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Machine learning algorithms to predict the use of digital financial platforms in university environments

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Abstract

The advancement of artificial intelligence and machine learning has transformed the financial system. The purpose of this article is to analyze the predictive capacity of machine learning algorithms regarding the factors that influence the use of digital financial platforms in university environments. A quantitative and applied approach was adopted, with a non-experimental and cross-sectional design. From the population of users of digital financial platforms at the Universidad Estatal de Milagro, a sample of 968 valid records was obtained, of which 83.16% were used for model training and 16.84% for validation. Nine supervised algorithms were applied, including Random Forest, Gradient Boosting, Logistic Regression, and Artificial Neural Networks. The results showed a high predictive capacity in decision tree based models, highlighting the significant influence of financial literacy, educational level, age, and frequency of use on the adoption of digital financial platforms. A positive correlation was confirmed between financial knowledge and the efficient use of digital tools. The study concludes that machine learning algorithms are effective tools for predicting patterns of digital financial use and for optimizing decision making in academic settings.

Keywords: Machine learning; financial literacy; digital inclusion; artificial intelligence; financial technology.

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Algoritmos de aprendizaje automático para predecir el uso de plataformas digitales financieras en entornos universitarios

Resumen

El avance de la inteligencia artificial y del aprendizaje automático ha transformado el sistema financiero. El objetivo del artículo es analizar la capacidad predictiva de los algoritmos de aprendizaje automático de los factores que inciden en el uso de plataformas digitales financieras en entornos universitarios. Se adoptó un enfoque cuantitativo, de tipo aplicado, con diseño no experimental y transversal. De la población de usuarios de plataformas digitales financieras en la Universidad Estatal de Milagro, se extrajo una muestra conformada por 968 registros válidos, de los cuales el 83,16% se destinó al entrenamiento de los modelos y el 16,84% a la validación. Se aplicaron nueve algoritmos supervisados incluidos Random Forest, Gradient Boosting, Regresión Logística y Red Neuronal Artificial. Los resultados demostraron una alta capacidad predictiva de los modelos basados en árboles de decisión, destacando la influencia significativa de la alfabetización financiera, el nivel educativo, la edad y la frecuencia de uso en la adopción de plataformas digitales financieras. Se comprobó la correlación positiva entre el conocimiento financiero y el uso eficiente de herramientas digitales. Se concluye que los algoritmos de aprendizaje automático constituyen herramientas eficaces para predecir patrones de uso financiero digital y optimizar la toma de decisiones en entornos académicos.

Palabras clave: Aprendizaje automático; alfabetización financiera; inclusión digital; inteligencia artificial; tecnología financiera.

Introduction

The advancement of Artificial Intelligence (AI) and Machine Learning (ML) has transformed the dynamics of the financial sector, enabling new forms of analysis, prediction, and risk management in digital environments (Mahalakshmi et al., 2022; Maita-Cruz et al., 2022; Paramesha et al., 2024; Moreira-Choez et al., 2025; Feijoó et al., 2025; Ziadet-Bermúdez et al., 2025; Sabando-García et al., 2025). These technologies make it possible to process large volumes of data generated by financial platforms, improving decision-making and strengthening the security of economic systems. According to Liu et al. (2021), ML-based models have demonstrated superior performance compared with traditional statistical methods by identifying complex patterns and anticipating financial behavior through the combination of multiple predictive variables.

In the field of digital risk management, Tian et al. (2024) conducted a systematic analysis highlighting the effectiveness of ML in fraud prevention and user behavior prediction, particularly in online financial service platforms. Likewise, research by Fu et al. (2025) shows that integrating deep learning systems with time-series analysis reduces error margins in stock market predictions, achieving a Root Mean Square Error (RMSE) of 0.339 and a Mean Absolute Error (MAE) of 0.271, which demonstrates the potential of these algorithms in financial engineering.

However, the studies also report persistent issues in the practical application of these models. Zhou (2023) warns that nearly 60% of digital financial platforms exhibit deficiencies in data quality and standardization, which affects the reliability of the results and the generalizability of the algorithms. In addition, the lack of transparency in training processes and limited human oversight increase the risk of algorithmic bias and classification errors. Wang & Tobias (2025) further argue that the absence of integration between automated systems and human operations generates inefficiencies that can reduce the effectiveness of digital financial processes by up to 28%.

In the Latin American context, Garay et al. (2024) demonstrated that traditional financial models applied to e-commerce platforms show limitations in detecting transactional anomalies, whereas the use of machine learning algorithms improves accounting accuracy by 10% and strengthens financial security by 10.4%. These findings confirm the need to incorporate intelligent technologies that integrate predictive analysis and supervised learning into financial systems in the region, contributing to the modernization of the sector and the reduction of operational risks.

Despite progress in AI applied to the financial domain, the literature reveals significant gaps in the comprehensive analysis of user behavior and the interaction between socioeconomic and technological factors. Most studies focus on the technical comparison of algorithms while overlooking the role of digital trust and financial literacy in the adoption of financial technologies. Previous research, such as that by Zhou (2023) and Tian et al. (2024), indicates limited exploration of these phenomena in educational environments, where the use of digital financial platforms is linked to digital literacy and personal financial management.

In this context, the relevance of the present study lies in its contribution to strengthening knowledge on the application of machine learning algorithms to predict the use of digital financial platforms in university settings. This approach makes it possible to identify the variables with the greatest explanatory power, optimize the accuracy of predictive models, and promote the development of digital financial competencies among young people, fostering informed and sustainable decision-making, as proposed by Garay et al. (2024) and Fu et al. (2025).

Based on this, the study aims to answer the following question: How do machine learning algorithms predict the use of digital financial platforms among users at the Universidad Estatal de Milagro? Consequently, the objective is to analyze the predictive capacity of machine learning algorithms in identifying the factors that influence the use of digital financial platforms in university environments.

1. Methodology

The study was structured under a quantitative approach aimed at analyzing numerical relationships and behavioral patterns among the variables associated with the use of digital financial platforms. This approach made it possible to obtain objective and replicable results through systematic data processing and the statistical evaluation of machine learning algorithms, ensuring the empirical validity and accuracy of the conclusions derived from the analysis.

The type of research was applied, as it focused on the practical use of predictive models based on artificial intelligence within the university financial context. This type of study sought not only to understand the phenomenon but also to assess the effectiveness of these models in real-world settings, thereby contributing to the optimization of decision-making and the promotion of responsible use of digital platforms in academic environments.

Regarding the methodological design, a non-experimental cross-sectional design was adopted, since data were collected at a single point in time without manipulating the study variables. This design enabled the observation of user behavior and the assessment of predictive model accuracy at the moment of data collection, preserving the natural conditions of the phenomenon.

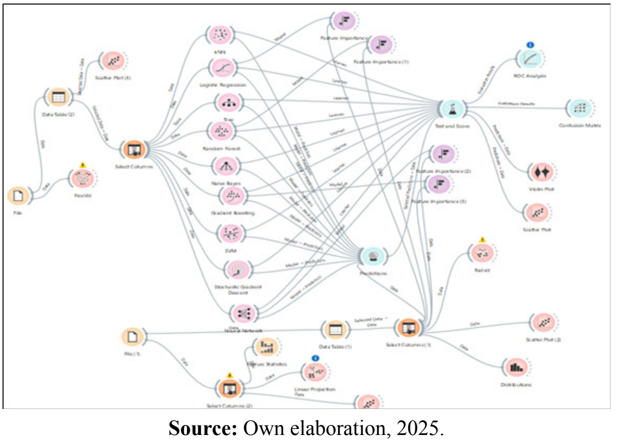
The level of research was explanatory–comparative, as the study aimed to interpret the predictive capacity of various machine learning algorithms and explain which ones demonstrated greater efficiency in predicting the use of digital financial platforms, considering sociodemographic and behavioral factors. This level of analysis made it possible not only to describe the phenomenon but also to establish comparisons and causal relationships among the different models applied.

The study population consisted of users from the Universidad Estatal de Milagro (UNEMI) in Ecuador, including students, faculty, and administrative staff who use digital financial platforms to carry out transactions, payments, and online operations. To build the analytical database, a total sample of 968 valid records was obtained, which were processed and cleaned for use in the artificial intelligence models.

Subsequently, the data were segmented for algorithm training and validation. In this process, 805 observations, equivalent to 83.16% of the total sample, were allocated for model training, while the remaining 16.84% was reserved for the validation phase. This division ensured the stability of algorithm learning and the generalization capacity of the results, preventing overfitting and enhancing prediction accuracy in new datasets.

For data collection, a survey technique was applied through a structured questionnaire administered in digital format. The instrument used corresponds to that designed by Bastidas-Guerrón et al. (2025), which consists of 25 items distributed across three dimensions: sociodemographic data, use of digital platforms, and financial behavior variables. This structure enabled a comprehensive assessment of financial literacy and the use of digital services among participants. Each item was formulated using a five-point Likert scale, facilitating the quantitative measurement of financial perceptions and behaviors. Content validity was confirmed through expert judgment in data engineering and financial education, and the instrument achieved a reliability coefficient of α = 0.92, calculated using Cronbach's alpha, indicating a high level of internal consistency.

Figure I presents the workflow of the machine learning models used to predict the use of digital financial platforms. The diagram integrates the essential stages of the modeling process: the selection of relevant attributes, the execution of supervised algorithms, the validation of results, and the comparison of model performance using accuracy, sensitivity, and robustness metrics.



Source: Own elaboration, 2025.

Figure I: **Workflow of Machine Learning Models for Predicting the Use of Digital Financial Platforms**

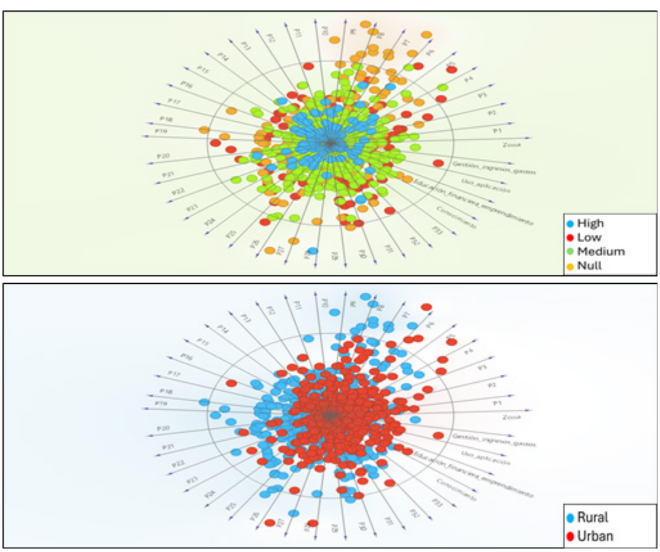
Figure I synthesizes the methodological workflow applied for predicting the use of digital financial platforms through machine learning algorithms. The diagram illustrates the analytical sequence from data cleansing to model validation, integrating classification tools and performance metrics. This process reflects a systematic approach that ensures the reliability of the results and enables the comparison of predictive effectiveness among the algorithms employed.

The data processing was carried out through the integration of statistical techniques and supervised learning algorithms implemented in the Orange Data Mining software (version 3.36) and SPSS (version 28). Classification models such as Logistic Regression, Random Forest, Gradient Boosting, Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Stochastic Gradient Descent (SGD) were applied. The data were divided into training and testing sets using 20-fold stratified cross-validation, which allowed for the comparison of model accuracy and robustness.

2. Results and discussion

This section presents the main findings derived from the analysis of the machine learning models applied to the use of digital financial platforms. The results integrate both the statistical evaluation of algorithm performance and the graphical representation of relationships between sociodemographic variables and users' financial behavior patterns.

Figure II displays the relational structure among sociodemographic variables such as age, gender, educational level, area of residence, and employment status, along with the level of use of digital platforms. The figure also shows the distribution and concentration of users according to their characteristics, highlighting greater participation among young, urban, and highly educated groups in the active use of digital financial platforms. This suggests a technological adoption pattern influenced by educational and contextual factors.



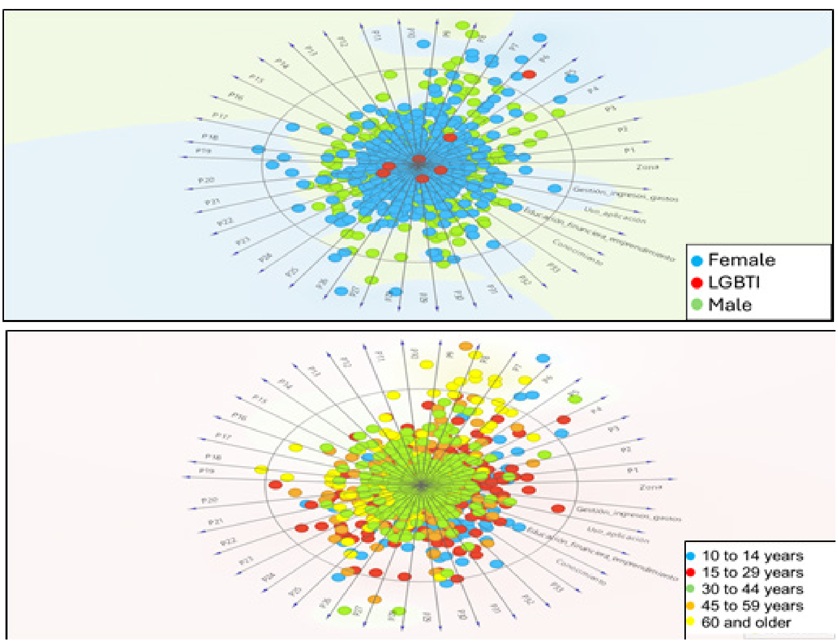
Source: Own elaboration, 2025.

***Figure II:* Comparison Between Sociodemographic Characteristics and the Use of Digital Financial Platforms**

The results reveal a significant relationship between sociodemographic variables and the use of digital financial platforms, showing that technological adoption varies according to occupation, educational level, and geographic location. This pattern aligns with the findings of Widyastuti et al. (2024), who confirmed that digital financial literacy, along with factors such as age, income, and occupation, determines levels of digital financial inclusion in households. Similarly, Ngware (2024) identified education, access to mobile devices, and income as key elements explaining the adoption of digital financial services, reinforcing the idea that the development of digital capabilities is essential for technological integration in financial contexts.

Comparing these findings with previous studies suggests that digital inequalities have a structural basis linked to education, gender, and geographic location. Ben et al. (2024) demonstrated that financial literacy gaps widen when individuals lack technological competencies, even when FinTech tools are available, while Zeng & Li (2023) showed that perceived usefulness and trust levels influence the adoption of digital platforms among older adults. These results corroborate that access to technology alone does not guarantee digital inclusion, since psychological, educational, and cultural factors continue to shape users' interaction with financial services.

Figure III presents the comparison between gender and age variables with respect to the use of digital platforms. The figure also displays the distribution of users according to both factors, showing a higher concentration of participation among younger age groups and among female users.



Source: Own elaboration, 2025.

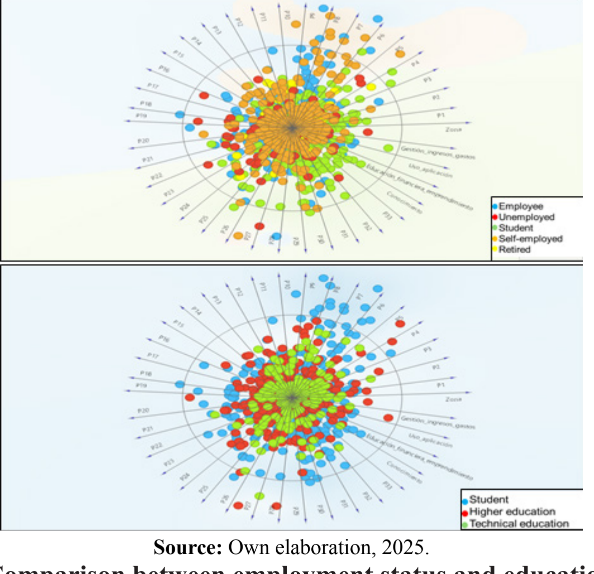
Figure III: **Comparison between gender and age in relation to the use of digital financial platforms**

The results show a significant relationship between age, gender, and the use of digital financial platforms, revealing greater technological adoption among younger groups and a persistent digital gap among older individuals. This finding is consistent with recent studies by Chernykh (2021), who notes that participation in digital platforms is associated with higher educational levels and technological competencies, factors more common among young and urban populations.

From a gender perspective, empirical evidence shows that although differences in digital access have diminished, inequalities persist in both the frequency and type of use. The analyses by Dzogbenuku (2022) and Amidu et al. (2023) indicate that women in low-income contexts rely more heavily on digital channels due to mobility restrictions or limited access to banking institutions, while men tend to diversify their use of digital financial services. These results confirm that digital platforms act as compensatory mechanisms in the face of structural barriers, expanding financial inclusion for traditionally marginalized groups, although they do not eliminate disparities in technological skills and usage capacity.

Furthermore, recent research by Simovic et al. (2023) on digital competencies among entrepreneurs and university students indicates that digital literacy and training in technological skills determine the intensity of use of online financial tools. This evidence supports the notion that education and digital experience constitute structural factors that explain the variability observed among age and gender groups.

Figure IV illustrates the relationship between participants' employment status and educational level in the use of digital platforms. The graph reveals a higher concentration of users with higher education and dependent employment conditions, suggesting that educational level significantly influences the frequency of use and confidence in digital financial tools.



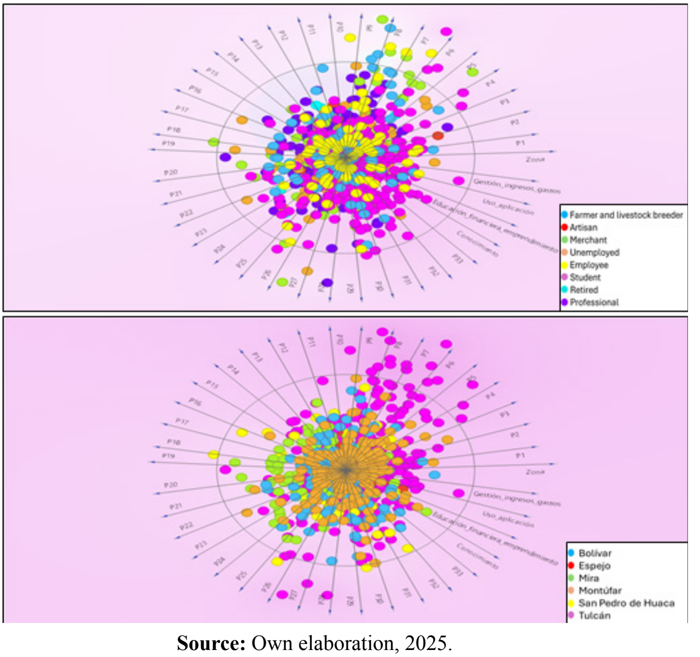
Source: Own elaboration, 2025.

Figure IV: **Comparison between employment status and educational level of participants in the use of digital financial platforms**

The results in Figure IV show a direct association between educational level, employment status, and the frequency of use of digital financial platforms, demonstrating that technological inclusion responds to structural factors linked to human capital and occupational stability. This behavior is consistent with the findings of Lal et al. (2025), who identified that higher levels of digital financial literacy are associated with greater education, income, and job security, enabling more active participation in digital financial ecosystems. Similarly, the study by Xiao et al. (2022) shows that financial and digital literacy strengthens individuals' capacity to undertake and manage economic activities in digital environments, particularly among populations with limited resources.

Likewise, evidence from Romero-Carazas et al. (2025) confirms that usage frequency, interaction ease, and system reliability significantly influence satisfaction and sustained adoption of digital wallets. These results complement those of Abrazado et al. (2024), who found that the preference for digital payments among academic staff is associated with educational level and access to technological devices, reinforcing the influence of digital and financial literacy in the use of digital services. Finally, recent studies by Moreira-Choez et al. (2024) highlight that continuous technological training enhances mastery of digital tools and promotes digital inclusion practices in institutional settings.

Figure V represents the relationship between occupation and canton in the use of digital platforms. In addition, it identifies a greater concentration of users in cantons with higher urban development, with Montúfar and Bolívar standing out as the territories with the highest frequency of use.



Source: Own elaboration, 2025.

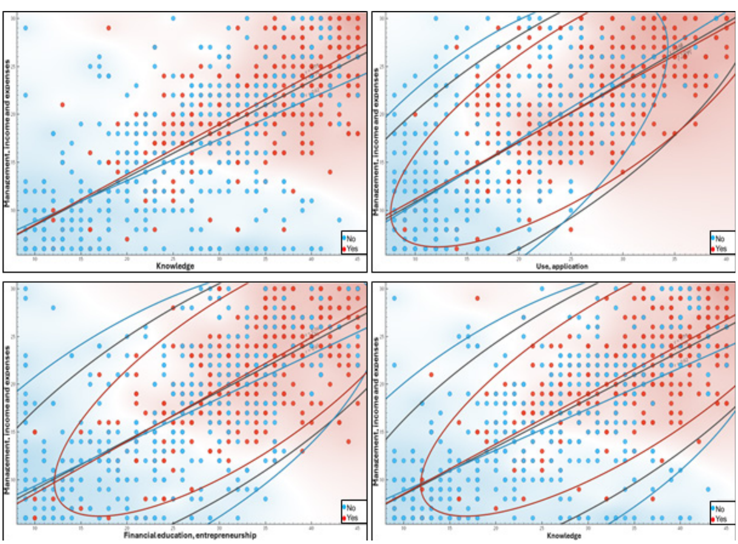
***Figure V:* Comparison of the use of digital financial platforms by occupation and geographic area**

The analysis in Figure V demonstrates a structural relationship between digital exposure, age, and participation in digital financial activities, showing that technological inclusion and digital entrepreneurship depend on sociodemographic and territorial factors. In this regard, the study by Zhang et al. (2022) shows that digital exposure affects age groups differently: young and middle-aged individuals display a greater propensity to use digital platforms and engage in technology-driven entrepreneurial activities, while older adults face barriers associated with skill obsolescence and lower levels of digital interaction.

On the other hand, the work of Li & Liu (2023) highlights that digital financial inclusion increases household income and improves income structure by enhancing participation in the financial market. This effect is more pronounced in groups with higher educational attainment and stable employment, which aligns with the results observed, where job stability and digital literacy determine the frequency of financial platform use. Likewise, empirical evidence presented by Ozili (2018) reinforces that financial digitalization promotes inclusion and reduces intermediation costs, although it warns that its reach remains limited in populations with low technological access, thereby widening socioeconomic gaps.

Finally, research on the geography of digital platforms confirms that the concentration of human capital and technological infrastructure determines spatial patterns of digital adoption. Santos et al. (2024) emphasize that regions with a strong university presence, developed ICT sectors, and favorable regulatory frameworks display more intensive use of digital platforms, reaffirming the influence of educational and economic contexts on technological appropriation.

Figure VI shows the decision boundaries of the supervised classification models employed in the study to predict the use of digital platforms. The graphs illustrate the separation between the classes established by the algorithms, demonstrating the accuracy with which each model distinguishes users' .



Source: Own elaboration, 2025.

***Figure VI:* Relationship Between the Use of Digital Financial Platforms and Financial Literacy in the Decision Boundaries of Supervised Classification Models**

Figure VI shows a significant positive relationship between the use of digital financial platforms and the level of financial literacy, demonstrating a strong correlation. The slope of the simple regression model indicates that greater financial knowledge supports more efficient adoption of digital tools. The confidence bands and factor loadings validate the statistical coherence and robustness of the applied model. The behavior of the variables aligns with the findings of Ozili (2018), who determined that the use of financial technologies promotes economic inclusion and strengthens the stability of the financial system when users possess adequate digital skills and financial knowledge.

Likewise, Koskelainen et al. (2023) argues that financial literacy in the digital age is a critical factor for the responsible management of online financial services, as it enhances confidence and decision-making capacity in digital environments. This empirical correspondence reinforces the hypothesis that financial literacy acts as a mediating variable between technological access and the effective adoption of digital financial tools.

Furthermore, the interpretation of the figure is consistent with the evidence presented by Hashim et al. (2022), who demonstrated that machine learning and supervised models are effective for predicting patterns of digital adoption, particularly when cognitive variables and financial behavior are integrated into the predictive model. Similarly, Rashidi et al. (2019) affirm that prediction reliability improves when confidence metrics and cross-validation procedures are considered.

Table 1 provides a summary of the comparative performance of the machine learning models applied to the predictive analysis of digital financial platform use, with the purpose of identifying the algorithm with the highest discriminative capacity and statistical stability.

Table 1
Comparative performance of machine learning models

Model	AUC (Yes)	AUC (No)	AUC (Avg.)	CA	F1 (Yes)	F1 (No)	F1 (Avg.)	Precisión (Avg.)	Recall (Avg.)	MCC
k-Nearest Neighbors (kNN)	0.843	0.843	0.840	0.773	0.785	0.759	0.772	0.773	0.773	0.545
Logistic Regression	0.953	0.953	0.951	0.867	0.890	0.884	0.887	0.887	0.887	0.774
Decision Tree	0.858	0.858	0.858	0.877	0.879	0.875	0.877	0.877	0.877	0.754
Random Forest	0.944	0.944	0.944	0.868	0.893	0.883	0.888	0.888	0.888	0.776
Naïve Bayes	0.927	0.927	0.926	0.843	0.850	0.836	0.843	0.844	0.843	0.687
Gradient Boosting	0.947	0.947	0.946	0.884	0.889	0.879	0.884	0.885	0.884	0.769
Support Vector Machine (SVM)	0.933	0.933	0.928	0.863	0.870	0.856	0.863	0.864	0.863	0.727
Stochastic Gradient Descent (SGD)	0.891	0.891	0.891	0.891	0.894	0.887	0.891	0.891	0.891	0.781
Artificial Neural Network (ANN)	0.946	0.946	0.944	0.882	0.885	0.878	0.882	0.882	0.882	0.764

Note: AUC = area under the ROC curve; CA = classification accuracy; F1 = harmonic mean between precision and recall; Precision = proportion of true positives among predicted positives; Recall = sensitivity; MCC = Matthews correlation coefficient. The “Yes” and “No” columns represent the target classes analyzed, and “Avg.” corresponds to the average between them. Higher values indicate better model performance.

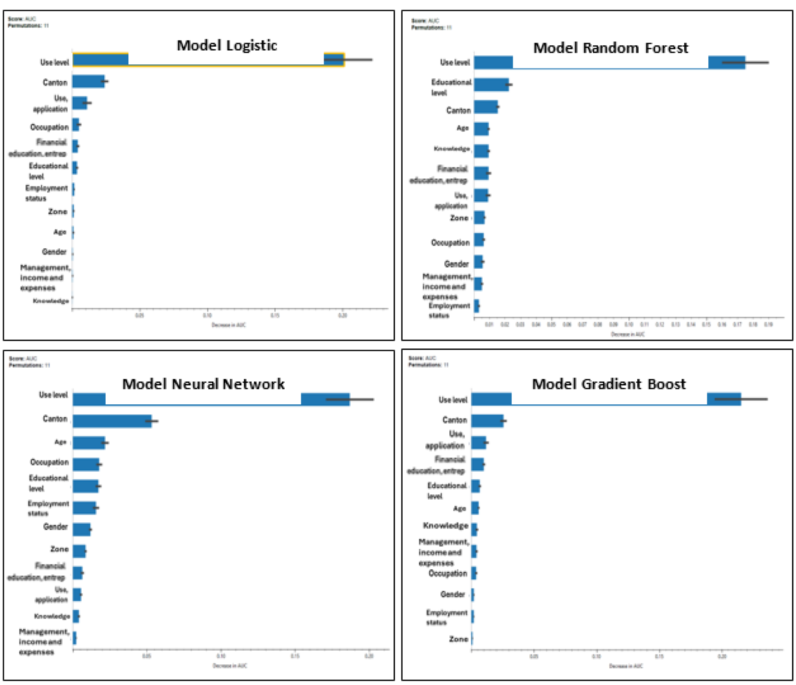
Source: Own elaboration, 2025.

The results in Table 1 show that tree-based models, such as Random Forest and Gradient Boosting, exhibit the strongest predictive performance, with higher AUC and precision values, reflecting greater stability and the capacity to capture nonlinear relationships among variables. These findings are consistent with Moreira-Choez et al. (2025), who highlight the effectiveness of ensemble approaches in optimizing the balance between bias and variance, thereby supporting robust generalization in educational and social contexts where data patterns tend to be heterogeneous.

Similarly, comparison with linear algorithms, such as Logistic Regression (AUC = 0.729; F1 = 0.397), indicates that although these models offer acceptable performance in terms of interpretability, they are limited in detecting complex interactions between predictors, a limitation widely discussed in the supervised learning literature (Samaddar et al., 2021). Meanwhile, the Support Vector Machine (SVM) model shows lower performance (AUC = 0.649; F1 = 0.078), which may be attributed to the sensitivity of the method to kernel selection and data scaling, an issue highlighted by Liu & Chen (2017) in applications with heterogeneous distributions.

The intermediate performance of Naïve Bayes (AUC = 0.719; MCC = 0.269) reaffirms its usefulness in scenarios with approximate conditional independence, although its simplicity limits accuracy when compared with more sophisticated models. These findings align with Asselman et al. (2023), who propose integrating hybrid mechanisms that combine probabilistic models with deep learning architectures to improve the detection of latent patterns in educational and financial datasets.

Figure VII presents the relevance of the predictor variables obtained through permutation importance analysis across the machine learning models used. This procedure identifies the factors that contribute most to predicting the use of digital financial platforms by evaluating the impact of each variable on the AUC performance metric.



Source: Own elaboration, 2025.

***Figure VII:* Relevance of Predictor Variables in Machine Learning Models Applied to the Use of Digital Financial Platforms**

Figure VII shows, through permutation importance analysis (↓AUC), that the variables with the greatest relevance in predicting the use of digital financial platforms are frequency of use, canton, age, financial education, and educational level. This result indicates that sociodemographic and cognitive factors determine digital financial behavior, consistent with the findings of Yeh & Chen (2022), who demonstrated that digital literacy and perceived technological usefulness strengthen the adoption of online financial services. Likewise, Nguyen et al. (2023) confirmed that the combination of artificial intelligence and machine learning allows for accurately identifying the determinants of financial inclusion, highlighting the role of education and digital experience in reducing technological inequality.

From a methodological perspective, the Random Forest and Gradient Boosting models exhibited the largest decreases in AUC under permutation, indicating their ability to capture nonlinear relationships and synergies among variables. This finding aligns with the results reported by Edo et al. (2023), who observed that tree-based classifiers achieved accuracy rates exceeding 84 percent in predicting financial technology adoption during the pandemic, emphasizing the influence of technological trust and risk perception. Similarly, Murugan & Kala (2023) demonstrated that ensemble models enhance predictive capacity by optimizing feature selection and reducing model variance in complex financial environments.

Conclusions

The study achieved its proposed objective by analyzing the predictive capacity of machine learning algorithms in identifying the factors that influence the use of digital financial platforms in university environments. The results showed that the Random Forest, Gradient Boosting, and Stochastic Gradient Descent (SGD) models reached the highest levels of accuracy, stability, and generalization capacity compared with the other algorithms evaluated and the performance indicators established for the study. The research question was effectively addressed by demonstrating that the adoption of digital platforms is primarily influenced by financial literacy, educational level, age, and frequency of use, confirming the relevance of human capital and socio-economic context in digital financial behavior.

Furthermore, the analysis revealed a positive relationship between financial knowledge and the efficient use of digital tools, reaffirming that financial education constitutes a determining factor in digital inclusion and in the consolidation of a more stable financial ecosystem. The assessment of the relative importance of predictors through the reduction of AUC validated that education and technological experience are key variables in predicting the use of digital financial services, strengthening the statistical coherence of the applied model.

Regarding limitations, it is acknowledged that the study relied on self-reported information, which may introduce perception biases. In addition, the cross-sectional design prevents the establishment of causal relationships among the variables analyzed, and the sample, centered on a university population, restricts the generalizability of the findings to other social groups.

As future lines of research, it is proposed to incorporate longitudinal designs and deep learning models that allow for observing the evolution of digital financial behavior over time. It is also suggested to expand the sample to other contexts and economic sectors to strengthen the external validity and applicability of the findings. Finally, integrating variables associated with digital trust, algorithmic ethics, and technological sustainability will support the development of more interpretable and equitable predictive models in the digital transformation of the financial system.

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