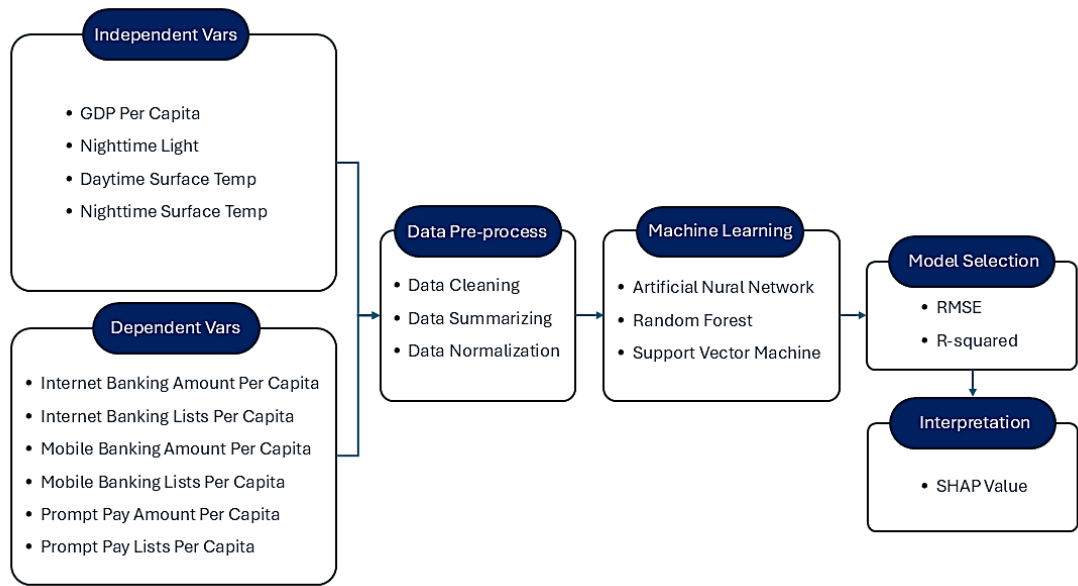
The SHAP Value

$$\phi_i(x) = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} [f_x(S \cup \{i\}) - f_x(S)] \quad (3)$$

where $|F|$ stands for the total number of features in the dataset and $|S|$ stands for the number of features currently in subsets S . In addition, $f_x(S \cup \{i\})$ stands for the prediction of the model when a feature is added to subset and $f_x(S)$ stands for the prediction using only features in subsets S . The indicator can present multidimensional features of prediction including importance, direction, and feature value pattern across the models.

Though the analysis strategy mentioned above enhances the predictive power, it also has certain limitations. For instance, it does not establish causal relationships, which can hinder the implementation and monitoring of strategic policies. Additionally, the lack of spatial data from official surveys limits the ability to conduct in-depth analyses for specific areas. As a result, this investigation provides predictions only at the national level to come across the limitation as the following analytic frameworks presented below.

Figure 4
Analytical Framework of This Paper



RESULTS

The results of the analysis are divided into three sections, each focusing on a different type of usage to explore their variations. The first set of analyses examines internet banking predictions, followed by mobile banking predictions and PromptPay predictions.

This separation provides detailed insights into each user group, as their determinants may differ significantly. For instance, internet banking users typically require comprehensive banking services, such as account management, fund transfers, and bill payments. In contrast, mobile banking and PromptPay users are more likely to seek basic banking services. This distinction highlights the importance of subgroup analysis in the investigation.

Before proceeding with the quantitative analysis and prediction, it is crucial to conduct an overview of the raw data that have been collected. The statistics use in this section include mean, standard deviation, max value,

and min value to examine the distribution and range of data.

The empirical findings reveal that mobile banking transactions make the most significant contribution to the economy, with an average of 52,831.93 THB per capita a month, followed by internet banking transactions (33,139.87 THB) and PromptPay transactions (30,453.20 THB). This data suggests a growing preference for portable banking options in Thailand, as evidenced by the overwhelming number of mobile banking and PromptPay transactions.

For the geospatial data obtained from satellite imagery indicates that, during the observation period, the average daytime surface temperature across the country was 29.63 degrees Celsius, while the average nighttime surface temperature was 21.87 degrees Celsius. Socio-economic activity, as represented by nighttime light intensity, averaged 0.95 units nationwide. Other variables, such as GDP per capita, showed averages of 7,051.03 THB, as summarized in Table 2.

Table 2*Descriptive Statistics*

	Mean	Std. Dev.	Max	Min
Internet Banking Amounts per Capita	33,139.87	6,596.87	48,327.69	22,511.46
Internet Banking Lists per Capita	0.57	0.20	0.85	0.23
Mobile Banking Amounts per Capita	52,831.93	29,432.74	96,801.62	9,155.67
Mobile Banking Lists per Capita	16.07	13.06	43.17	1.11
PromptPay Amounts per Capita	30,453.20	22,048.40	65,204.53	50.46
PromptPay Lists per Capita	10.24	9.34	29.45	0.01
GDP per Capita	7,051.03	328.18	7,628.58	6,436.79
Daytime Surface Temperature	29.63	2.17	34.31	25.48
Nighttime Surface Temperature	21.87	1.71	24.83	15.83
Nighttime Light Density	0.95	0.30	1.56	0.01

At first glance, it can be concluded that digital transactions in Thailand are increasing significantly to support economic activity. Although individual income remains relatively low compared to advanced economies, the demand for transactions continues to grow, as shown in Appendix A.

These findings underscore the critical role of digital transactions in driving economic growth and emphasize the need for policymakers to closely monitor this trend to ensure its sustainability. The following section presents a comparative analysis of digital transaction predictions using a machine learning approach in the context of Thailand, with further details provided below.

Internet Banking Prediction: Amounts per Capita

All machine learning models were trained and tested using a 70:30 data split. For internet banking amount per capita, the Random Forest algorithm produced the strongest performance, with the lowest average RMSE of 0.1757 across 30 trials and the highest

R-squared value of 0.5909. This indicates that Random Forest provided the most accurate and stable prediction among the three algorithms, as shown in Figure 5.

To further interpret the Random Forest model, SHAP values were used to examine feature importance, direction, and value patterns, as presented in Figure 6.

Figure 6 showed that nighttime light had the widest SHAP distribution, indicating that nighttime economic activity was the most influential predictor of internet banking amount per capita. However, its effect was nonlinear. Some high nighttime light observations reduced the prediction, while others strongly increased it. This suggests that only highly concentrated or digitally active economic areas generated strong positive effects.

GDP per capita showed a clearer income-related pattern. Low-income provinces strongly reduced the predicted amount, whereas higher-income provinces tended to increase it. This confirms that income capacity remained an important foundation for digital banking value. By contrast, temperature-based indicators contributed more modestly.

Figure 5
Comparison of Average RMSE and R-squared Values Obtained for the Predictions of Three Algorithms for Internet Banking Amounts per Capita

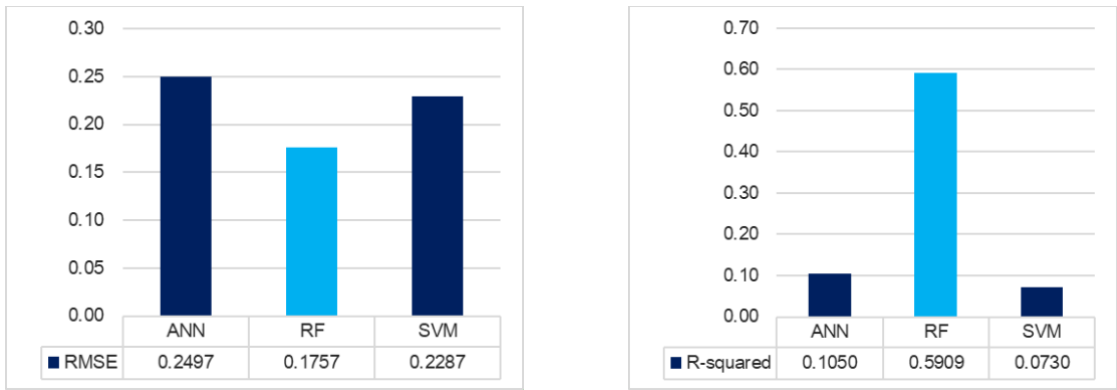
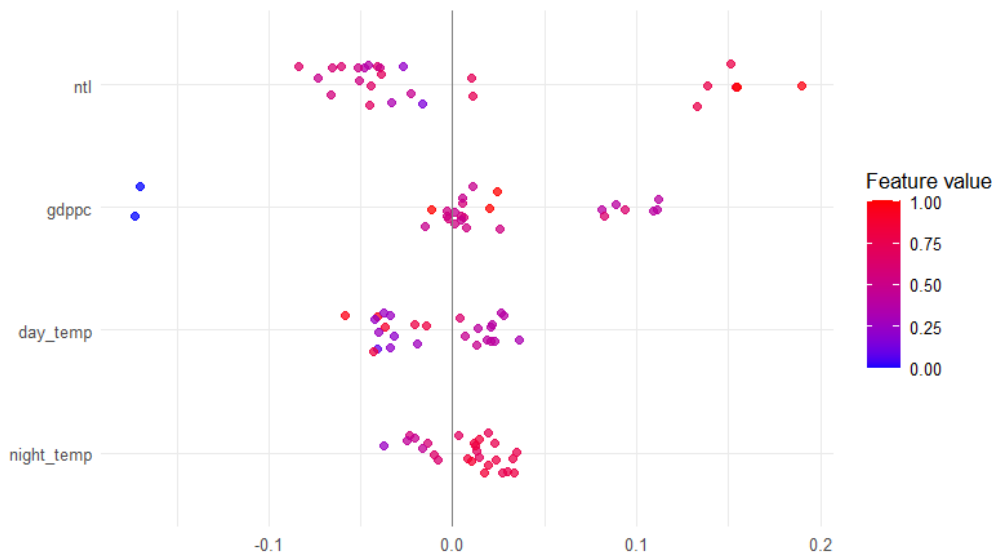


Figure 6
SHAP Values for the Predictions of RF Algorithms for Internet Banking Amounts per Capita



Daytime temperature showed a mixed effect, reflecting its context-dependent role as a proxy for industrial or daytime urban activity. Nighttime temperature made a slightly positive contribution, suggesting that areas with stronger nighttime urban or economic intensity tended to have higher predicted internet banking amounts. Overall, the results indicate that internet banking value was shaped by both income capacity and the spatial concentration of economic activity, especially nighttime economic intensity.

Internet Banking Prediction: Transactions per Capita

For internet banking transactions per capita, the Random Forest algorithm again showed outstanding predictive performance. It achieved the lowest average RMSE of 0.2223 across 30 trials and the highest R-squared value of 0.5471, as shown in Figure 7. These results confirm that Random Forest was the most suitable model for predicting internet banking transaction frequency.

The SHAP results further indicate that GDP per capita was the most influential predictor, with the

widest SHAP distribution. Low-income observations strongly reduced predicted transaction intensity, while higher-income observations mostly contributed positively. This suggests that income capacity played a central role in explaining the frequency of internet banking use. Areas with stronger purchasing power and higher economic capacity were more likely to generate more frequent transactions per person.

Daytime land surface temperature also showed a meaningful but nonlinear effect. Some higher temperature values increased the prediction, while others reduced it. This indicates that daytime temperature captured different forms of

daytime economic activity, such as industrial zones, commercial areas, or central business districts, but its contribution depended on local context.

Nighttime light had a more moderate role, with most SHAP values concentrated around zero, although some higher nighttime light observations increased predicted transactions. This suggests that nighttime economic activity was relevant, but weaker than income in explaining transaction frequency. Nighttime temperature showed the smallest contribution, indicating that nighttime urban or industrial heat intensity had only a limited role in this prediction.

Figure 7
Comparison of Average RMSE and R-Squared Values Obtained for the Predictions of Three Algorithms for Internet Banking Transactions per Capita

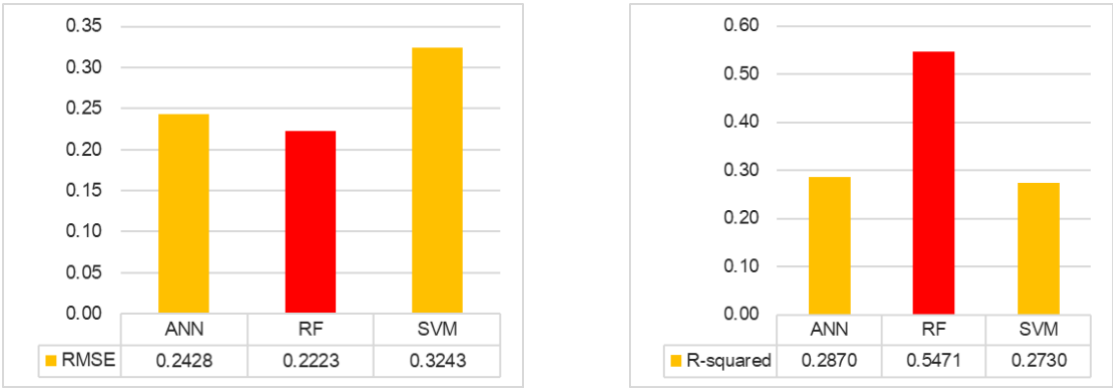
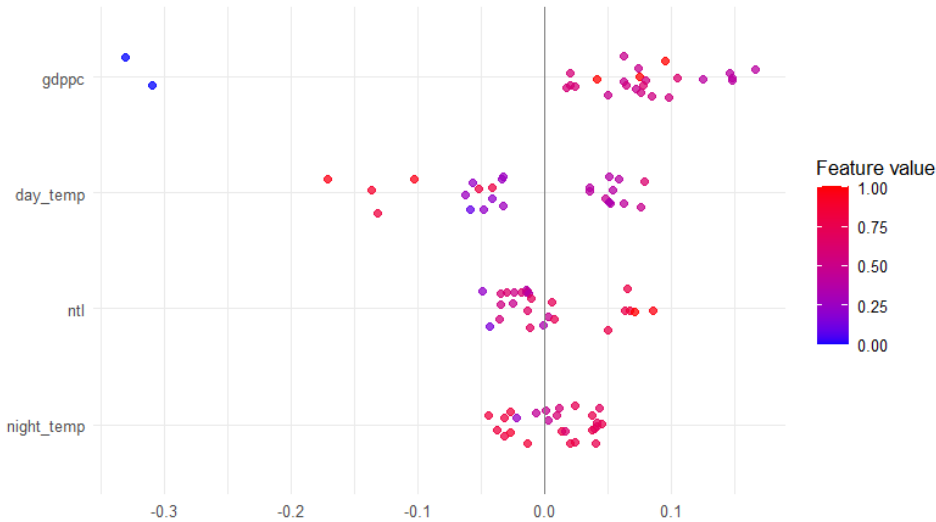


Figure 8
SHAP Values for the Predictions of RF Algorithms for Internet Banking Transactions per Capita



Mobile Banking Prediction: Amounts per Capita

In accordance with mobile banking amount per capita, the Random Forest algorithm yielded the lowest average RMSE of 0.2015 and the highest R-squared value of 0.6338. This indicates that Random Forest provided the strongest predictive performance among the three algorithms, as shown in Figure 9.

Figure 10 presents SHAP values based on the Random Forest algorithm. The results show that GDP per capita had the widest SHAP distribution and was the dominant predictor. Low-income observations strongly reduced predicted mobile banking amounts per capita, while higher-income observations mostly increased it. This pattern suggests that income capacity was a key structural factor behind mobile banking values. Provinces with higher economic capacity were more likely to generate larger mobile banking amounts per person.

Nighttime light also had an important but nonlinear contribution. Most observations were located on the negative side, suggesting that moderate levels of nighttime economic activity

did not always increase mobile banking amounts. However, some high nighttime light observations produced strong positive SHAP values. This implies that mobile banking values increased mainly in areas where nighttime economic activity reached a sufficiently high level, possibly reflecting stronger urban concentration, commercial activity, and digital financial readiness. Nighttime temperature made a smaller and more balanced contribution, while daytime temperature had the weakest effect. These results suggest that temperature-based indicators added spatial context, but their predictive role was more limited than income and nighttime light.

Mobile Banking Prediction: Transactions per Capita

For mobile banking transactions per capita, the Random Forest algorithm also demonstrated the strongest performance. The model produced the lowest average RMSE of 0.1985 and the highest R-squared value of 0.5983, as shown in Figure 11.

Figure 9

Comparison of Average RMSE and R-Squared Values Obtained for the Predictions of Three Algorithms for Mobile Banking Amounts per Capita

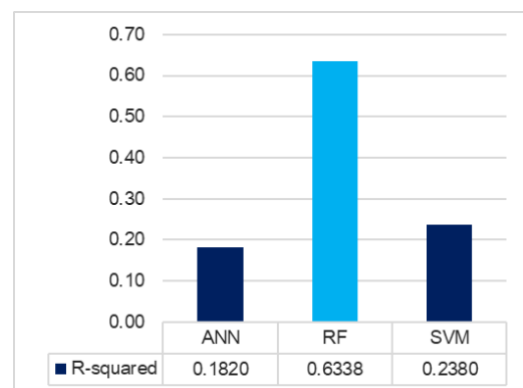
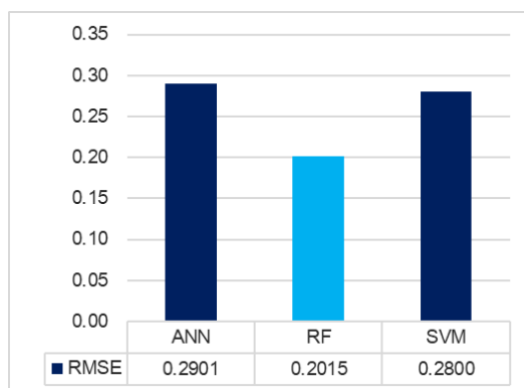


Figure 10
SHAP Values for the Predictions of RF Algorithms for Mobile Banking Amounts per Capita

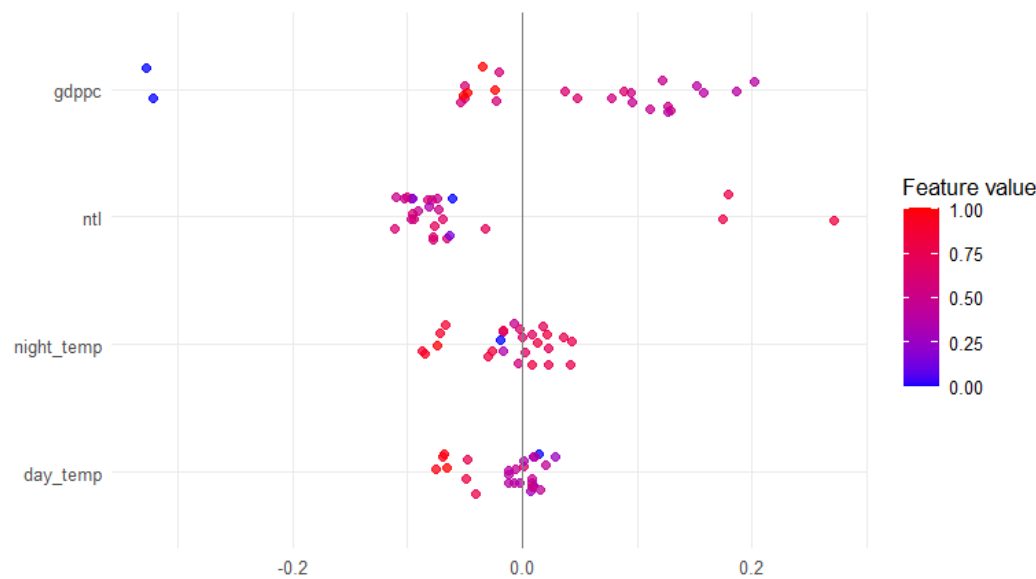
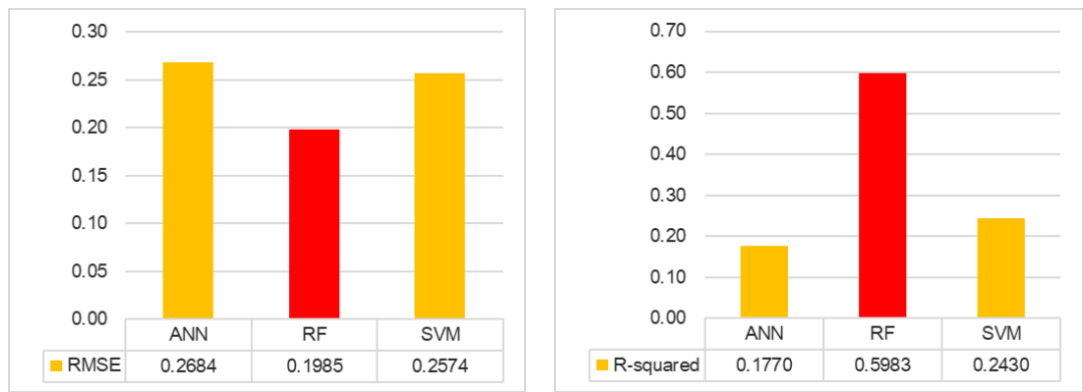


Figure 11
Comparison of Average RMSE and R-Squared Values Obtained for the Predictions of Three Algorithms for Mobile Banking Transactions per Capita



Further, Figure 12 displays SHAP values based on the Random Forest algorithm for mobile banking transactions per capita. The results indicate that nighttime light was the most influential predictor, with the widest SHAP distribution. This suggests that nighttime economic activity plays an important role in explaining frequencies of mobile banking transactions. However, the effect was nonlinear. Many observations with moderate to high nighttime light values reduced predicted transactions, while a small group of high nighttime light observations strongly increased

the prediction. This implies that mobile banking transactions increased mainly in areas where nighttime economic concentration was sufficiently strong and closely linked with digital financial activity. GDP per capita was also a clear contributor. Low-income observations reduced predicted transaction frequency, while higher-income provinces generally increased it. This confirmed that income capacity remained an important structural factor behind mobile banking use. Nighttime temperature showed a smaller and

mixed effect, suggesting that nighttime urban or industrial heat intensity provided additional information on economic concentration. Daytime temperature showed the smallest contribution, indicating that daytime economic activity had limited influence on mobile banking transaction frequency.

PromptPay Prediction: Amounts per Capita

In the case of PromptPay predictions, the Random Forest algorithm achieved the lowest average RMSE of 0.1920 and the highest R-squared value of 0.6858. This confirmed its superior predictive performance compared with the other algorithms, as shown in Figure 13.

Figure 12

SHAP Values for the Predictions of RF Algorithms for Mobile Banking Transactions per Capita

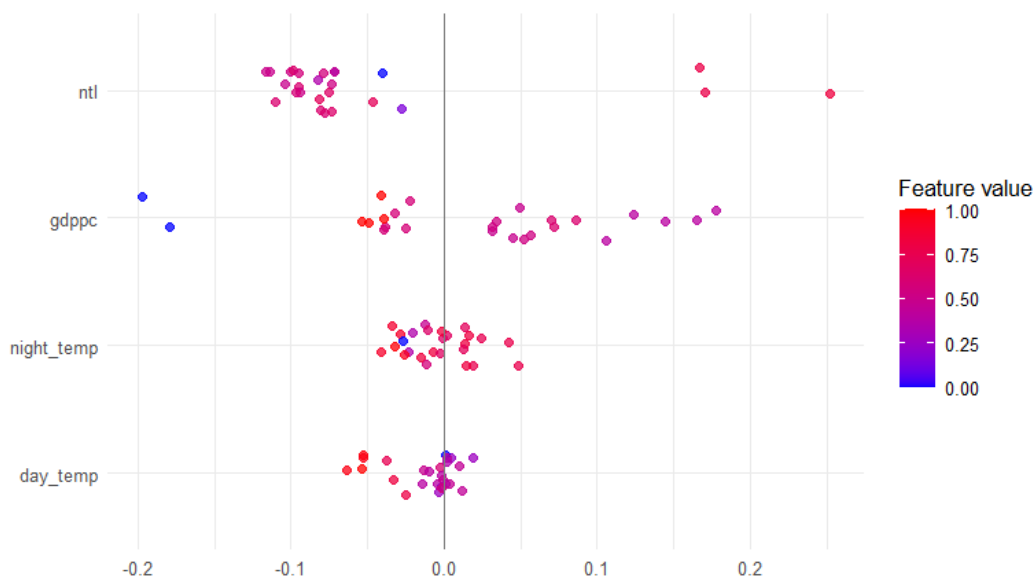
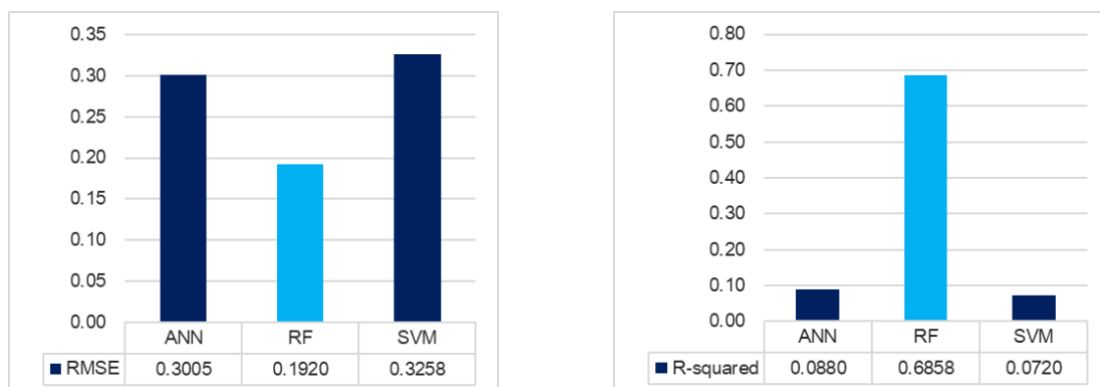


Figure 13

Comparison of Average RMSE and R-Squared Values Obtained for the Predictions of Three Algorithms for PromptPay Amounts per Capita



The SHAP value was further employed to display the most influential predictor. As in Figure 14, the results show that nighttime light had the widest SHAP distribution, indicating its central role in explaining PromptPay amount per capita. Most observations were slightly below zero, but several high nighttime light observations strongly increased the prediction. This suggests a nonlinear relationship. Areas with moderate nighttime light did not necessarily generate higher PromptPay amounts, while highly concentrated urban or commercial areas were more likely to raise predicted transaction value.

Once again, GDP per capita also contributed substantially. Low-income observations strongly reduced predicted PromptPay amount per capita, whereas higher-income provinces generally contributed positively. This implies that income capacity remains an important economic foundation for digital payment values. Nighttime temperature had a smaller but visible contribution, suggesting that nighttime urban or industrial heat intensity captured additional information on local economic activity. Daytime temperature had the weakest effect, indicating that daytime economic activity did not consistently translate into higher PromptPay value.

PromptPay Prediction: Transactions per Capita

For PromptPay transactions per capita, the Random Forest algorithm again emerged as the best predictive model. It yielded the lowest average RMSE of 0.2021 and the highest R-squared value of 0.6371, as presented in Figure 15.

The SHAP results in Figure 16 showed that nighttime light was the most influential predictor. Its wide SHAP distribution suggests that nighttime economic activity played a central role in explaining PromptPay transaction frequency. However, the relationship was nonlinear. Many observations with moderate to high nighttime light values reduced predicted transactions, while a small group of high nighttime light observations strongly increased them. This suggests that PromptPay transaction frequency rose mainly in areas with highly concentrated economic and digital financial activity, rather than in all areas with visible nighttime activity.

GDP per capita again showed an important contribution. Low-income observations strongly reduced predicted PromptPay transactions per capita, while higher-income provinces generally contributed positively. This pattern indicates that income capacity supported more frequent PromptPay use. Nighttime temperature had a smaller but moderate effect, with higher values tending to move slightly toward the positive side. This suggests that urban density or nighttime economic intensity added some predictive information. Daytime temperature showed the weakest contribution, indicating that daytime industrial or commercial activity had limited influence on PromptPay transaction frequency.

In summary, the Random Forest algorithm emerged as the outstanding model for predicting digital financial transactions in this study. Its strength was not limited to predictive performance but also extended to interpretability through SHAP analysis. The findings suggest that digital financial transactions in Thailand were mainly driven by income capacity and the spatial concentration of economic activity, with Random Forest providing the most effective framework for both prediction and interpretation.

Figure 14
SHAP Values for the Predictions of RF Algorithms for PromptPay Amounts per Capita

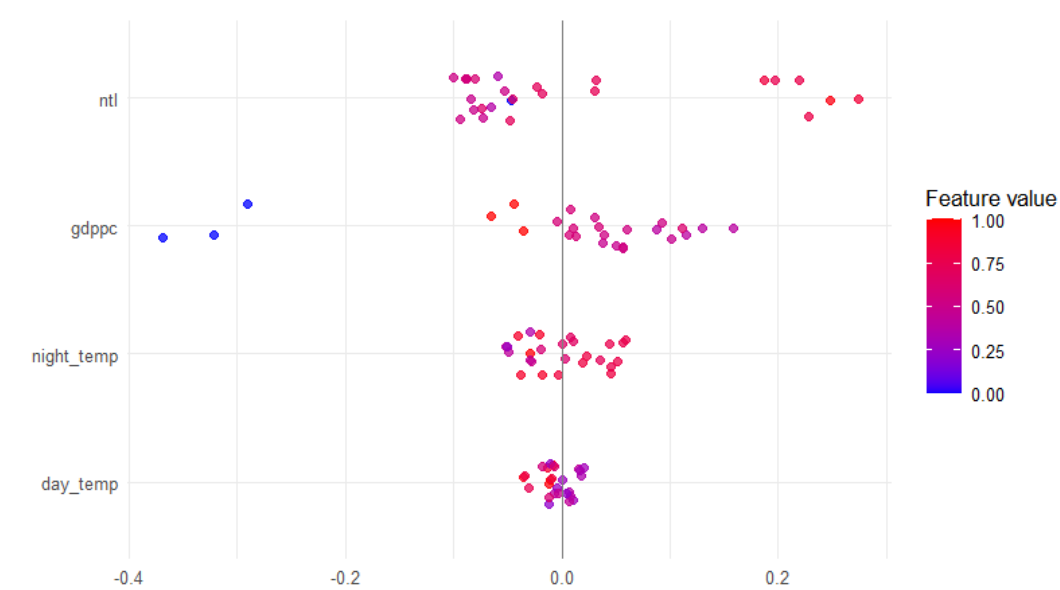


Figure 15
Comparison of Average RMSE and R-Squared Values Obtained for the Predictions of Three Algorithms for PromptPay Transactions per Capita

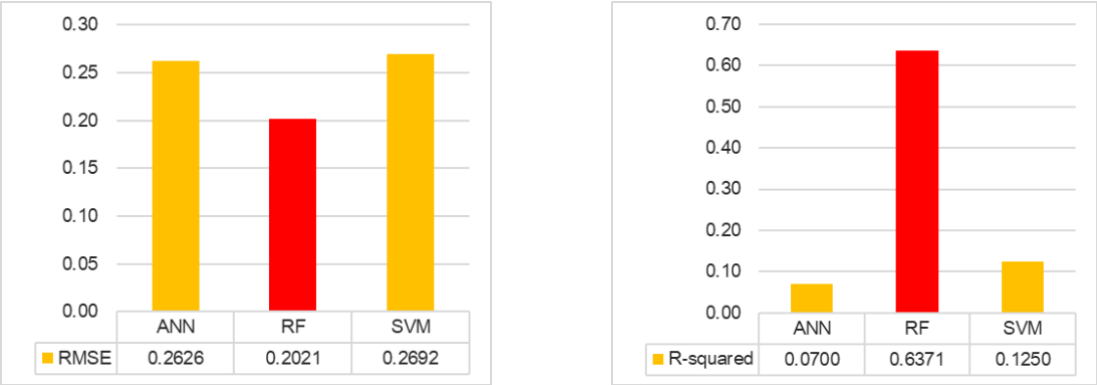


Figure 16
SHAP Values for the Predictions of RF Algorithms for PromptPay Transactions per Capita

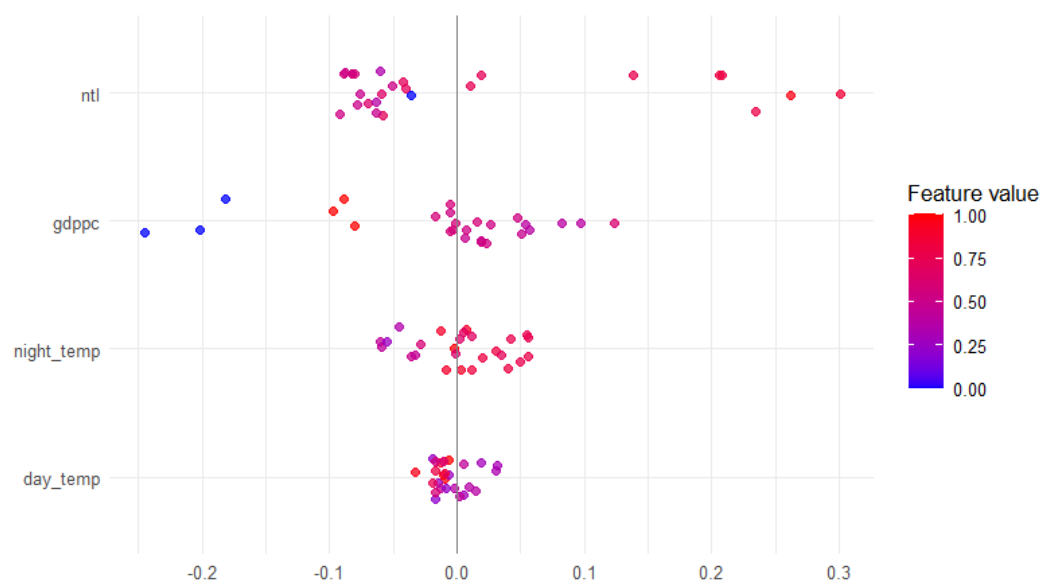


Table 3
Summary of Methods for Predicting Digital Transactions

	Outstanding Algorithm	Most Influential Factor	Remark
Internet Banking Amounts per Capita	RF	Nighttime light	Transaction value was strongly linked with nighttime economic concentration.
Internet Banking Lists per Capita	RF	GDP per capita	Transaction frequency was mainly explained by income capacity.
Mobile Banking Amounts per Capita	RF	GDP per capita	Higher income capacity supported larger mobile banking values.
Mobile Banking Lists per Capita	RF	Nighttime light	Transaction frequency was associated with urban and nighttime economic intensity.
PromptPay Amounts per Capita	RF	Nighttime light	PromptPay value increased in areas with stronger economic concentration.
PromptPay Lists per Capita	RF	Nighttime light	Frequent PromptPay use was linked with concentrated urban and commercial activity.

DISCUSSION

The empirical findings of this study reveal that socio-economic indicators, particularly population density, GDP per capita, and nighttime light intensity serve as dominant predictors of digital transaction activity across all banking platforms. These results align with previous studies demonstrating the strong association between satellite-derived proxies and economic dynamism. In particular, the predictive strength of nighttime light intensity corroborates evidence from Prasertsoong and Puttanapong (2022) and Dasgupta (2022), who identified luminosity as a reliable proxy for income distribution, infrastructure concentration, and regional productivity. Similarly, the relationship between temperature indices and transaction activity supports findings by Dissanayake et al. (2019) and Puttanapong & Lim (2024), who emphasized that spatial thermal variations reflect industrial activity and socio-economic development. Together, these consistencies suggest that satellite-derived measures can effectively capture the geographic heterogeneity of Thailand's digital economy, bridging the gap between macroeconomic statistics and local financial behaviors.

Moreover, the superior predictive performance of artificial neural networks (ANNs) over traditional models reinforces the growing body of research advocating for machine learning integration in economic forecasting (Bansal et al., 2020; Khachiyan et al., 2022). This finding confirms that non-linear models can better capture complex interdependencies among geospatial, demographic, and economic variables than conventional econometric frameworks. Consistent with Abbate et al. (2024), the integration of satellite-based data with advanced ML algorithms provides a scalable and interpretable approach to real-time economic prediction. By demonstrating that digital transaction patterns can be robustly forecasted through satellite and socio-economic indicators, this study not only validates the conceptual evolution outlined by Donaldson & Storeygard (2016) but also extends the frontier of digital economy research toward spatially adaptive, data-rich modeling paradigms.

RECOMMENDATIONS

The findings of this study suggest that satellite-derived indicators can serve as complementary tools for monitoring Thailand's digital economy. Nighttime light intensity and surface temperature indicators should not be viewed as substitutes for official financial statistics, but as additional signals that can improve the timeliness and spatial sensitivity of digital transaction monitoring. This recommendation is consistent with the broader evidence from Thai spatial and geospatial studies, which shows that satellite data are useful for observing economic activity, urban expansion, and regional heterogeneity, while still requiring careful interpretation alongside administrative data.

Second, policy design should recognize that digital transaction activity is closely associated with the concentration of socio-economic activity. The results show that population density and GDP per capita are repeatedly important predictors across transaction types, indicating that digital financial activity remains linked to areas with stronger economic concentration. Therefore, national digital finance strategies should be complemented by area-sensitive policies that target lower-density and lower-income areas. Such policies may include expanding digital infrastructure, improving mobile internet access, strengthening merchant acceptance of digital payments, and promoting digital financial literacy among rural and lower-income populations.

Third, the use of machine learning should be incorporated into Thailand's digital economy monitoring system, but with a differentiated role for each algorithm. Artificial neural networks show strong predictive performance for most transaction categories, especially mobile banking and PromptPay transactions. However, the results also show that internet banking amount prediction performs better under SVM in terms of prediction error, while RF provides stronger explanatory power. Therefore, policymakers should not rely on the single best algorithm. A more practical approach is to use ANN for high-accuracy forecasting, RF for interpretability and variable prioritization, and SVM as a robustness benchmark for specific transaction outcomes. This would make the monitoring system both predictive and explainable.

Fourth, future policy applications may benefit from moving beyond national-level monitoring toward subnational digital finance analytics and early-warning systems. Several comparable Thai studies on urban expansion (Prasertsoong & Puttanapong, 2025), elderly debt, income distribution (Kitipacharadechatron & Phasuk, 2025), and neighborhood connectedness (Janjamlah & Kaewlai, 2025) emphasize that spatial heterogeneity matters and that one-size-fits-all policies are often insufficient. Similarly, digital financial inclusion in Thailand is likely to vary across provinces, municipalities, and neighborhood types. Once subnational transaction data become available, satellite-derived indicators can be integrated with financial transaction statistics, population data, GDP per capita, and policy-event information to identify areas where digital financial activity is expanding, stagnating, or lagging behind. In this way, satellite-based and machine-learning prediction systems could function not only as descriptive tools but also as early-warning mechanisms for inclusive digital development. Rapid increases in predicted transaction activity may indicate economic dynamism, financial innovation, or policy-induced adoption, whereas weak predicted activity in economically vulnerable areas may signal digital exclusion and the need for targeted interventions.

LIMITATIONS

Despite its contributions, this study has several limitations. First, the analysis is based on national-level monthly data from 2018 to 2024, comprising 84 observations. Although this provides useful temporal variation, the sample size remains limited for machine learning applications, particularly for artificial neural networks, which generally perform better with larger datasets. Therefore, the predictive performance should be interpreted with caution, especially when generalizing the results beyond the observed period.

Second, there is a spatial aggregation limitation. While the satellite indicators are spatially explicit, the digital transaction variables are measured at the national level. This creates a mismatch between the spatial richness of the explanatory

variables and the aggregate nature of the dependent variables. As a result, this study cannot directly identify province-level, district-level, or neighborhood-level patterns of digital transaction behavior. This limitation is similar to other Thai spatial studies that rely on aggregated spatial units, where local socio-economic variation may be partially hidden by the level of aggregation.

Third, the study focuses on prediction rather than causality. The results show that population density, GDP per capita, nighttime light intensity, and surface temperature indicators are useful for forecasting digital transaction activity. However, these associations should not be interpreted as causal effects. For example, higher nighttime light intensity may reflect greater economic activity, but the model does not prove that changes in nighttime light directly cause changes in digital transactions. This distinction is important for policy interpretation.

Fourth, satellite-derived indicators are only proxies for socio-economic activity. Nighttime light intensity may capture urbanization, infrastructure, commercial density, and economic concentration, while surface temperature may reflect industrial activity, land-use patterns, or environmental conditions (Hansasooksin et al., 2024). However, these variables do not directly measure digital behavior, banking access, smartphone ownership, internet quality, consumer trust, platform usability, merchant acceptance, or digital literacy. Future research should therefore integrate satellite data with direct indicators of digital infrastructure and financial inclusion.

Fifth, the study does not explicitly account for policy shocks, structural breaks, or extraordinary events during the observation period. Thailand's digital transactions from 2018 to 2024 may have been affected by the COVID-19 pandemic, government transfer schemes, PromptPay promotion, regulatory changes, financial technology campaigns, and changes in consumer behavior. Similar to studies using historical land-use or spatial growth models, predictions based on past patterns may become less reliable when unexpected economic, social, or policy changes occur. Future research should incorporate policy dummy variables, event-based models, or structural break tests to improve robustness.

Sixth, the model evaluation mainly relies on RMSE and R-squared. These metrics are useful for comparing predictive performance, but they do not fully explain the internal mechanisms of machine learning models. Although RF provides some interpretability through variable importance and minimal depth, future studies should apply explainable artificial intelligence techniques, such as partial dependence plots, to improve transparency and policy relevance.

CONCLUSION

This paper attempts to investigate the prediction of digital transactions in Thailand using satellite data. The contributions of this paper are twofold: (1) It introduces a novel approach to predicting digital transactions through the application of spatial data from satellite imagery. Given that Thailand still lacks efficient monitoring of digital transactions and the conventional approaches are costly and time-consuming, spatial features such as nighttime light intensity and daytime surface temperature can be used as alternatives to improve real-time monitoring by policymakers for the robust prediction; (2) The results indicate that the Random Forest algorithm provides the strongest overall predictive performance for most digital transaction categories.

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APPENDIX

Appendix A. The Mean Value of Each Variable Overtime

	2017	2018	2019	2020	2021	2022	2023	2024
Internet Banking Amounts per Capita	25,607.42	29,524.41	29,580.30	28,754.51	34,220.45	40,858.13	42,555.72	43,677.30
Internet Banking Lists per Capita	0.26	0.36	0.57	0.54	0.73	0.76	0.75	0.82
Mobile Banking Amounts per Capita	12,023.74	22,086.21	34,590.90	50,614.38	72,113.19	85,362.78	89,741.59	92,320.34
Mobile Banking Lists per Capita	1.66	3.63	6.63	12.07	20.20	28.80	37.29	42.46
PromptPay Amounts per Capita	510.06	7,729.32	17,269.38	27,208.98	42,552.49	55,364.28	60,023.66	60,623.94
PromptPay Lists per Capita	0.14	1.46	3.40	7.13	13.10	19.28	25.64	28.35
GDP per Capita	6,436.79	7,124.56	7,628.58	7,001.85	7,070.51	6,913.05	7,171.81	7,171.81
Daytime Surface Temperature	30.92	30.90	28.60	27.41	31.39	29.81	28.44	28.90
Nighttime Surface Temperature	20.92	22.80	22.96	19.86	21.52	22.89	22.29	20.01
Nighttime Light Density	0.87	0.79	0.89	0.97	0.99	0.92	1.21	1.36

Appendix B. Correlation Analysis Between Internet Banking Transactions and Satellite Data

Variables		X1	X2	X3	X4	X5	X6
Internet Banking Amounts per Capita	X1	1.000					
Internet Banking Lists per Capita	X2	0.800	1.000				
GDP per Capita	X3	0.180	0.389	1.000			
Daytime Surface Temperature	X4	-0.112	-0.185	-0.265	1.000		
Nighttime Surface Temperature	X5	0.302	0.143	0.067	-0.080	1.000	
Nighttime Light Density	X6	0.251	0.132	0.322	0.491	-0.111	1.000

Appendix C. Correlation Analysis Between Mobile Banking Transactions and Satellite Data

Variables		X1	X2	X3	X4	X5	X6
Mobile Banking Amounts per Capita	X1	1.000					
Mobile Banking Lists per Capita	X2	0.957	1.000				
GDP per Capita	X3	0.194	0.128	1.000			
Daytime Surface Temperature	X4	-0.171	-0.169	-0.265	1.000		
Nighttime Surface Temperature	X5	0.322	0.329	0.067	-0.080	1.000	
Nighttime Light Density	X6	0.079	0.108	0.322	0.491	-0.111	1.000

Appendix D. Correlation Analysis Between PromptPay Transactions and Satellite Data

Variables		X1	X2	X3	X4	X5	X6
PromptPay Amounts per Capita	X1	1.000					
PromptPay Lists per Capita	X2	0.968	1.000				
GDP per Capita	X3	0.196	0.122	1.000			
Daytime Surface Temperature	X4	-0.195	-0.161	-0.265	1.000		
Nighttime Surface Temperature	X5	0.325	0.323	0.067	-0.080	1.000	
Nighttime Light Density	X6	0.092	0.112	0.322	0.491	-0.111	1.000