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Determinantes de la confianza en los bancos mexicanos: un análisis de aprendizaje automático de las Encuestas Nacionales de Inclusión Financiera 2021–2024.

Determinants of Trust in Mexican Banks: Machine-Learning Analysis of the 2021–2024 Financial Inclusion Surveys

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Abstract
Public confidence in banks' deposit protection and compliance with obligations is essential to foster financial inclusion. Accordingly, this research studies individual-level predictors, regional/national infrastructure and safety indicators, demographic and socioeconomic covariates, focusing on the 2021 and 2024 surveys of Mexico's National Financial Inclusion Survey (ENIF). The research question is: "What factors predict Bank Trust (TIB) among Mexican adults?" An end-to-end machine learning process was employed using Random Forest, XGBoost, LightGBM, and CatBoost set frameworks with stacking, and a survey-weighted logistic regression specification, to address statistical and predictive relevance. The variables which augment confidence in a bank are related to a higher financial literacy rate, better risk diversification strategies, greater per capita incomes per household, as well as proximity to banks. Age and internet access are also important variables for such assessments. The CatBoost model has a robust AUC value for the accuracy recovery of 0.734. The proposed study contributes to two different major objectives: (i) the application of a combination of econometric models with modern machine learning algorithms.

Keywords: trust in banks; financial inclusion; machine learning; survey methods; Mexico

JEL: G21; D14; O16; C55; C25

Resumen
La confianza pública en la protección de los depósitos bancarios y en el cumplimiento de las obligaciones es esencial para fomentar la inclusión financiera. En consecuencia, esta investigación estudia predictores a nivel individual, infraestructura regional/nacional e indicadores de seguridad, así como covariables demográficas y socioeconómicas, centrándose en las encuestas de 2021 y 2024 de la Encuesta Nacional de Inclusión Financiera (ENIF) de México. La pregunta de investigación es: ¿Qué factores predicen la Confianza en los Bancos (TIB) entre los adultos mexicanos?". Se empleó un proceso integral de aprendizaje automático utilizando los marcos Random Forest, XGBoost, LightGBM y CatBoost con *stacking*, así como una especificación de regresión logística ponderada por encuesta, para abordar la

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relevancia estadística y predictiva. Las variables que incrementan la confianza en un banco están relacionadas con una mayor tasa de alfabetización financiera, mejores estrategias de diversificación del riesgo, mayores ingresos per cápita por hogar, así como la proximidad a los bancos. La edad y el acceso a internet también son variables importantes para dichas evaluaciones. El modelo CatBoost presenta un valor AUC robusto para la recuperación de la precisión de 0.734. El estudio propuesto contribuye a dos objetivos principales diferentes: (i) la aplicación de una combinación de modelos econométricos con algoritmos modernos de aprendizaje automático.

Keywords: confianza en los bancos; inclusión financiera; aprendizaje automático; métodos de encuesta; México.

JEL: G21; D14; O16; C55; C25

Introduction

This research examines the determinants of trust in banks (TIB) in Mexico using individual-level data from the National Survey of Financial Inclusion (ENIF)'s 2021 and 2024 waves. This study's major research question is: "What predicts TIB among Mexican adults?" When depositors trust that banks will safeguard their deposits and honor commitments, the cost of transactions is low and the markets of credit and savings are more efficient (Knack & Zak, 2003). From a socio-psychological perspective, trust itself denotes voluntary vulnerability based on positive beliefs about a counterparty's ability and kindness (Hu et al., 2019). Applied to the context of banking, this refers to depositor confidence regarding intermediaries to behave responsibly and truthfully, thereby encouraging participation in formal financial services (Ahmad et al., 2021).

In addition to individual characteristics, our empirical framework includes state-level infrastructure measures (ATMs, branches, TPOS-equipped establishments) and INEGI's Safety perception index as higher-level controls. To compare machine learning classifiers to standard estimates of the logistic regression model. While our analysis will take into consideration state-specific infrastructure measures, the direct relationship between micro-trust metrics and national aggregates is a topic for future research. ENIF 2021-2024 offers micro-data for the six regions in Mexico. In consideration of the disparate confidence level that the public may have toward the financial system, our analysis will focus on the variation of Trust in Banking (TIB) for individual conditions. Persistent distrust is a barrier; this study identifies which attributes and contexts predict trust to safeguard deposits and honor obligations.

The aim of this study is twofold. First, it aims to determine which individual, and contextual factors have the largest bearing on TIB among Mexican adults. Second, it endeavors to estimate the contribution of banking infrastructure and digital service provision to confidence using machine-learning algorithms (Chen & Guestrin, 2016) for prediction and logistic regression for inferential work.

We hypothesized here that greater financial capability—more financial knowledge and more disciplined money-management practices—would be accompanied by greater TIB. We also posited that access to the internet and smartphones (digital inclusion) and usage of internet/mobile banking, along with denser local financial infrastructure (branches, ATMs, and point-of-sale terminals), would each positively correlate with TIB. We predicted a positive correlation of perceived neighborhood security with TIB and lower TIB in less safe local conditions. For demographics, we predicted a positive effect of education and income to increase TIB and a nonlinear (inverted-U) effect of age. We finally predicted risk attitudes consistent with contemporary portfolio theory—understanding the risk–return trade-off and support of diversification—to forecast TIB and investigated whether the mean TIB is different from 2021 to 2024 levels conditioning upon covariates.

Consistent with these expectations, our empirical analysis reveals that infrastructural and digital-access variables are the strongest predictors of depositor confidence. In logistic regression, a one-unit increase in digital-access (smartphone ownership and household internet availability) raises the probability of trusting banks (TIB = 1) by approximately 8 percentage points (pp) ($p < .001$), with branch-network availability showing a positive marginal effect on TIB, whereas normalized ATM density exhibits a statistically significant negative marginal effect. These results highlight the usefulness of combining machine learning with classical econometric approach to analyze emerging markets. These findings highlight the usefulness of combining nonlinear machine learning with classical methods to analyze trust in emerging markets. 2. Literature Review Trust in financial institutions is essential to financial inclusion and the efficient functioning of banking systems.

This work, through the inclusion of granular constructs for trust and national infrastructure metrics, has a number of contributions to make to literature and policy. This work advances theories about institutional forms of trust that show how physical and virtual banking infrastructure complement each other and encourage deposits and applies machine learning for accuracy and conformity with policy relevance.

Literature Review

Trust in financial institutions is essential to financial inclusion and the efficient functioning of banking systems. A broad international literature point that higher levels of institutional trust are positively associated with bank account ownership, the use of formal financial services, and overall financial stability (Fungáčová et al., 2019). In emerging economies with greater informality and uncertain institutions, trust is crucial for individuals' participation in the formal financial sector.

From an institutional perspective, past research emphasize regulation, banking supervision, and deposit-insurance schemes as mechanisms that reduce uncertainty and promote systemic trust (Knell & Stix, 2015). However, further studies indicate that the perceived credibility on these warrants among depositors are just as important as their effectiveness (Butzbach, 2016). Therefore, poor enforcement, limited transparency, or low awareness of consumer protections may undermine trust even in the presence of formal safeguards.

More over, evidence from empirical research suggests that trust in banks is a multidimensional construct shaped by economic, social, and psychological factors. Mayer, Davis, and Schoorman (Mayer et al., 2006) propose a framework to understand organizational trust, which comprehends three key dimensions: ability, benevolence, and integrity. This framework has been widely applied to financial institutions. A research by Cruijsen, de Haan, and Roerink (van der Cruijsen et al., 2021), employing European survey data, shows that higher levels of financial knowledge are associated with greater trust in banks and financial authorities. In contrast, negative personal experiences with financial institutions tend to wear away trust in a persistent manner.

Recent studies have highlighted the growing relevance of digital financial inclusion to physical banking infrastructure in influencing levels of trust in financial institutions. For example, banking trust could be boosted by improved digital safety as well as improved service quality and handling of client data (Bijlsma et al., 2022). On the other hand, adoption in technology cannot guarantee improved trust if concerns in these two areas still linger (Koomson et al., 2023). Similarly, physical bank branches often function as “symbols of trust,” although their marginal importance may decline as digital channels expand (Sakong & Zentefis, 2024).

Contextual conditions, especially perceived public security, is another factor that plays a significant role in shaping institutional trust. In the Mexican context, Blanco (2013), who analyzed the impact of insecurity and crime victimization on support and satisfaction in institutions, shows that lower trust in public and financial institutions are associated with higher levels of crime and insecurity. This finding concurs with comparative evidence suggesting that local insecurity operates as an indirect channel through which confidence in banks and other formal institutions is weakened (Broekhoff et al., 2024).

Scholarship in methodology views machine learning as a way to improve empirical economics by increasing the precision of prediction and simplifying complex problems, thus complementing other methods instead of displacing them, especially in policy studies ((Mullainathan & Spiess, 2017). Nonetheless, the literature overlooks the strength of hybrids that combine machine learning methods with causal inference.

More recent studies have used machine learning algorithms for analyzing trust in banks, proposing that trust in banks cannot be fully explained using econometric analysis, due to possible nonlinearities or interaction patterns (Adamyk et al., 2019). Based on World Values Survey data, using an integrated approach combining both econometric tools and machine learning algorithms, Adamyk et al. (2019) analyzed how different factors interact to influence trust in banks. The study confirms that individual properties and global trust have proved to play an important role in forming trust in banks. Forecasting approaches will provide enhanced effectiveness if they are theoretically informed and integrated with techniques for improved clarity.

However critical these advances have been, the literature that applies them to Mexico is very limited, especially in the area of nationally representative surveys using machine learning tools and theories of trust.

The National Financial Inclusion Surveys carried out in Mexico in 2021 and 2024 present a unique opportunity to close the gap, since these surveys include comprehensive information on financial behavior, feelings of security, availability of financial infrastructure, and opinions. The goal of the current research work is to perform a comprehensive study on the determinants of trust in banks using the aforementioned tools, with direct policy implications regarding financial inclusion in Mexico.

Empirical evidence on determinants of trust in banks

Prior studies link higher financial knowledge to greater trust in banks, with similar patterns for broader financial institutions—supporting the view that knowledge and disciplined money management raise TIB (van der Cruijsen et al., 2021). Digital access and use tend to complement trust when security and reliability are credible; during COVID-19, trust in banks' payment services rose alongside digital payments, but mere uptake without security/UX improvements does not necessarily increase trust (Jafri et al., 2024). Physical presence also matters: branches act as "symbols of trust," and branch/ATM density is associated with inclusion and service confidence (Sakong & Zentefis, 2024). In Mexico and the region, perceived insecurity depresses institutional trust, implying higher TIB where neighborhood security is stronger(Blanco, 2013).

Trust generally increases with income and follows mixed, life-cycle patterns by education and age; attitudes aligned with the risk–return trade-off and diversification correlate with higher confidence in financial services (Fungáčová & Weill, 2019; Jafri et al., 2024). Historically, a sizable share of unbanked adults in Mexico cited lack of trust as a barrier, while recent waves emphasize income/need; accordingly, we model TIB jointly with digital inclusion, financial infrastructure, and perceived security to capture the main channels through which confidence is formed.

Theoretical Framework

Trust in banking rests on a firm belief that institutions will safeguard assets, honor commitments, and act with integrity (Mayer et al., 2006). This belief is shaped by three core dimensions— technical competence, benevolence toward depositors, and adherence to ethical norms—which together determine depositor confidence in both individual banks and the broader financial system (Butzbach, 2016).

Formal structures such as regulation, deposit insurance, and supervisory oversight provide "Structural assurances" that reduce uncertainty and reinforce institutional trust (Zucker, 1986). At the same time, sociological perspectives remind us of that trust functions as a shortcut under uncertainty, relying on reputational signals and probabilistic judgments in the absence of complete information (Luhmann, 2018).

Within Mexico's financial landscape, depositor trust emerges from judgments about a bank's solvency and fairness, filtered through cultural norms and moral beliefs (Alraheb et al., 2019). Confidence is forged both through formal channels—such as CNBV oversight and IPAB insurance—and informal influences like branch reputation and community word-of-mouth, reflecting the coexistence of traditional banking, rural microfinance, and digital platforms.

Analyzing financial behavior requires understanding the interplay between personalized trust, developed through repeated interactions, and systemic trust, based on market protection and stability. Pooled cross-sectional ENIF data (2021 and 2024) offers insights into the factors influencing bank choices.

Methodology

Data Sources and Sample

We use the 2021 and 2024 waves of Mexico's ENIF, conducted by CONAIF and collected by INEGI. ENIF is a nationally representative household survey covering financial behaviors, perceptions, and access/infrastructure in urban and rural areas. A stratified, multistage cluster design ensures national and regional representativeness; across both waves 30,548 households were surveyed (15,291 in 2021; 15,257 in 2024), with oversampling of small localities (<2,500 inhabitants). Response rates were 91% (2021) and 90.5% (2024). After standard cleaning (listwise deletion and removal of incomplete records), the final analytic sample is 27,056 adults—13,554 (2021) and 13,502 (2024). Both waves had INEGI Ethics Committee approval, complied with Mexico's data-protection law, obtained informed consent, and were released in anonymized form.

Variable Construction

Dependent Variable: Trust in Banks (TIB)

Following Sztompka's (Sztompka, 1999) "Reflected Trustworthiness" framework, we operationalize TIB as a composite of five binary indicators embedded in Section 11 of ENIF ("Confianza y protección") (INEGI, 2022). Respondents answered "Sí" (Salazar-Cruz & Román-Reyes) (1) or "No" (2) to each of the following statements:

1. P11_1_1. "Si tuviera que solicitar servicios de un banco… ¿considera que recibiría toda la información necesaria?" (Trust that the bank will provide complete information)

2. P11_1_2. "… ¿considera que resolverían su necesidad o problema económico?" (Trust that the bank will resolve its economic needs/problems)

3. P11_1_3. "… ¿considera que estaría seguro su dinero?" (Trust that the bank will keep funds safe)

4. P11_1_4. "… ¿considera que resolverían sus quejas y reclamaciones?" (Trust that the bank will handle complaints)

5. P11_1_5. "… ¿considera que protegerían sus datos personales?" (Trust that the bank will protect personal data)

Each item (P11_1_1 – P11_1_5) was recoded as a binary indicator (1 = "Sí"; 0 = "No"; missing if "No sabe/No contestó"). A summative index (TRUST_SUM) was constructed as the sum of these five dummies, yielding a discrete scale ranging from zero (no trust in any dimension) to five (full trust on all five dimensions). For models requiring a continuous input, we also compute a normalized average (TIB = TRUST_SUM / 5), which ranges from 0 to 1.
The TIB index draws on items that directly map onto the trust dimensions proposed by Mayer et al. (2006): two items capture ability (e.g., technical competence of banks and perceived security of deposits), two assess benevolence (e.g., banks' concern for customer welfare and fairness in fee practices), and one reflects integrity (e.g., transparency in communication and adherence to ethical standards).

Key Predictors

Financial knowledge, behavior, and attitudes (measurement framework)

We measure financial capability in components to preserve construct validity and 2021–2024 comparability. Knowledge is an ENIF 5-item index (interest/inflation) common to both waves—not the Lusardi–Mitchell "Big Three," which requires a diversification-knowledge item absent in ENIF(Lusardi & Mitchell, 2011). Behavior is captured by a Financial Accountability Index (budgeting/record-keeping) aligned with OECD-INFE (Atkinson & Messy, 2012). Attitudes (risk–return recognition; preference for diversification) enter as separate controls; we therefore do not form a 2024-only OECD composite.
Financial knowledge (ENIF 5-item). We construct a financial knowledge index from five factual items on interest and inflation available in ENIF-2021 and ENIF-2024 (INEGI, 2022; 2025). This ENIF-based measure is not the Lusardi & Mitchell "Big Three," which includes a diversification-knowledge item that ENIF does not provide consistently across waves (Lusardi & Mitchell, 2011). Four items originate from Section 12 (interest calculations and inflation adjustment), and one item originates from Section 4.7 (inflation definition). Each indicator is coded as 1 if the respondent's answer is correct, and 0 otherwise, as follows:

1. Inflation Definition (P4_7_1) (INEGI, 2022): Respondents evaluate whether "*Inflation means that the price of things increases*". A correct response (code 1, "True") was coded as fknowledge_inflation = 1; any other response (codes 2, 8, 9) was coded as 0.

2. Simple Interest (P13_1) (INEGI, 2022), (P12_1) (INEGI, 2025): Respondents answer the question, "*If you lend 25 pesos to a friend and the next week they return the 25 pesos, how much did you pay in interest?"* The correct answer ("Nothing," code 1) was coded as fknowledge_interest_simple = 1; any other response (codes 2–4, 9x) was coded as 0.

3. Annual Interest(P13_2) (INEGI, 2022), (P12_2) (INEGI, 2025): Respondents evaluate "*Let's suppose that you deposit 100 pesos in a savings account that gives 2% a year, without deposits or withdrawals, how much will you have at the end of the year?*" The correct answer ("102 pesos," code 2) was coded as fknowledge_interest_annual = 1; all other codes were coded as 0.

4. Compound Interest (P13_3) (INEGI, 2022), (P12_3) (INEGI, 2025): Respondents evaluate "*If you deposit 100 pesos reinvesting the interest, what will you have at the end of five years?*" The correct answer ("110 pesos," code 2, since 100 × (1.02)^5 ≈ 110.41) is coded as fknowledge_compound = 1; all other codes are coded as 0.

5. Inflation-Adjusted Value (P13_4) (INEGI, 2022), (P12_4) (INEGI, 2025): Respondents evaluate "*If you are given 1,000 pesos but you have to wait a year with inflation of 5%, could you buy the same?*" The correct answer ("No," code 2) was coded as fknowledge_inflation_corrected = 1; all other responses (codes 1, 3, 4, 9x) were coded as 0.

Subsequently, these five binary variables are summed to create a composite financial knowledge score (fknowledge_score), such that fknowledge_score ∈ {0, 1, 2, 3, 4, 5}:

$$fknowledge_{score} = fknowledge_{inflation} + fknowledge_{interest_{simple}} + fknowledge_{interest_{anual}} + fknowledge_{compound} + fknowlededge_{inflation_{adjuste}}$$

This raw score was then normalized to a continuous index (Financial Knowledge Index) bounded between zero and one, defined as:

$$Financial_{knowledge_{index}} = \frac{fknowledge_{score}}{5}$$

Higher values of Financial Knowledge Index correspond to greater overall financial-knowledge proficiency.

Financial accountability index. Coded as Financial Accountability Index we operationalize financial accountability as a composite measure of six core budget- and expense-tracking behaviors, all drawn from ENIF (INEGI, 2022, 2025) survey items P4_1 and P4_2 sub-questions. For each respondent *i*, we define the binary indicators as follows:

1. $budg\_record_i$ = 1 if respondent “maintains a written record of income and expenses” (P4_1=1);
2. exp_note_i = 1 if they “annotate expenses” (P4_2_1=1);
3. sep_funds_i = 1 if they “separate payment funds from daily spending” (P4_2_2=1);
4. rec_notes_i = 1 if they “track receipts/debts to avoid missed payments” (P4_2_3=1);
5. $mgmt\_app_i$ = 1 if they “use an app or tool for expense tracking” (P4_2_4=1);
6. $autopay_i$ = 1 if they “have automatic (domiciled) bill payments” (P4_2_5=1).

These six indicators are summed to yield a financial accountability score,

$$fa_{score} = \sum_{j=1}^{6} behavior_{i_j}$$

and ranges from 0 (no behaviors) to 6 (all behaviors). We then normalized this value to a 0–1 index.

$$Financial_{accountability_{incex}} = \frac{fa_{score}}{6}$$

This index captures the extent to which each respondent actively monitors and manages their personal finances. In OECD-INFE terminology, this index corresponds to the behavior pillar and is modeled separately from knowledge and attitudes (Atkinson & Messy, 2012).

Risks. Attitudes (risk perceptions). In line with Lusardi & Mitchell (2011) and OECD-INFE guidance, risk perceptions are treated as attitudes, not knowledge. We therefore include two attitudinal indicators from ENIF (INEGI, 2022; 2025):

- First, Risk_opportunity captures awareness of the trade-off between easy gains and losses. Specifically, Risk_opportunity is set to 1 if the respondent affirms the statement *“If someone offers you the chance to win money easily, you can easily lose it too”* (P4_7_2 = 1), and 0 otherwise.
- Second, a variable labeled Risk_diversify captures belief in diversification by coding as one respondent who agrees with “*It's better to save money in two or more ways or places than just one*” (P4_7_3 = 1), and 0 otherwise.

In subsequent analyses, both Risk_opportunity and Risk_diversify enter as distinct predictors: the former gauges sensitivity to potential losses associated with high-return opportunities, whereas the latter reflects a preference for spreading financial resources across multiple saving channels. These attitudinal variables are not included in the Financial Knowledge Index; under the OECD-INFE view they belong to the attitudes pillar, and under the LM view they are distinct from factual knowledge.

Demographic and Socioeconomic Controls

- Age and Age Squared: (Allen et al., 2016) (INEGI, 2025) Respondent’s age in years (Courbage & Nicolas, 2021); age_sq = AGE^2 to capture nonlinear age effects.
- Sex: (SEXO) (INEGI, 2022, 2025) Sex (0 = female; 1 = male).
- Educational attainment (NIV) (INEGI, 2022, 2025): was grouped into five levels: none, elementary, middle school, high school, and higher education. For the survey-weighted logistic regression, schooling enters as four dummies (elementary, middle, high, higher), with no schooling as the

omitted reference; marginal effects are interpreted relative to this base. For machine-learning models (Random Forest, XGBoost, LightGBM, CatBoost), the same categories are encoded via one-hot vectors to avoid imposing ordinality and to capture nonlinearities and interactions. Responses of "don't know/unstated" are set to missing. This approach aligns the regression tables and ML features and replaces the incorrect min–max "Scholar_norm" description.

- Marital Status: (P3_2) (INEGI, 2022, 2025). Three dummies: MARRIED, where "Vive con su pareja en unión libre" ("lives with their partner in a common-law union) and "Está casada(o)" (married) status were considered jointly; SINGLE, for "Es soltera(o)"; and, UNPARTNERED, for which "Está separada(o)" (apart) , "Está divorciada(o)" (divorced), and "Es viuda(o)" (widow/widower) were considered in this category.
- Labor-Force Participation (LFP) (P3_5) (INEGI, 2022, 2025): LFP = 1 if currently employed, self-employed or searching for job; 0 if out of the labor force such as students, retired or housewife.
- Monthly Household Income (thousand Pesos): Monthly household income was constructed from two ENIF items: the reported earnings amount (P3_11A) and frequency of payment (P3_11B) (INEGI, 2022, 2025). Specifically, P3_11A records the respondent's gross earnings in pesos (ranging from 00000 = "No recibe ingresos" to 90000, with 98000 = "98 000 y más" and 99888 = "No responde"). P3_11B indicates the payment interval (1 = semanal, 2 = quincenal, 3 = mensual, 4 = anual). To convert all observations into a common monthly metric, the following algorithm was applied:

$$income_{monthly} = \begin{cases} P3\_11A * 4.345 & if\ P3\_11B = 1\ (weekly) \\ P3\_11A * 2.173 & if\ P3\_11B = 2\ (biweekly) \\ P3\_11A & if\ P3\_11B = 3\ (monthly) \\ P3\_11A\ /\ 12 & if\ P3\_11B = 4\ (annual) \end{cases}$$

- Observations coded P3_11A = 00000 ("no income") or P3_11A = 99888 ("no responde" no response) were set to zero. The resulting income_monthly variable (in pesos) was then rescaled to thousands of pesos (income_m_thous = income_monthly / 1 000) to improve interpretability. For inclusion in the machine-learning models, income_m_thous was normalized to the [0, 1] interval using min-max scaling:

$$income_{norm} = \frac{income_{m_{thous}} - \min(income_{m_{thous}})}{\max(income_{m_{thous}}) - \min(income_{m_{thous}})}$$

This procedure ensured the comparability of monthly income across all respondents, regardless of their original pay frequency.

Behavioral/Infrastructural Control

- Cash usage index. This index is constructed from two ENIF (INEGI, 2022, 2025) survey items: one for small purchases (P7_1_1) and one for large purchases (P7_1_2).
  For minor purchases, the use of cash is coded 3, also for major purchases. For each good, a binary indicator is formed, where 1 denotes the use of cash and 0 denotes the non-use.
  Finally, the two binary indicators are averaged to construct the Cash_usage_index, ranging from 0 to 1. A value of 1 indicates using cash on big and small purchases, while 0 indicates no cash usage. Intermediate values represent partial use of cash. The index averages values from both responses and is used in regression and machine-learning models to predict bank trust.
- Digital access. The digital access variable measures respondents' accessibility to digital services, such as owning a smartphone (P3_14) (INEGI, 2022, 2025), where a response of 'yes' is coded as 1 and 'no' is coded as 0. It also includes Internet access in the household (P0_4_2) (INEGI, 2022,

2025), with ‘yes’ coded as 1 and ‘no’ coded as 0. The results are then averaged from both responses and used to predict trust in banks through regression and machine-learning models.

Financial-Infrastructure and Regional Variables

We include four state-level variables drawn from INEGI (INEGI, 2025) banking-establishment and public-security databases:

State-Level Banking Infrastructure:

- ATM_number_norm is the number of ATMs in respondent’s region (INEGI, 2022, 2025), normalized between [0,1].
- Bank_branches_norm is the number of bank branches in the respondent’s region (INEGI, 2022, 2025), normalized between [0,1].
- Estab_TPOS_norm is the number of establishments with point-of-sale terminals in the respondent’s region (INEGI, 2022, 2025), normalized between [0,1].
- Security perception. Designated as the Safety_perception_index, this variable assesses the population's perception of security within the corresponding region. The data is from the *Encuesta Nacional de Victimización y Percepción sobre Seguridad Pública* (ENVIPE) (INEGI, 2021). Is an indicator of the percentage of Mexicans who feel secure in their municipality, neighborhood, or house. This indicator is constructed from INEGI's (2021, 2023) national household surveys and represents insecurity perception and not a crime rate. The Regional Security Perception Index was weighted by each state’s population for this study. Subsequently, the Safety Perception Index was normalized using the min-max method to obtain values ranging between 0 and 1.

Each respondent was assigned a value for these four variables corresponding to their state of residence. In all regression and ML models, these counts (and the index) are entered as continuous covariates, capturing how regional banking infrastructure and security conditions shape individual trust in banks.

Regional and Locality Controls:

- Locality size. Refers to the population size of the respondent’s locality as identified by ENIF (INEGI, 2022, 2025). The categories were: 1 = 100,000 inhabitants or more; 2 = 15,000 to 99,999 inhabitants; 3 = 2,500 to 14,999 inhabitants; 4 = less than 2,500 inhabitants. This variable was coded as Locality_size_norm*,* where the values are between 0 and 1, from normalization to the categories.
- Region: ENIF (INEGI, 2022, 2025) is divided into six geographic regions: 1 = Northwest, 2 = Northeast, 3 = Occident-Bajio, 4 = Mexico City, 5 = South Central-Orient; 6 = South. These regions were coded as one-hot using dummy variables.
- Year: This is a binary variable that indicates the ENIF year, where 0 represents 2021 and 1 represents 2024.

Empirical Strategy

The empirical approach comprises two complementary techniques: (1) logistic-regression models to estimate the marginal effects and statistical significance of predictors on a binary trust outcome; and (2) tree-based machine-learning (ML) algorithms, to capture nonlinearities and interactions while assessing relative feature importance.

Dependent Variable Specification

Because the principal research question is “Which factors predict TIB among Mexican adults?” we define a binary target as:

$$TIB_i = \begin{cases} 1 \; if \; TIB_{AVG} > 0.5 \\ 0 \; if \; TIB_{AVG} \leq 0.5 \end{cases}$$

Logistic-Regression Model
We begin with a baseline logistic-regression specification:

$$\begin{aligned} TIB_i = \ & \alpha + \beta_1 Sex_i + \beta_2 Age_{sqr_i} + \beta_3 Education_i + \beta_4 Civil\ Status_i + \beta_5 LFP_i + \beta_6 Income_{norm_i} \\ & + \beta_7 Financial_{knowledge_{index_i}} + \beta_8 Financial_{accountability_{index_i}} + \beta_9 Risk_{opportunity_1} \\ & + \beta_{10Risk_{diversify_i}} + \beta_{11} Digital_{access_i} + \beta_{12} Cahs_{usage_{index_i}} + \beta_{13} Locality_{size_{norm_i}} \\ & + \beta_{14} Bank_{branches_{norm_i}} + \beta_{15} ATM_{number_{norm_i}} + \beta_{16} Estab_{TPOS_{norm_i}} \\ & + \beta_{17} Safety_{perception_{index_i}} + \beta_{18} Region_i + \beta_{19} Year_i + \varepsilon \end{aligned}$$

where:

- Education was a dummy variable for elementary, middle school, high school and higher. Edu_none (no education) is omitted from the analysis.
- Civil Status are dummy variables for Married_partnered and Unpartnered. Single is omitted.
- LFP is a dummy variable where 1 is a participant and 0 is a non-participant.
- Regions are dummies for regions 1–5 (Region 6 = South is omitted).

Coefficients are reported as average marginal effects (dy/dx) in the sample means (Williams, 2012).

Multicollinearity diagnostics
We evaluated for multicollinearity by using variance inflation factors (VIF). The mean VIF was 2.64, with a small subset of expected temporospatial controls (year and regional infrastructure variables) exhibiting higher values, all remaining below conservative thresholds. (Salmerón et al., 2020). In fact, these are manifestations of expected temporospatial relationships, not a problem of linear dependence. Thus, it is apparent that multicollinearity is not a problem that affects stability and interpretation of coefficients. Also, multicollinearity is largely a problem of parametric inference, and tree machine learning models used in this analysis do not suffer from multicollinearity.

Machine-learning Models
This study employs four tree-based machine-learning classifiers to model individual trust in banks. In addition, a stacking ensemble is implemented as a complementary approach to assess whether combining base learners improves predictive performance. All features were provided to the machine-learning pipeline as a pre-encoded matrix: categorical predictors were converted to their numeric representations in advance, and continuous variables were normalized with values between [0, 1]. Automated validation procedures systematically evaluate data for out-of-range values, target imbalances, and feature-integrity concerns, thereby ensuring high data quality prior to modeling.
Predictive modeling leverages a sophisticated ensemble architecture comprising four complementary base learners:

- Random Forest for robust bagging (Mullainathan & Spiess, 2017)
- XGBoost for regularized gradient boosting (Chen & Guestrin, 2016)
- LightGBM for high-performance, leaf-wise boosting (Ke et al., 2017)
- CatBoost for seamless categorical handling (Prokhorenkova et al., 2018)

Base-model predictions are fused via a stacking ensemble: a LightGBM meta-learner integrates the out-of-fold predictions from each base learner. Stratified 5-fold cross-validation (Berrar, 2019) guides both hyperparameter tuning and performance estimation, whereas sigmoid and isotonic calibration refine the reliability of the predicted probabilities.
The hyperparameter optimization is fully automated. An initial RandomizedSearchCV phase quickly explores broad parameter ranges, after which Optuna conducts multi-objective tuning while simultaneously optimizing the accuracy, F1-score, and ROC-AUC. Memory-management routines dynamically monitor

RAM usage and downcast data types where possible, thereby enabling efficient training on large survey datasets.

Model evaluation is comprehensive, encompassing:

- Classification metrics (accuracy, precision, recall, F1-score)
- Ranking metrics (ROC-AUC, average precision)
- Calibration metrics (log loss, reliability diagrams)

This is, model performance is evaluated using complementary metrics, including the area under the receiver operating characteristic curve (ROC–AUC) and the precision–recall area under the curve (PR–AUC). While ROC–AUC summarizes the model's ability to discriminate between outcomes across classification thresholds, PR–AUC places greater emphasis on correct classification of the positive class, which is particularly informative in settings with class imbalance.

In addition to individual classifiers, a stacking approach is employed. Stacking is an ensemble-learning technique that combines the predictions of multiple base models to generate a final prediction, potentially improving performance by exploiting the strengths of different algorithms. All machine-learning models used in this study are tree-based, meaning they rely on recursive partitioning of the data and are well suited to capturing nonlinear relationships and interaction effects.

Optimal decision thresholds are identified via Youden's J statistic, and a suite of visual diagnostics—ROC and precision-recall curves, feature-importance bar plots, and correlation heatmaps—facilitates transparent comparison across models.

To elucidate the drivers of banking trust, the pipeline integrates interpretable-ML techniques. SHAP (Lundberg & Lee, 2017) provides local and global explanations using TreeExplainer, LinearExplainer, and KernelExplainer, generating interactive force, dependence, and summary plots. Permutation-importance analyses and model-specific feature rankings were further accompanied by statistical significance testing to confirm the robustness of the identified predictors.

Statistical validity was ensured by the following:

- Variance Inflation Factor analyses to detect multicollinearity
- Parametric coefficient estimation for interpretable effect sizes
- Confidence intervals around predicted probabilities
- Model diagnostics, including residual analysis and goodness-of-fit tests

Inference and robustness considerations

Statistical inference, including standard errors and confidence intervals, is conducted within the logistic regression framework, where coefficient estimation and hypothesis testing are well defined. In contrast, the primary objective of the machine-learning models is predictive performance rather than parameter inference. Accordingly, robustness in the machine-learning context is assessed through out-of-sample validation and performance stability across alternative algorithms and metrics.

Specifically, model performance is evaluated using cross-validation procedures and complementary metrics such as ROC–AUC and precision–recall AUC. Consistent results across models provide evidence of robustness to model specification and sample variation. This combined approach allows the analysis to benefit from formal statistical inference in the econometric model while exploiting the flexibility of machine-learning methods to capture nonlinearities and heterogeneous effects.

Results

Logistic Regression Results

Survey-weighted logistic regression was used to identify the individual-level determinants of TIB = 1). The estimation sample included 27,056 respondents (design degrees of freedom = 2,171), representing a population per year as shown in Table 1, of:

Table 1
Population representation ENIF 2021, 2024

Year	Population
2021	90,328,320
2024	94,221,441
Total	184,549,761

Source: Authors' elaboration with data from INEGI (2021, 2025)

The overall model was highly significant (F (27, 2145) = 41.92, $p < .001$). Tables 2 and 3 present the full coefficient estimates and average marginal effects, respectively.
The analysis of marginal effects (dy/dx) revealed several salient factors that influence individuals' trust in banks. Notably, the squared term for age demonstrated that as respondents' ages increased to higher extremes, the probability of reporting trust in banks decreased substantially -25.8 pp. Educational attainment emerged as a significant predictor, with completion of secondary education associated with a +7.4 pp, and higher education yielding a comparable effect +7.2 pp, relative to those without formal education.

Household income, measured as a one-unit increase in normalized income, was robustly associated with greater trust in banks (+58.8 pp). Financial knowledge (+19.4 pp) and financial accountability (+13.3 pp) were also strong positive determinants. In terms of access to financial services, greater digital accessibility corresponded to a 7.5 pp increase in trust, whereas higher dependence on cash (-4.5 pp) and residency in smaller urban localities (-3.5 pp) were associated with lower trust levels.

Table 2
Logistic regression coefficients

TIB	Coefficient	Std. Err.	P>t
Sex	0.0153181	0.0432281	0.723
Age_sqr	-1.1799730***	0.1372356	0.000
Elementary	-0.0664667	0.0610764	0.277
Middle school	0.1385063	0.0730802	0.058
Highschool	0.3381847***	0.068433	0.000
Higher	0.3308259***	0.0749043	0.000
Married_partnered	-0.1403426**	0.0518044	0.007
Unpartnered	-0.0900615	0.0685769	0.189
LFP	-0.1083240*	0.051841	0.037
Income_norm	2.6875290***	0.4314828	0.000
Financial_knowledge_index	0.8873147***	0.1529521	0.000
Financial_accountability_index	0.6079980***	0.0823243	0.000
Risk_opportunity	0.1739683***	0.0442976	0.000
Risk_diversify	0.2363627***	0.0446844	0.000

Digital_access	0.3434786***	0.0697817	0.000
Cash_usage_index	-0.2045666**	0.0761589	0.007
Locality_size_norm	-0.1578039**	0.0600514	0.009
Bank_branches_norm	2.4021510*	1.15286	0.037
ATM_number_norm	-5.4898470*	2.630328	0.037
Estab_TPOS_norm	3.9191910*	1.789483	0.029
Safety_perception_index	2.6854610***	0.7285679	0.000
Region_Northwest	1.2151530**	0.3884239	0.002
Region_Northeast	2.5338500*	0.9912105	0.011
Region_Occident_Bajio	-1.1799070*	0.4874668	0.016
Region_Mexico_City	2.1992760**	0.6555795	0.001
Region_CentralSouth_Orient	-0.3814723*	0.1557763	0.014
Year	0.1022517	0.1949696	0.600
_cons	-2.8954170***	0.8024116	0.000

Survey-weighted average marginal effects; robust standard errors clustered at PSU; weights = FAC_PER; strata = EST_DIS; PSU = UPM_DIS
*** p<.001, ** p<.01, * p<.05
Source: Own calculations based on INEGI (2020–2025)

Table 3
Marginal effects

	dy/dx	**std. err.**	**P>t**
Sex	0.0033531	0.0094619	0.723
Age_sqr	-0.2582902***	0.0298098	0.000
Elementary	-0.0145492	0.0133679	0.277
Middle school	0.0303183	0.0159884	0.058
Highschool	0.0740269***	0.0148813	0.000
Higher	0.0724161***	0.0163479	0.000
Married_partnered	-0.0307203**	0.0113132	0.007
Unpartnered	-0.019714	0.0150006	0.189
LFP	-0.0237116*	0.0113534	0.037
Income_norm	0.5882865***	0.0940043	0.000
Financial_knowledge_index	0.1942287***	0.0333362	0.000
Financial_accountability_index	0.1330877***	0.0178853	0.000
Risk_opportunity	0.0380808***	0.0096809	0.000
Risk_diversify	0.0517386***	0.009731	0.000

Digital_access	0.0751857***	0.0152294	0.000
Cash_usage_index	-0.0447786**	0.016667	0.007
Locality_size_norm	-0.0345425**	0.0131446	0.009
Bank_branches_norm	0.5258187*	0.2522871	0.037
ATM_number_norm	-1.2017000*	0.5756083	0.037
Estab_TPOS_norm	0.8578912*	0.3916022	0.029
Safety_perception_index	0.5878338***	0.1593508	0.000
Region_Northwest	0.2659908**	0.0849523	0.002
Region_Northeast	0.5546470*	0.2168825	0.011
Region_Occident_Bajio	-0.2582758*	0.106701	0.016
Region_Mexico_City	0.4814105**	0.1433888	0.001
Region_CentralSouth_Orient	-0.0835024*	0.0341324	0.015
Year	0.0223824	0.0426762	0.600

Survey-weighted average marginal effects; robust standard errors clustered at PSU; weights = FAC_PER; strata = EST_DIS; PSU = UPM_DIS
*** p<.001, ** p<.01, * p<.05
Source: Authors' own calculations based on INEGI (2020–2025)

Regarding institutional infrastructure, a one-unit increase in the density of bank branches was positively related to trust (+52.6 pp), whereas a similar increase in ATM availability exhibited a negative association (-120.2 pp). The presence of point-of-sale (POS) terminals was also positively associated with trust in banks (+85.8 pp).

Perceptions of safety within the banking environment also contributed substantially; a one-unit increase in perceived safety resulted in a +58.8 pp increase in trust. Attitudinal factors, such as risk tolerance measured by opportunity-seeking (+3.8 pp) and diversification preferences (+5.2 pp), were both significantly positively correlated.

With respect to sociodemographic characteristics, being married (-3.1 pp) and participation in the labor force (-2.4 pp) were marginally associated with reduced trust. Regional heterogeneity was evident: compared to the reference region, respondents in the Northeast (+55.5 pp) and Mexico City (+48.1 pp) exhibited greater trust in banks, whereas those in the Occident-Bajio (-25.8 pp) and Central-South-Orient (-8.4 pp) regions reported lower levels of trust.

The goodness-of-fit test for the survey-weighted logistic model yielded the following:

$$F\,(9, 2163) = 2.26,\ p = 0.0164.$$

Under the null hypothesis, the model is correctly specified, and its predicted probabilities do not systematically differ from the observed outcomes. We reject this null hypothesis because p<0.05, indicating that there remains a statistically significant lack of fit even after accounting for our 27 predictors and survey design. Therefore, it is necessary to utilize machine-learning models, which are designed to capture complex nonlinearities and interactions, as a complementary approach to uncover patterns that the logistic model may not detect.

Machine-Learning Results

Because TIB = 1 constitutes the majority class in our hold-out sample (16 338/27 056 ≈ 60.39 %), the baseline precision in a Precision–Recall framework is 0.6039, not "near zero." In other words, a naïve classifier that randomly labels observations as "trust" with the same frequency as in the data would achieve an average precision of 0.6039. Therefore, we assessed our models' lift over the baseline when reporting the PR-AUC (Saito & Rehmsmeier, 2015).
Table 4 reports the performance of the four machine-learning classifiers and the stacking ensemble, benchmarked against a random baseline. A baseline precision of 0.6039 reflects at 60.39 % prevalence of TIB = 1 in the hold-out set, indicating that a random classifier would correctly flag trusting respondents only at that rate. Among the algorithms, CatBoost attained the highest PR-AUC (0.7339) and the strongest ROC-AUC (0.6634), along with low log-loss (0.6503) and narrowly outperforming RandomForest (PR-AUC = 0.7317; ROC-AUC = 0.6617; log-loss = 0.6526). However, RandomForest was ultimately preferred owing to its superior probability calibration and lower variance in log-loss across cross-validation folds. XGBoost and LightGBM delivered nearly identical discrimination (PR-AUC ≃ 0.731; ROC-AUC ≃ 0.662), underscoring the robustness of tree-based ensembles, whereas the stacking ensemble underperformed (PR-AUC = 0.7233; ROC-AUC = 0.6492), suggesting limited incremental benefit from combining these models.

Table 4

Classifier results comparison: four base learners and one stacking ensemble

Model / Baseline	PR-AUC	ROC-AUC	Log-loss	Opt. Threshold	Accuracy	Precision	Recall	F_1
Baseline (random)	0.6039	–	–	–	–	–	–	–
RandomForest	0.7317	0.6617	0.6526	0.5262	0.6114	0.7226	0.5786	0.6427
XGBoost	0.7315	0.6613	0.6473	–	0.6216	0.7111	0.6288	0.6674
LightGBM	0.7309	0.6614	0.6427	0.5151	0.6353	0.7001	0.6928	0.6964
CatBoost (best single model)	0.7339	0.6634	0.6503	0.4942	0.6310	0.7056	0.6674	0.6860
Stacking Ensemble	0.7233	0.6492	0.6371	0.6199	0.6035	0.7049	0.5906	0.6427

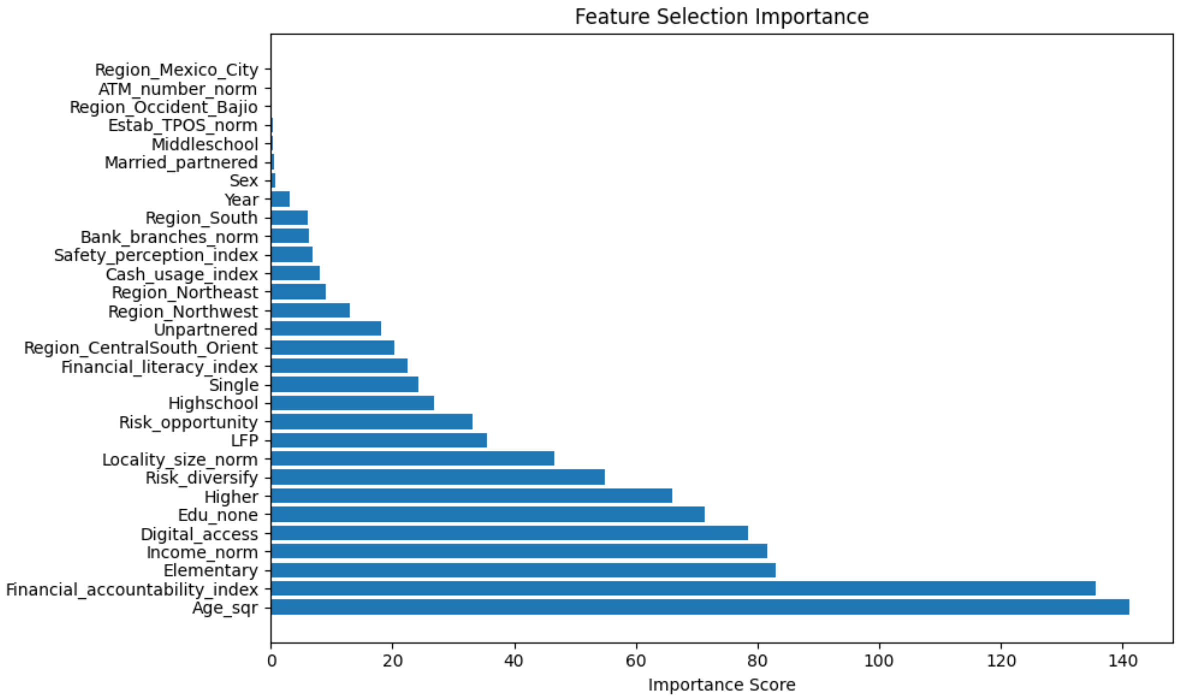
Source: Authors' calculations using ENIF 2021 (INEGI, 2022) and ENIF 2024 (INEGI, 2025)

Feature importance

The feature-importance chart (Figure 1) ranks each predictor by how much it reduces impurity (or "gain") across all trees in the best single model.
To investigate the determinants of model performance, several key patterns emerge from the feature importance analysis. The most important predictor is the squared age variable (Age_sqr), which has an importance value of almost 140. This result shows the strong nonlinear relation of age to trust: Trust levels are maximized in mid-adult life, with a sharp decrease when age is either low or high.

Figure 1

Feature selection importance



Source: Authors' elaboration using data from INEGI (INEGI, 2020)

Financial Accountability Index reaches an importance measure of over 130. This underscores the primary value of individuals' perceived financial capability and reports an attitudinal measure second only to age in terms of predictive power. Socioeconomic status and access to major resources variables formed the subsequent level of predictive variables, whose importance measures usually resided in the 70–90 interval. This list consisted of education attainment (eminently so at 'none' and at the elementary level), normalized household income (Income_norm), and access to computers (digital access). Higher education is another feature of this area. Overall, these results indicate the primary role education, income, and digital access play in discriminating between those who reported trusting and those who did not.

A second group of predictors, with mid-level importance values between 40 and 65, consists of attitudinal and contextual factors like risk preferences (Risk_diversify and Risk_opportunity), locality size (Locality_size_norm), participation in the labor force (LFP), and the Financial Knowledge Index. These factors have a significant impact on trust predicted, although their relative strength is moderate when we consider the stronger socioeconomic drivers. Finally, demographic and infrastructural variables, such as sex, marital status, regional indicators, ATM density, and POS-terminal density had the lowest importance scores (below 30). These findings suggest that, once the principal attitudinal and structural factors are accounted for, such demographic and infrastructural characteristics contribute only marginal predictive value to the model.

Overall, the ranking confirms that demographic nonlinearity (Courbage & Nicolas, 2021) and financial attitudes (accountability and knowledge) are the engines of the model, while basic socioeconomic status and digital access further sharpen its discrimination, and purely geographic or infrastructural measures play only a minor role.

Synthesis and Comparison

Both approaches converge on the centrality of socioeconomic status and financial attitudes for TIB: household income, financial accountability, and digital access consistently rank among the top predictors in the logistic and ML models. They also agree that risk-diversification attitudes and digital engagement are positively associated with trust. Where they differ is informative: ML surfaces a pronounced nonlinear age profile—captured by the squared term (Age_sqr)—with trust peaking in mid-adulthood and tapering at younger and older ages; the logistic model flags Age_sqr as significant but less richly. ML further elevates the role of basic educational attainment, suggesting interactions and multi-path mechanisms that parametric models may understate. By contrast, regional indicators are significant in the logistic regressions but fall in ML importance rankings, likely because tree-based ensembles absorb spatial heterogeneity through finer individual-level features.

Taken together, the methods are complementary. Both identify shared foundations—financial capability and access—while ML adds value by revealing nonlinearities and interactions that standard specifications obscure. The emerging narrative is that trust in banks is anchored in material and perceptual access to financial resources, yet the pathways that build trust are multidimensional and context-sensitive.

Discussion

Key Findings

This study employs both survey-weighted logistic regression and tree-based machine-learning (ML) models to identify the key determinants of TIB among Mexican adults. Both approaches converged on the centrality of socioeconomic status and financial-attitudinal factors—household income, financial accountability, and digital access emerged as the top predictors of depositor confidence. The enhanced ML pipeline further uncovered a pronounced nonlinear age effect: trust peaked in mid-adulthood and declined at both younger and older extremes. Educational attainment, especially the distinction between no formal education and elementary level, also exhibited heightened importance in ML models, suggesting multidimensional pathways linking basic schooling to trust that are not fully captured by parametric methods.

Geographic dummies, while significant in the logistic framework, played only a minor role in the ML ranking, implying that ensemble methods internalize spatial heterogeneity through more granular individual predictors. Finally, attitudinal measures of risk diversification and engagement with digital financial services positively contribute to trust, underscoring the interplay between risk orientation and fintech adoption.

At the algorithmic level, CatBoost attained the highest discrimination (PR-AUC = 0.7339; ROC-AUC = 0.6634) before calibration and narrowly outperformed RandomForest. However, Random Forest's superior probability calibration and lower log-loss variance recommended it for policy-relevant applications. The feature-importance analysis of the best single model highlighted Age_sqr (≈ 140) and the Financial Accountability Index (≈ 130) as the dominant drivers of predictive performance, followed by education, normalized income, and digital access (importance scores of 70–90). Mid-range factors (scores ~40–65) included perceived neighborhood security, risk attitudes, locality size, labor-force participation, and financial knowledge, while purely demographic or infrastructural variables (sex, marital status, regional indicators, ATM/POS density) contributed marginally.

Comparison with Prior Literature

These findings corroborate theoretical accounts that emphasize the joint role of structural assurances (e.g., deposit insurance and regulatory quality) and individual capabilities (financial knowledge and accountability) in fostering institutional trust (Mayer, Davis, & Schoorman, 2006; Zucker, 1986). The nonlinear age pattern we uncover is consistent with life-cycle effects on financial behavior (Courbage & Nicolas, 2021). The pronounced role of digital access accords with evidence that improvements in digital payments can elevate trust in banks' services (Bijlsma et al., 2022) and with systematic reviews highlighting trust and security as central to FinTech adoption (Jafri et al., 2024). At the same time, the literature cautions that mere uptake without credible security and usability gains may not raise trust—an observation aligned with our result that digital access matters most when paired with favorable security perceptions (del Carmen Díaz-Peña et al., 2025).

Our comparatively smaller effects for ATM/POS density relative to digital access are compatible with work showing that branches often function as "symbols of trust," whose marginal salience can diminish as digital channels expand and service reliability is signaled through other means (Sakong & Zentefis, 2024). The positive income gradient and the mixed, life-cycle-shaped patterns for education and age fall within the ranges documented in cross-country analyses of trust in banks and in recent European evidence on trust in payment services (Fungáčová et al., 2019). Finally, the positive association between perceived neighborhood security and TIB echoes Mexico-specific findings that crime and insecurity depress institutional trust (Blanco, 2013). Our findings show that in Mexico, digital access, safety perceptions, and visible infrastructure together influence trust in banks.

Limitations

There are several caveats that warrant consideration. First, the survey-weighted logistic model exhibited a statistically significant lack of fit ($F(9,2163)=2.26$, $p=0.0164$), implying that complex nonlinearities remain unmodeled by parametric approaches. Second, the cross-sectional design of the ENIF waves limits causal inference and may be subject to reporting bias. Third, national-level financial indicators (e.g., deposit/GDP) were not directly linked in the individual-level analysis; future work could integrate macro-micro models to strengthen external validity.

Conclusion

This study illustrates that TIB of Mexican adults has a confluence of socioeconomic status, financial-behavioral practices, and digital experiences. Household income and financial responsibility emerge as among the very best predictors of TIB in survey-weighted logistic regression and machine-learning models, and the nonlinear life-cycle pattern—reaching its maximum at mid-life and declining at young and oldest ages—emerges most clearly for tree-based learners. Lower levels of education appear more significant within non-parametric analyses, which aligns with the notion that schooling may influence trust through multiple channels. Furthermore, digital access indicators and diversification attitudes demonstrate that both secure engagement with fintech and prudent financial behavior play central roles in supporting trust. From a methodological perspective, ensemble learning algorithms such as CatBoost and Random Forest demonstrate superior discriminatory ability (PR-AUC $\approx$ 0.73) and enhance diagnostic feature analysis. These findings suggest that machine learning approaches can effectively complement and extend traditional econometric inference methods.

They imply three practical levers for regulators and institutions: establish stronger financial-capability programs—with emphasis on accountability practices and core education—so confidence grows at scale; install safe and equitable digital infrastructure and digital literacy, with tailored assistance for young and old adults with particular barriers to online banking; and transmit service reliability and consumer protections so that trust cues are salient. These types of initiatives can augment personal confidence and, as a side effect, support further macro objectives such as increasing the bank-deposit/GDP ratio and sustaining inclusive growth. Because the design is cross-sectional, causal inference is limited. A natural next step is panel-based machine-learning with macro/financial shocks to trace trust trajectories over time (Knell & Stix, 2015; Butzbach, 2016), interpret model-based importances/SHAP patterns with formal theories of trust for sharper mechanisms (Sztompka, 1999), and apply natural experiments—like deposit-insurance reforms—to estimate impacts of policies. Including explicit macro–micro linkages between aggregate financial indicators and trusting individuals would further improve external validity. In combination, predictive analytics and evaluation driven by theory offer practical guidance for bolstering trust and inclusion in Mexico's banking system.

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