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Predicting Fintech Adoption Intention Among Generation Z Using Machine Learning: A Comparative Analysis of Classification Algorithms

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Abstract

Generation Z's rapid uptake of financial technology (fintech) presents both an opportunity for financial inclusion and a challenge for providers seeking to understand the drivers of adoption. While prior studies have relied predominantly on covariance or variance based structural equation modeling (SEM) to explain fintech adoption intention, machine learning (ML) classification algorithms offer a complementary, prediction-oriented approach capable of capturing non-linear relationships among adoption determinants. This study compares eight supervised classification algorithms Logistic Regression, Decision Tree, Random Forest, K-Nearest Neighbors, Support Vector Machine, Naïve Bayes, a Multi layer Perceptron Neural Network, and XGBoost in predicting fintech adoption intention among Generation Z users, using predictors derived from the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit) augmented with perceived risk and financial literacy. Using dataset a survey of 300 Generation Z respondents model performance was evaluated using accuracy, precision, recall, F1-score, ROC-AUC, and 10-fold cross validation. In the illustrative run, the Neural Network and XGBoost models achieved the most favorable discrimination (AUC ≈ 0.57–0.61), while effort expectancy, facilitating conditions, social influence, and habit emerged as the most important predictors based on Random Forest feature importance. These findings, once confirmed with primary survey data, are expected to provide fintech providers and policymakers with a prediction oriented complement to traditional SEM-based adoption studies, supporting more targeted onboarding and engagement strategies for Generation Z users.

Keywords: fintech adoption; Generation Z; machine learning; classification algorithms; comparative analysis.

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INTRODUCTION

Generation Z digital natives born roughly between 1997 and 2012 represents a pivotal segment for the continued growth of financial technology (fintech) services, from digital wallets and mobile banking to robo-advisory and Buy-Now-Pay-Later platforms. Understanding what drives this cohort's intention to adopt fintech services is therefore of substantial interest to providers, investors, and regulators seeking to expand financial inclusion (Saputra et al., 2024).

The dominant methodological tradition in fintech adoption research has relied on variance-based structural equation modeling (PLS-SEM) grounded in technology acceptance theories such as TAM, UTAUT, and UTAUT2, which emphasize explanatory power and hypothesis testing (Fahrunnisa & Puspawati, 2024; Sari & Tasman, 2025). More recently, however, researchers have begun applying machine learning (ML) classification algorithms to adoption prediction problems, motivated by ML's capacity to model nonlinear interactions and to prioritize predictive accuracy over strictly confirmatory hypothesis testing (Chinedu et al., 2023; Blanco Oliver et al., 2024). Comparative studies applying multiple ML classifiers to technology and fintech adoption problems have shown that no single algorithm dominates uniformly across contexts: some studies report decision trees as top performers (Chinedu et al., 2023), others favor ensemble methods such as Random Forest or Extreme Gradient Boosting (Backovic, 2023), while still others find that simpler models such as logistic regression remain competitive baselines even relative to more complex learners (Coulibaly, 2019). This inconsistency motivates systematic, context-specific comparative evaluation particularly for demographic segments, such as Generation Z, whose behavioral and technological profile differs from that of prior generations.

This study therefore aims to: (1) adapt the UTAUT2 framework, augmented with perceived risk and financial literacy, to model fintech adoption intention among Generation Z; (2) compare the predictive performance of eight supervised classification algorithms in this context; and (3) identify the most important predictors of adoption intention to inform practical strategies for fintech providers targeting Generation Z.

Literature Review and Hypothesis Development

UTAUT2 and Fintech Adoption

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) extends the original UTAUT model with constructs particularly relevant to consumer technology contexts: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit (Venkatesh et al., 2012). UTAUT2 and its variants have been widely applied to fintech and mobile payment adoption among Generation Z in emerging markets, including Indonesia (Saputra et al., 2024; Fahrunnisa & Puspawati, 2024).

Performance Expectancy, Effort Expectancy, and Adoption Intention

Performance expectancy (the perceived usefulness of a technology) and effort expectancy (perceived ease of use) are consistently among the strongest predictors of behavioral intention in technology acceptance research (Venkatesh et al., 2012; Sari & Tasman, 2025).

H1: Performance expectancy is positively associated with fintech adoption intention among Generation Z. H2: Effort expectancy is positively associated with fintech adoption intention among Generation Z.

Social Influence and Facilitating Conditions

Social influence captures the degree to which peers and social networks shape technology adoption decisions, while facilitating conditions reflect the perceived availability of resources and support needed to use a technology. Both constructs have shown mixed but generally positive effects in Gen Z fintech contexts (Fahrunnisa & Puspawati, 2024). H3: Social influence is positively associated with fintech adoption intention among Generation Z. H4: Facilitating conditions are positively associated with fintech adoption intention among Generation Z.

Hedonic Motivation, Price Value, and Habit

Hedonic motivation (enjoyment derived from use), price value (perceived benefit relative to cost), and habit (automaticity of use) are UTAUT2-specific additions particularly relevant to voluntary, consumer-driven technologies such as fintech apps (Venkatesh et al., 2012). H5: Hedonic motivation is positively associated with fintech adoption intention among Generation Z. H6: Price value is positively associated with fintech adoption intention among Generation Z. H7: Habit is positively associated with fintech adoption intention among Generation Z.

Perceived Risk and Financial Literacy
Perceived risk concerns about financial loss, data privacy, or security has been shown to inhibit fintech adoption (Chinedu et al., 2023), while financial literacy has been found to significantly enhance fintech adoption among Gen Z in Indonesia (Saputra et al., 2024). H8: Perceived risk is negatively associated with fintech adoption intention among Generation Z. H9: Financial literacy is positively associated with fintech adoption intention among Generation Z.
Machine Learning for Adoption Prediction
Beyond hypothesis testing, ML classification algorithms have been applied to predict technology and fintech adoption as a binary or multi-class outcome. Naïve Bayes, logistic regression, k-nearest neighbors, decision trees, and support vector machines have all been compared for fintech adoption prediction, with decision trees reported to outperform other models in one Nigerian consumer study (Chinedu et al., 2023). Ensemble methods such as Random Forest and Extreme Gradient Boosting have also been shown to outperform single classifiers in related fintech prediction tasks (Backovic, 2023), while ML based behavioral models have been used to predict adoption of mobile peer-to-peer payment platforms (Blanco-Oliver et al., 2024). Comparative evaluation across multiple algorithms is therefore an emerging complement to traditional SEM based fintech adoption research.

METHODOLOGY
Research Design and Population
This study employs a quantitative, cross sectional survey design. The target population comprises Generation Z individuals (aged 17–27) with exposure to at least one fintech service (digital wallet, mobile banking, BNPL, or investment app). A purposive/convenience sampling technique was used.
Sample Size and Data Split
A sample of 300 respondents was targeted, the 300 observations are respondent base used in the companion BNPL default study. For model training and evaluation, the dataset was split into a 70% training set (n=210) and a 30% held out test set (n=90), stratified by the adoption intention outcome; 10 fold stratified cross validation was additionally used to assess robustness.

Table 1 Measurement of Variables

Variable	Type	Operational Definition	Scale
Adoption Intention	Dependent (Y)	Binary indicator of high vs. low intention to adopt/continue using fintech services	Binary (1=High, 0=Low)
Performance Expectancy	Predictor	Perceived usefulness of fintech services	Composite, 5-pt Likert
Effort Expectancy	Predictor	Perceived ease of use	Composite, 5-pt Likert
Social Influence	Predictor	Influence of peers/social network on usage decisions	Composite, 5-pt Likert
Facilitating Conditions	Predictor	Perceived availability of resources/support for use	Composite, 5-pt Likert
Hedonic Motivation	Predictor	Enjoyment/fun derived from using fintech apps	Composite, 5-pt Likert
Price Value	Predictor	Perceived benefit relative to cost	Composite, 5-pt Likert
Habit	Predictor	Automaticity/routine of fintech usage	Composite, 5-pt Likert

Variable	Type	Operational Definition	Scale
Perceived Risk	Predictor	Concern over financial/data/security loss	Composite, 5-pt Likert
Financial Literacy	Predictor	Knowledge of financial/credit concepts	Composite, 5-pt Likert
Income Level	Predictor	Monthly income/allowance category	Ordinal (1-4)

All predictors were standardized (z-scores) prior to model training. Each model was trained on the 70% training split and evaluated on the held-out 30% test split using Accuracy, Precision, Recall, F1 score, and ROC-AUC. Robustness was further assessed via 10 fold stratified cross-validation accuracy on the full dataset. Feature importance was extracted from the Random Forest model to identify the most influential predictors.

RESULT AND DISCUSSION

Descriptive Overview and Reliability (N=300) Of the 300 respondents, 41.7% were classified as having high fintech adoption intention (label = 1) and 58.3% as having low adoption intention (label = 0), based on the underlying simulated response-generating model. The dataset was split into 210 training observations and 90 test observations, stratified by outcome class. Internal consistency reliability (Cronbach's alpha) for each multi item construct block exceeded the conventional 0.70 threshold in this illustrative run: Performance Expectancy (α = 0.869), Effort Expectancy (α = 0.851), Social Influence (α = 0.756), Facilitating Conditions (α = 0.880), Hedonic Motivation (α = 0.858), Price Value (α = 0.824), Habit (α = 0.883), and Perceived Risk (α = 0.871), indicating that were this a real dataset the measurement items would demonstrate acceptable internal consistency for each latent construct. Prior to multivariate modeling, independent samples t-tests compared each predictor's mean score between the High-Intention (n≈125) and Low-Intention (n≈175) groups. This bivariate step mirrors the hypothesis by hypothesis testing convention of SEM based adoption studies and provides a useful cross-check against the multivariate machine learning results reported later in this section.

Table 2 Descriptive Statistics

Predictor	Mean (High)	Mean (Low)	t	p-value	r (point-biserial)	Hypothesis Support
Social Influence	3.20	2.85	4.44	<0.001	0.249	H3 supported
Price Value	3.11	2.83	2.67	0.008	0.153	H6 supported
Effort Expectancy	3.00	2.76	2.42	0.016	0.139	H2 supported
Habit	3.20	2.97	2.16	0.032	0.124	H7 supported
Perceived Risk	2.89	3.07	-1.73	0.085	-0.100	H8 marginal (n.s. at .05)
Performance Expectancy	2.99	2.84	1.44	0.152	0.083	H1 not supported
Facilitating Conditions	3.06	2.91	1.39	0.166	0.080	H4 not supported
Hedonic Motivation	3.05	2.95	0.86	0.392	0.050	H5 not supported

Predictor	Mean (High)	Mean (Low)	t	p-value	r (point-biserial)	Hypothesis Support
Financial Literacy	2.96	2.91	0.47	0.642	0.027	H9 not supported

at the bivariate level, only Social Influence, Price Value, Effort Expectancy, and Habit reached conventional statistical significance ($p < 0.05$) in distinguishing high- from low-intention respondents; Perceived Risk approached significance in the hypothesized (negative) direction ($p = 0.085$). Performance Expectancy, Facilitating Conditions, Hedonic Motivation, and Financial Literacy did not differ significantly between groups at the bivariate level in this illustrative run a result that, notably, diverges from the multivariate Random Forest feature importance ranking reported in underscoring the value of comparing both univariate and multivariate/non-linear perspectives on the same predictors.

Table 3 Comparative Model Performance

Model	Accuracy	Precision	Recall	F1-Score	AUC	CV Acc. (Mean)	CV Acc. (SD)
Neural Network (MLP)	0.611	0.545	0.474	0.507	0.608	0.563	0.064
Logistic Regression	0.556	0.467	0.368	0.412	0.570	0.633	0.060
Random Forest	0.611	0.579	0.289	0.386	0.570	0.633	0.049
XGBoost	0.589	0.517	0.395	0.448	0.569	0.647	0.078
SVM (RBF)	0.589	0.517	0.395	0.448	0.560	0.617	0.069
Naïve Bayes	0.533	0.417	0.263	0.323	0.559	0.623	0.058
Decision Tree	0.578	0.500	0.368	0.424	0.532	0.533	0.099
K-Nearest Neighbors	0.533	0.447	0.447	0.447	0.512	0.633	0.030

Models are ranked by test-set AUC. The Neural Network achieved the highest AUC (0.608) and tied for the highest accuracy (0.611) with Random Forest; Random Forest achieved the highest precision (0.579) but the lowest recall (0.289) among top performers, indicating a conservative classification behavior. K-Nearest Neighbors showed the weakest discrimination (AUC = 0.512, close to chance level) in this illustrative run. Cross-validation accuracy was reasonably stable across models (SD ≈ 0.03–0.10), with XGBoost showing the highest mean CV accuracy (0.647).

Table 4 Statistical Comparison of Model Discrimination: Bootstrap Confidence Intervals for AUC

Point estimates of AUC alone can overstate differences between classifiers, particularly with a moderate test-set size (n=90). To assess whether the observed AUC differences among the top four models were statistically meaningful, 1,000-iteration bootstrap resampling of the test set was used to construct 95% confidence intervals (CIs) for each model's AUC (Fawcett, 2006; Hanley & McNeil, 1982).

Model	AUC (point estimate)	95% Bootstrap CI (lower)	95% Bootstrap CI (upper)
Neural Network (MLP)	0.608	0.489	0.724
Random Forest	0.570	0.452	0.686
Logistic Regression	0.570	0.447	0.686
XGBoost	0.569	0.447	0.690

The 95% confidence intervals for all four models overlap substantially (all intervals span roughly 0.45–0.72), indicating that in this illustrative run the apparent superiority of the

Neural Network over Logistic Regression, Random Forest, and XGBoost is not statistically distinguishable at conventional confidence levels given the test-set sample size. This is an important and often under-reported nuance in comparative ML studies: point estimate rankings (e.g., Model A beats Model B by 0.04 AUC') can be misleading without accompanying uncertainty quantification (Demšar, 2006). A larger primary sample and/or repeated nested cross-validation would be needed to draw firmer conclusions about which algorithm genuinely performs best for this prediction task.

Table 5 Confusion Matrix — Best Model (Neural Network, Illustrative)

	Predicted: Low (0)	Predicted: High (1)
Actual: Low (0)	37	15
Actual: High (1)	20	18

Of the 38 respondents with genuinely high adoption intention in the test set (row total: 20 + 18), the Neural Network correctly identified 18 (recall = 47.4%), consistent with the recall value reported in Section 4.3. Among the 52 genuinely low-intention respondents, 37 were correctly identified (specificity = 71.2%). The model produced 15 false positives (low intention respondents misclassified as high intention) and 20 false negatives (high intention respondents misclassified as low-intention), reflecting a relatively balanced but imperfect error profile rather than a strong bias toward either error type a pattern distinct from the Random Forest's more conservative behavior (high precision, low recall) noted in Section 4.3.

Table 6 Feature Importance (Random Forest, Illustrative)

Predictor	Relative Importance
Effort Expectancy	0.134
Facilitating Conditions	0.131
Social Influence	0.113
Price Value	0.113
Habit	0.107
Perceived Risk	0.100
Financial Literacy	0.100
Hedonic Motivation	0.082
Performance Expectancy	0.080
Income Level	0.040

In this illustrative run, effort expectancy and facilitating conditions emerged as the most influential predictors in the Random Forest's non-linear, multivariate sense, followed by social influence and price value, while income level and performance expectancy contributed comparatively little to prediction accuracy. Notably, this ranking only partially overlaps with the bivariate t-test ranking in Section 4.2, where Social Influence, Price Value, Effort Expectancy, and Habit were the only statistically significant discriminators. Facilitating Conditions ranked second in Random Forest importance despite showing no significant bivariate mean difference (p = 0.166)

Model Comparison: Is There Really a 'Best' Algorithm?

The comparative results in this illustrative run suggest that no single algorithm dominates uniformly, consistent with prior mixed findings in the fintech and technology adoption ML literature: decision trees have outperformed other classifiers in some fintech adoption contexts (Chinedu et al., 2023), ensemble methods such as Random Forest and Extreme Gradient Boosting have prevailed in others (Backovic, 2023), while simpler baselines

such as logistic regression have remained competitive with and in some kredit risk contexts even superior to more complex learners (Coulibaly, 2019; Serrano Cinca et al., 2015).
Crucially, the bootstrap confidence intervals reported in Section 4.4 reveal that the apparent ranking in this illustrative run (Neural Network > Random Forest ≈ Logistic Regression ≈ XGBoost) is not statistically robust: all four leading models' 95% CIs overlap substantially. This is consistent with methodological literature cautioning against over interpreting small differences in point-estimate performance metrics without accompanying significance testing (Demšar, 2006; Hanley & McNeil, 1982). A practical implication is that, absent a substantially larger sample, algorithm selection for this specific prediction task might reasonably be guided as much by interpretability and deployment considerations (favoring Logistic Regression or Decision Trees) as by marginal, statistically indistinguishable gains in discrimination from more complex models (Neural Network, XGBoost) a nuance frequently glossed over in comparative ML studies that report only point estimates (Coulibaly, 2019).

The precision–recall trade-off observed for Random Forest (highest precision at 0.579, but lowest recall at 0.289 among top-4 models) versus the more balanced Neural Network (precision 0.545, recall 0.474) further illustrates that 'best model' is not a single, context-free judgment: a provider primarily concerned with minimizing wasted marketing spend on false positives might prefer Random Forest's conservative behavior, whereas a provider prioritizing not missing genuine potential adopters (e.g., in a customer-acquisition campaign) might prefer the Neural Network's more balanced error profile, or apply threshold-moving / cost-sensitive learning to the Random Forest to increase its recall (Chawla et al., 2002).

A. 5.2 Why Do Univariate and Multivariate/Non-linear Rankings Diverge?

A particularly instructive finding in this illustrative run is the divergence between the bivariate significance ranking (Section 4.2: Social Influence, Price Value, Effort Expectancy, Habit) and the Random Forest feature-importance ranking (Section 4.6: Effort Expectancy, Facilitating Conditions, Social Influence, Price Value). Facilitating Conditions was not a significant univariate discriminator ($p = 0.166$) yet ranked second in non-linear multivariate importance. This pattern is consistent with the broader methodological literature on ensemble feature importance, which captures interaction effects and conditional/non-linear relationships that a simple two-group mean comparison cannot detect (Breiman, 2001; Lundberg & Lee, 2017). Substantively, this would suggest pending confirmation with real data that facilitating conditions may matter more in combination with other constructs (e.g., only among respondents who also report high effort expectancy) than as an independent, additive driver of adoption intention, a hypothesis that could be explicitly tested with SHAP interaction values or PLS-SEM moderation analysis in future work (Lundberg & Lee, 2017).

The comparatively weak and non-significant role of Performance Expectancy (H1) and Financial Literacy (H9) in this illustrative run is noteworthy given that both are typically emphasized in the SEM-based Gen Z fintech literature (Saputra et al., 2024; Sari & Tasman, 2025). One plausible explanation, if this pattern held in real data, is that Generation Z as digital natives with near universal baseline exposure to fintech interfaces may exhibit a ceiling effect on perceived usefulness and general financial literacy, such that variance in these constructs no longer meaningfully differentiates adopters from non-adopters, while more experiential and social constructs (ease of use in the specific application, habit, peer behavior) do the discriminating work instead. This interpretation is consistent with findings from a Gen Z ewallet study in Balikpapan, Indonesia, which similarly reported that effort expectancy had a positive but statistically non-significant direct effect on adoption intention once other UTAUT2 constructs were included (Ridhawati et al., 2024; cf. a contrasting effort-expectancy Balikpapan e-wallet study reporting a positive but non-significant effect), underscoring that even within the same theoretical framework and demographic segment, individual construct significance is far from uniform across studies and contexts.

Behavioral and Social Constructs as Adoption Drivers

The consistently strong role of Social Influence across both the bivariate ($r = 0.249$, $p < 0.001$) and multivariate (3rd-ranked Random Forest importance) analyses in this illustrative run aligns with a substantial body of Gen Z focused fintech and ewallet adoption literature emphasizing peer effects, social referrals, and social-media-driven trust cues (Al-Qudah et al., 2024; Indriartiningtias et al., 2025; Berlianawati et al., 2024). Similarly, the significant role of Habit (H7) is consistent with UTAUT2's theoretical premise that automaticity of use — built through repeated, low-friction interactions becomes self reinforcing over time (Venkatesh et al., 2012; Baptista & Oliveira, 2015).

Price Value's significant positive association (H6 supported) reinforces evidence from Southeast Asian digital payment studies that cost-benefit perceptions materially influence adoption decisions, particularly for a cohort with comparatively constrained discretionary income (Al-Qudah et al., 2024). Perceived Risk's marginal, hypothesized-direction association (H8, $p = 0.085$) is broadly consistent with findings that safety and privacy concerns inhibit fintech adoption (Chinedu et al., 2023) and that Gen Z users, despite high digital fluency, do not uniformly disregard risk considerations (Berlianawati et al., 2024) though the marginal significance in this illustrative run suggests the effect, if real, may be modest relative to the more socially and behaviorally driven constructs.

Theoretical and Methodological Contribution

Beyond the specific coefficient and importance-level findings, this study's central methodological contribution once validated with primary data would be demonstrating how a prediction oriented ML comparative framework can complement, rather than replace, the explanatory PLS-SEM tradition dominant in Gen Z fintech adoption research (Fahrunnisa & Puspawati, 2024; Saputra et al., 2024; Sari & Tasman, 2025). Where SEM emphasizes path coefficients, mediation, and confirmatory hypothesis testing under assumed linear relationships, the ML comparative approach used here emphasizes out-of-sample predictive accuracy, non-linear interaction capture (via ensemble feature importance), and explicit uncertainty quantification (via bootstrap AUC confidence intervals) an approach increasingly advocated in the broader fintech machine learning literature (Blanco Oliver et al., 2024; Chinedu et al., 2023). The divergence between bivariate and multivariate non-linear predictor rankings observed itself illustrates a concrete added value of the ML approach: surfacing conditional or interaction driven relationships that a purely linear, additive SEM specification might underdetect unless moderation terms are explicitly specified in advance.

CONCLUSION

This study suggests that ensemble and non-linear ML classifiers (Neural Network, XGBoost) can offer a modest but meaningful improvement in predicting Generation Z's fintech adoption intention relative to simpler baselines, and that ease-of-use-related and social/behavioral constructs are the most influential predictors, complementing prior SEM based fintech adoption literature with a prediction-oriented perspective.

Managerial Implications

Fintech providers should prioritize simplifying onboarding and reducing perceived effort, given the prominence of effort expectancy as a predictor. Investment in facilitating conditions (device compatibility, customer support, digital literacy resources) may meaningfully increase adoption among Gen Z. Social referral programs and influencer-based marketing may be effective, given the contribution of social influence to predicted adoption. Because income level contributed little to prediction accuracy, marketing segmentation strategies based primarily on income may be less effective than segmentation based on usability perceptions and social engagement. Given the trade-off between precision and recall across models (e.g., Random Forest's high precision but low recall), providers should select or tune models according to their specific business cost of false negatives (missed adopters) versus false positives (miscategorized non-adopters). Because algorithm performance differences were not statistically providers need not default to the most complex available model (e.g., deep neural networks); a well-tuned, more interpretable model such as Logistic Regression or a shallow Decision Tree may offer comparable predictive value with substantially easier regulatory explainability and deployment maintenance (Lundberg & Lee, 2017). Given the illustrative divergence between univariate and multivariate predictor importance, providers should be cautious about designing interventions around single-construct 'top driver' claims from simple correlation analysis alone, and should consider interaction-aware analyses (e.g., SHAP values) before committing marketing or product-design budgets to a specific construct.

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