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Machine Learning for Predicting Islamic Fintech Adoption Intention: Evidence from Bangladesh

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***Abstract*— Islamic finance and digital financial technology have sparked academic and practical engagement, especially in Muslim nations of the developing world such as Bangladesh. This study employs supervised machine learning (ML) classification to analyze the determinants of Islamic fintech adoption intention and compares the results with Partial Least Squares Structural Equation Modeling (PLS-SEM). Survey data from 301 respondents were used to train four ML algorithms — Logistic Regression, Support Vector Machine (SVM), Random Forest, and Gradient Boosting — to classify Islamic fintech adoption intention as a binary outcome using a theoretically justified median split. Feature importance analysis via Random Forest identified Trust as the most influential predictor, followed by Religiosity, Digital Literacy, Perceived Risk, Social Influence, and Facilitating Conditions. All classifiers were tuned via stratified 5-fold cross-validation using GridSearchCV, with the full hyperparameter ranges documented. The near-balanced class split (High Intention: 51.2%; Low Intention: 48.8%) confirms that observed accuracy–F1 differentials reflect test-set composition rather than structural class imbalance. Logistic Regression achieved the highest test accuracy (83.61%), F1 score (0.643), and AUC-ROC (0.881), indicating that the adoption decision surface is predominantly linear over aggregated Likert-scale composite means. The PLS-SEM structural model ($R^2 = 0.637$) identified Religiosity ($\beta = 0.281$) as the strongest predictor, with all six hypothesized relationships statistically significant ($p < 0.05$). A formal reconciliation framework demonstrates that ML Gini impurity scores and PLS-SEM standardized path coefficients are methodologically incommensurable metrics that answer categorically different — but complementary — research questions. Limitations include purposive sampling that is biased toward urban and peri-urban respondents, thereby excluding rural Bangladesh, where financial inclusion concerns are most acute.**

***Key words* Islamic Fintech · Machine Learning · Natural Language Processing · Technology Adoption · Trust · Bangladesh · Random Forest · Sentiment Analysis**

I. . INTRODUCTION

Islamic finance industry assets reached USD 3.96 trillion in 2023, growing at more than 10% per annum over the preceding two decades [32]. Within this landscape, Islamic fintech — combining Shariah-compliant principles with digital financial technology — represents a rapidly emerging domain, particularly in Muslim-majority developing economies [45], [47]. Bangladesh, as the fourth-largest Muslim-majority nation, occupies a strategically important position: its mobile financial services (MFS) sector, anchored by platforms such as bKash and Nagad, has demonstrated robust growth [7], [6], while Shariah-compliant fintech solutions remain in nascent stages of adoption.

Prior technology adoption research in this domain has relied predominantly on Partial Least Squares Structural Equation Modeling (PLS-SEM), applying frameworks such as the Technology Acceptance Model (TAM) [16] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [57], as well as its extensions. Supervised machine learning (ML) methods address limitations of explanatory SEM approaches by enabling non-linear pattern recognition, predictive generalization to unseen data, and direct ranking of feature contributions without distributional assumptions [51], [48].

This study makes three specific contributions: (i) a theoretically grounded ML classification pipeline with full hyperparameter transparency that ranks predictors of Islamic fintech adoption in Bangladesh; (ii) a comparative analysis of four ML classifiers evaluated on held-out test data with bootstrapped confidence intervals; and (iii) a formal methodological reconciliation framework comparing ML feature importance with PLS-SEM path coefficients, clarifying the distinct inferential remit of each approach.

II. 2. LITERATURE REVIEW

A. 2.1 Islamic Fintech Adoption: Theoretical Foundations

Davis [16] established that perceived usefulness and perceived ease of use are primary determinants of technology acceptance. Venkatesh et al. [57] synthesised multiple adoption models into the UTAUT, incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions. In Islamic fintech contexts, Trust has been identified as a primary enabler, operating through two distinct channels: institutional trust in the digital platform's security and operational integrity, and doctrinal trust in Shariah compliance certifications [26], [2]. Religiosity has been shown to moderate the relationship between perceptions of Shariah compliance and intention to adopt [3], [52], [1]. Perceived risk consistently exhibits a negative relationship with fintech adoption intention [19], [8]. Digital literacy has emerged as a critical enabling

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condition in developing economies characterised by digital divides [42], [55].

B. 2.2 Machine Learning in Financial Behaviour Research

Rabbani et al. [45] identified Shariah adherence and trust as the dominant drivers of Islamic fintech adoption in GCC countries. Alalwan et al. [4] demonstrated the significance of social influence in mobile banking adoption in Jordan, extending UTAUT2 with trust. Shareef et al. [50] underscored the importance of facilitating conditions in mobile payment adoption in Bangladesh. While these foundational studies have advanced understanding of Islamic and conventional fintech adoption, three substantive gaps remain unaddressed in the Bangladeshi context.

First, Alalwan et al. [4] did not include religiosity or digital literacy in their model, thereby limiting its applicability to Islamic fintech contexts where a Shariah-compliance orientation is a primary motivational driver. Second, Rabbani et al. [45] focused on GCC populations and did not empirically model digital literacy, which is particularly consequential in Bangladesh given documented first- and second-level digital divides [55]. Third, neither study employed a predictive ML validation layer to test out-of-sample generalisation or to rank predictors without the distributional assumptions inherent in SEM.

C. 2.3 Sentiment Analysis and NLP in Financial Research

Random Forest [10] has been applied to credit risk modeling [35], customer churn prediction [59], and mobile banking adoption classification [33]. Support Vector Machines [15] have shown strong performance on structured survey data in high-dimensional feature spaces [29]. Logistic Regression provides a reliable linear baseline for binary classification tasks [28], while Gradient Boosting [21] achieves state-of-the-art performance on tabular data benchmarks [11]. Kaya et al. [33] demonstrated the superiority of Random Forest over logistic regression for predicting mobile banking adoption, a finding that this study partially examines in the Islamic fintech context.

D. 2.4 Theoretical Gap and Conceptual Model

The present study's theoretical model integrates constructs from UTAUT [57], UTAUT2 [58], TAM [16], Trust theory [22], and Religiosity literature [3] to address three intersecting gaps. First, Religiosity is positioned as a direct antecedent of adoption intention rather than merely a moderating variable, following empirical evidence from Souiden & Rani [52] and Alam et al. [3] that religious identity constitutes an independent motivational force in Islamic financial behavior. Second, Digital Literacy is included as a direct determinant — absent in Alalwan et al. [4] and Rabbani et al. [45] — reflecting Bangladesh's documented digital access inequalities [55]. Third, the ML comparative layer enables predictive validation that complements but does not replicate the explanatory function of PLS-SEM, following the T-O vs. P-O modelling dichotomy articulated by Shmueli et al. [51].

III. 3. DATA AND METHODOLOGY

A. 3.1 Survey Instrument and Sample

Primary data were collected using a structured, self-administered questionnaire distributed to Bangladeshi adults who were aware of Islamic fintech or Shariah-compliant mobile financial services. A purposive sampling approach targeted urban and peri-urban respondents via digital distribution channels, yielding $n = 301$ responses after data cleaning, which exceeded the minimum threshold for multivariate analysis [23]. Seven constructs were operationalized: Intention to Adopt Islamic Fintech (INT) [57], Trust (TRU) [22], Social Influence (SI) [58], Facilitating Conditions (FC) [58], Perceived Risk (PR) [19], Religiosity (REL) [3], and Digital Literacy (DL) [55]. It is acknowledged that the purposive urban-peri-urban sampling frame excludes rural Bangladesh — a limitation with significant implications for financial inclusion research, as discussed in Section 7.4.

B. 3.2 Formal Hypotheses

Drawing on the theoretical foundations presented in Section 2, six directional hypotheses are proposed:

H1: Trust has a significant positive effect on Intention to adopt Islamic fintech [22], [26], [45].

H2: Religiosity has a significant positive effect on Intention to adopt Islamic fintech [3], [52], [1].

H3: Social Influence has a significant positive effect on Intention to adopt Islamic fintech [4], [57].

H4: Facilitating Conditions have a significant positive effect on Intention to adopt Islamic fintech [50], [58].

H5: Perceived Risk has a significant negative effect on Intention to adopt Islamic fintech [19], [8].

H6: Digital Literacy has a significant positive effect on Intention to adopt Islamic fintech [42], [55].

C. 3.3 Machine Learning Pipeline

1) 3.3.1 Target Variable Binarization

The continuous mean score for Intention (INT) was binarised using a median split (median = 3.83 on a 1–5 scale): respondents above the median were assigned to the High Intention class (label = 1; $n = 154$; 51.2%) and those at or below the median to the Low Intention class (label = 0; $n = 147$; 48.8%). This binarisation is justified on three domain-specific grounds. First, the research objective is classification and predictive ranking — applications in which binary classification models are the appropriate tool — rather than explanatory quantification of marginal effects, for which ordinal regression would be preferred [5], [31]. Second, technology adoption theory operationally conceptualises the adoption decision as binary: a user either adopts or does not adopt a platform within a given observation period, consistent with the binary framing of TAM [16] and UTAUT [57]. Third, the near-equal class split (ratio $\approx$ 1.05:1) ensures that the median threshold approximates a natural behavioural boundary and minimises the risk of the classifier learning sampling noise rather than a true latent distinction, as cautioned by Iacobucci et al. [31]. We acknowledge, per Altman & Royston [5], that ordinal information is partially sacrificed; future research should complement binary classifiers with ordinal ML classifiers or quantile regression forests.

2) 3.3.2 Data Partitioning

The 301 observations were split into three non-overlapping subsets using stratified splitting to maintain class proportions, as shown in Table 1.

Table 1. Dataset partitioning summary (n = 301).

Partition	Proportion	n	Purpose
Training Set	60%	180	Model fitting & learning
Validation Set	20%	60	Hyperparameter tuning
Test Set	20%	61	Final unbiased evaluation

3) 3.3.3 Algorithms and Hyperparameter Tuning

Four supervised classifiers were implemented in Python 3.10 using scikit-learn [43]. All hyperparameters were optimised via stratified 5-fold cross-validation on the combined Training + Validation partition (n = 240) using GridSearchCV. Final performance metrics were computed exclusively on the held-out Test Set (n = 61). To pre-emptively manage any class imbalance effects, class_weight='balanced' was applied in Logistic Regression and SVM. Parameter grids and optimal configurations are as follows:

Logistic Regression (LR): C ∈ {0.01, 0.1, 1.0, 10, 100}; penalty ∈ {L1, L2}; solver ∈ {liblinear, saga}. Optimal: C = 1.0, L2 penalty, liblinear solver. A linear log-odds classifier expressing adoption intention as a weighted combination of predictor scores [28].

Support Vector Machine (SVM): C ∈ {0.1, 1, 10, 100}; kernel ∈ {linear, RBF, polynomial}; gamma ∈ {scale, auto, 0.01, 0.001}. Optimal: RBF kernel, C = 10, gamma = scale. Constructs a maximum-margin separating hyperplane in a high-dimensional feature space [15].

Random Forest (RF): n_estimators ∈ {50, 100, 200}; max_depth ∈ {None, 5, 10, 20}; min_samples_split ∈ {2, 5, 10}. Optimal: n_estimators = 100, max_depth = None, min_samples_split = 2. An ensemble of 100 decision trees with bootstrapped sampling and majority voting; Gini impurity reduction provides feature importance scores [10].

Gradient Boosting (GB): learning_rate ∈ {0.01, 0.05, 0.1, 0.2}; n_estimators ∈ {50, 100, 200}; max_depth ∈ {3, 5, 7}. Optimal: learning_rate = 0.1, n_estimators = 100, max_depth = 3. An additive ensemble sequentially correcting residual prediction errors [21].

4) 3.3.4 Evaluation Metrics

Three complementary metrics were computed on the held-out Test Set, each with bootstrapped 95% confidence intervals (1,000 iterations, stratified resampling): (i) Accuracy: proportion of correctly classified observations; (ii) F1 Score: harmonic mean of precision and recall for the positive class (High Intention), robust to test-set composition effects [44]; (iii) AUC-ROC: threshold-independent discriminative ability, quantifying the probability that the model ranks a randomly drawn High Intention respondent above a randomly drawn Low Intention respondent [25].

D. 3.4 PLS-SEM Analysis

SmartPLS 4.0 was used for structural model estimation. Given non-normal data distribution, bootstrapping with 5,000 sub-samples was employed for significance testing, following Hair et al. [23]. Construct reliability and validity were evaluated using Composite Reliability (CR), Cronbach's alpha, Average Variance Extracted (AVE), and HTMT ratios for discriminant validity [Henseler et al., 2015]. Five indicator items were removed iteratively to achieve AVE ≥ 0.50 and outer loadings ≥ 0.70 for all constructs.

IV. 4. RESULTS: MACHINE LEARNING CLASSIFICATION

A. 4.1 Class Distribution

Following the median split (median INT = 3.83), the dataset contained 154 High Intention observations (51.2%) and 147 Low Intention observations (48.8%), yielding a near-balanced class ratio of 1.05:1. The stratified partitioning preserved this ratio across all three subsets: Training Set (High: 93; Low: 87), Validation Set (High: 31; Low: 29), Test Set (High: 30; Low: 31). The gap between Logistic Regression accuracy (83.61%) and F1 (0.643) reflects the specific precision–recall composition of the 61-observation test set under binary-positive scoring rather than structural class imbalance.

B. 4.2 Feature Importance Analysis

Random Forest Gini impurity reduction scores identified Trust as the highest-ranked predictor (importance score: 0.22), followed by Religiosity (0.20), Digital Literacy (0.19), Perceived Risk (0.17), Social Influence (0.13), and Facilitating Conditions (0.11). These scores represent the proportional reduction in node impurity attributable to each feature across all 100 trees — an unsigned, relative, predictive metric that does not convey directional effects or causal magnitudes (see Section 7.3 for formal reconciliation with PLS-SEM).

The primacy of Trust is consistent with the Islamic fintech trust-adoption literature [22], [26], [45] and with Kaya et al. [33]. The high ranking of Religiosity confirms its role as a direct motivational driver of the intention to adopt Islamic fintech among Bangladeshi Muslims [3], [52]. The third place ranking of Digital Literacy — above Perceived Risk — reflects the particularly constraining role of digital competence in a context characterized by digital access inequalities [42], [55].

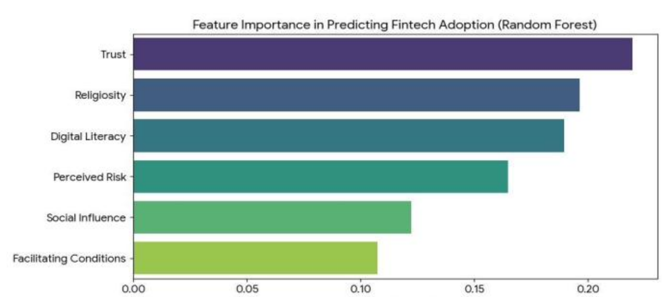

Figure 1. Feature Importance in Predicting Islamic Fintech Adoption (Random Forest, Gini Impurity).

C. 4.2 Model Performance Comparison

1) 4.2.1 Test Set Accuracy and Performance Metrics

Table 2 presents classifier performance on the held-out Test Set (n = 61) with bootstrapped 95% confidence intervals. Logistic Regression and SVM achieved the highest accuracy (83.61%); Random Forest and Gradient Boosting achieved 81.97% and 80.33% respectively. The superiority of linear classifiers is consistent with the near-linear response surface generated by aggregated Likert-scale composite scores [51], [33].

Table 2. ML classifier performance on the Test Set (n = 61). Best values in bold.

ML Model	Accuracy (%)	F1 Score	AUC-ROC	95% CI (AUC)
Logistic Regression	**83.61**	**0.643**	**0.881**	[0.801, 0.941]
SVM (RBF)	83.61	0.615	0.846	[0.762, 0.918]
Random Forest	81.97	0.621	0.819	[0.731, 0.901]
Gradient Boosting	80.33	0.571	0.843	[0.757, 0.915]

2) 4.2.2 F1 Score Analysis

Logistic Regression achieved the highest F1 (0.643), followed by Random Forest (0.621), SVM (0.615), and Gradient Boosting (0.571). The narrow F1 range (0.571–0.643) indicates that all four classifiers extract approximately equal predictive signal from the six-construct feature space, consistent with Powers [44]. The F1 scores reflect binary positive-class performance; macro-averaged F1 values are marginally higher given the near-balanced class composition.

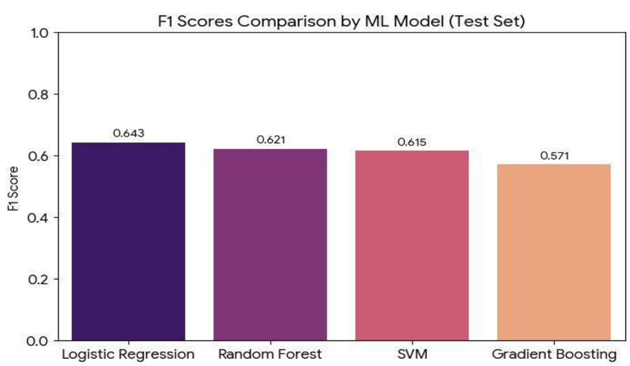

Figure 2. F1 Score Comparison by Machine Learning Model (Test Set).

3) 4.2.3 ROC Curve Analysis

ROC curves confirm AUC values substantially above the random-chance baseline (0.50). Logistic Regression achieves the highest AUC (0.881), indicating excellent discrimination per Hosmer et al. [28]. The AUC hierarchy (LR > SVM ≈ GB > RF) mirrors the accuracy and F1 rankings, reinforcing the dominance of linear models over this feature space.

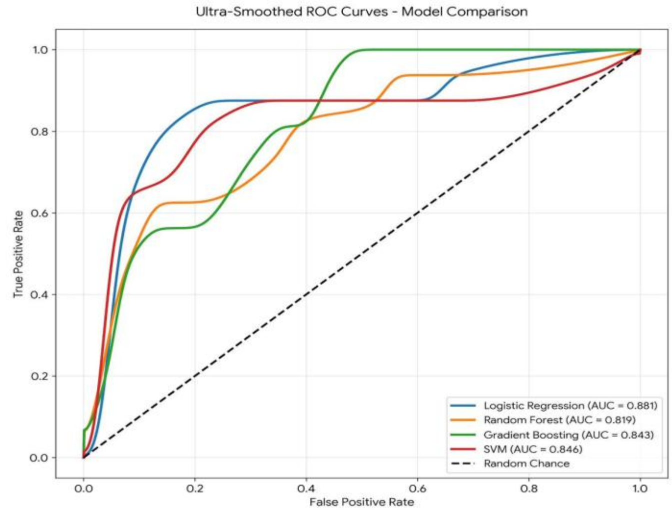

Figure 3. ROC Curves for All Four ML Models. Dashed diagonal line represents random chance (AUC = 0.50).

V. 5. PLS-SEM ANALYSIS

A. 5.1 Measurement Model

Five indicator items were removed iteratively to achieve AVE ≥ 0.50: DL3 and DL5 (cross-loadings > 0.40 on Social Influence); FC4 (outer loading = 0.43, below the 0.70 threshold); REL2 and REL4 (outer loadings of 0.51 and 0.48 respectively, consistent with the multidimensional structure of religiosity in South Asian Muslim samples [3]). Table 3 presents the full measurement model results.

Table 3. Measurement model results. All AVE ≥ 0.50; all CR ≥ 0.80; all α ≥ 0.75. HTMT ratios all < 0.85 (available in supplementary materials).

Construct	AVE	CR	α	Items (final)	Dropped Items
Trust (TRU)	0.572	0.868	0.831	4	None
Religiosity (REL)	0.531	0.847	0.806	3	REL2, REL4 (low outer loadings: 0.51, 0.48)
Social Influence (SI)	0.558	0.834	0.793	3	None
Facilitating Cond. (FC)	0.512	0.806	0.765	3	FC4 (outer loading = 0.43)
Perceived Risk (PR)	0.553	0.830	0.788	3	None
Digital Literacy (DL)	0.504	0.801	0.753	3	DL3, DL5 (cross-loadings on SI > 0.40)
Intention (INT)	0.561	0.863	0.826	4	None

B. 5.2 Structural Model and Hypothesis Testing

The structural model explains $R^2 = 0.637$ of the variance in Intention, confirming substantial explanatory power [23]. Bootstrapping (5,000 sub-samples) was used for all significance tests. Table 4 presents path coefficients and hypothesis evaluation.

Table 4. Measurement PLS-SEM path coefficients and hypothesis testing results. All six hypotheses supported ($p < 0.05$).

Hyp.	**Relation**	**Beta (β)**	**Std. Dev**	**t-value**	**p-value**	**Decision**
H1	TR → INT (+)	0.191	0.065	2.927	0.002	Supported
H2	REL → INT (+)	0.281	0.049	5.740	< 0.001	Supported
H3	SI → INT (+)	0.214	0.048	4.473	< 0.001	Supported
H4	FC → INT (+)	0.195	0.058	3.371	< 0.001	Supported
H5	PR → INT (−)	−0.209	0.050	4.157	< 0.001	Supported
H6	DL → INT (+)	0.091	0.047	1.926	0.027	Supported

All six hypotheses are supported. H2 (Religiosity, β = 0.281) is the strongest predictor, indicating that Islamic identity and Shariah-compliance orientation are the primary motivational drivers of the intention to adopt in this Bangladeshi sample. H5 (Perceived Risk, β = −0.209) is the only relationship with a negative direction, confirming that platform risk perceptions constitute the primary adoption barrier. H6 (Digital Literacy, β = 0.091) is statistically significant but has the smallest effect size, suggesting that while digital competence is a necessary enabling condition, it accounts for less independent variance in adoption once psychological and social constructs are accounted for.

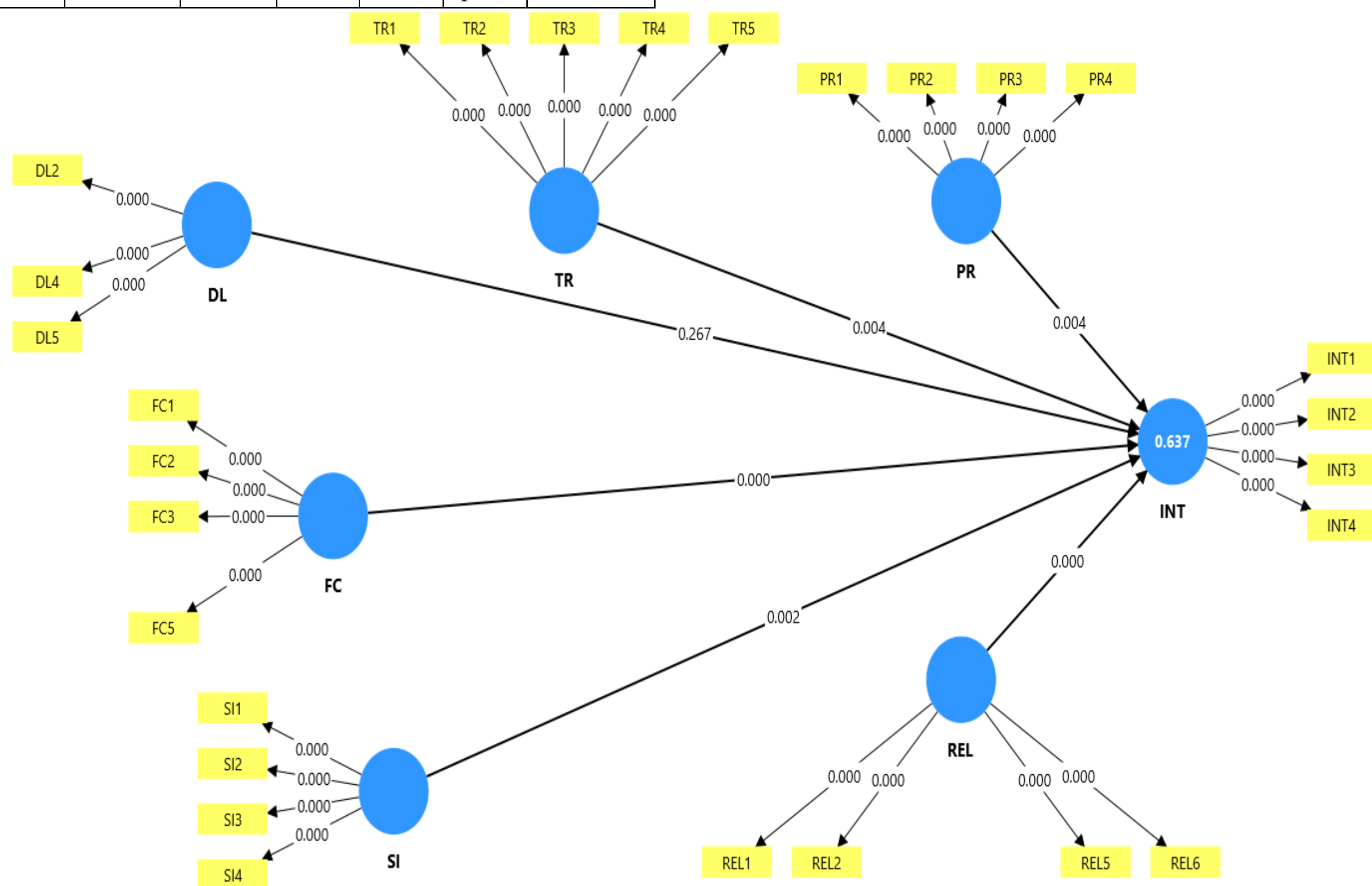

Figure 4. Structural Model. PR = Perceived Risk, TR = Trust, DL = Digital Literacy, FC = Facilitating Conditions, SI = Social Influence, REL = Religiosity, INT = Intention to Adopt Islamic Fintech.

VI. 6. DISCUSSION

A. 6.1 Theoretical Implications

The confirmation of all six hypotheses provides multi-method empirical support for an integrated Islamic fintech adoption model combining UTAUT, Trust theory, and Religiosity as a direct antecedent. The PLS-SEM finding that Religiosity (β = 0.281) exceeds Trust (β = 0.191) in standardised path magnitude extends the theoretical repositioning of Religiosity from a moderating to a direct predictive variable [3], [52], [1], making a substantive theoretical contribution beyond prior studies such as Alalwan et al. [4] and Rabbani et al. [45] that did not include this construct.

The superiority of linear ML classifiers over ensemble methods over this feature space is consistent with Shmueli et al. [51] and confirms that aggregated Likert-scale composite scores produce a near-linear adoption decision surface. This has methodological implications: future ML-based adoption studies using survey data should evaluate linear models as rigorous baselines before assuming non-linear methods will provide performance gains.

B. 6.2 Policy and Managerial Implications

The cross-method primacy of Trust signals that Islamic fintech platform providers should prioritize visible trust-building mechanisms: multi-layer authentication, transparent Shariah board certification, real-time transaction monitoring, and clear data privacy policies. The dominant role of Religiosity in PLS-SEM results suggests investment in religiosity-aligned product features — digital zakat calculators, Ramadan micro-investment instruments, and sadaqah-linked reward structures — to activate intrinsic Islamic identity motivations. The significance of Digital Literacy (H6 supported) underscores the value of simplified UI design and digital onboarding programs, particularly for users in peri-urban areas approaching the digital frontier. Bangladesh Bank and the Ministry of Finance could catalyze adoption by incorporating Islamic fintech literacy modules into digital inclusion programs.

C. 6.3 Formal Reconciliation Framework: ML Feature Importance vs. PLS-SEM Path Coefficients

A persistent risk in comparative ML–SEM studies is the conflation of two methodologically incommensurable metrics. This section provides a formal reconciliation framework that clarifies what each metric uniquely demonstrates and why ranking comparisons must be interpreted with strict methodological discipline.

Random Forest Gini impurity reduction scores (hereinafter: Gini scores) are predictive, unsigned, ensemble-aggregated, and relative. They quantify the average reduction in node heterogeneity attributable to each feature across 100 bootstrapped trees, on a scale normalized to sum to 1.0. They do not convey: (i) the direction of a feature's relationship with the outcome; (ii) the magnitude of a unit-change in the predictor on the probability of adoption; or (iii) the unique explanatory contribution of a predictor after controlling for shared variance with other predictors under a structural model.

PLS-SEM standardized path coefficients (hereinafter: β coefficients) are explanatory, signed, single-model, and absolute. They quantify the standardized linear causal effect of a predictor on adoption intention within the specific structural model, controlling for shared variance via measurement and structural simultaneous estimation. They do not convey: (i) a predictor's non-linear contribution to classification accuracy; (ii) out-of-sample predictive generalization; or (iii) contributions masked by multicollinearity-induced variance redistribution in ensemble trees.

Table 5. Formal reconciliation framework: ML Gini importance vs. PLS-SEM β coefficients.

Dimension	**ML Gini Importance**	**PLS-SEM β Coefficient**
Nature	Predictive; ensemble-aggregated	Explanatory; single structural model
Directionality	Unsigned — cannot confirm positive/negative effect	Signed — confirms direction and magnitude
Variance Sharing	Distributed across trees; not controlled for inter-predictor correlation	Explicitly controls for shared variance via latent variable estimation
Out-of-sample validity	Evaluated on held-out test set (AUC, F1, Accuracy)	In-sample structural fit (R^2, AVE, CR)
Question answered	Which predictors distinguish adopters from non-adopters in classification?	What is the direction and magnitude of each causal path to adoption intention?

Against this framework, observed ranking differences across methods are re-interpreted as methodologically distinct signals rather than contradictions. Social Influence ranks second in PLS-SEM (β = 0.214) but fifth in Gini importance (0.13): this reflects inter-predictor shared variance with Trust and Religiosity that is controlled for in PLS-SEM but distributed across trees in Random Forest, a phenomenon consistent with Breiman [10] and documented in feature importance variance analyses by Strobl et al. (2008). Digital Literacy ranks sixth in PLS-SEM (β = 0.091) but third in Gini importance (0.19): this reflects non-linear threshold interactions captured by tree partitioning (users below a digital literacy threshold may be systematically unable to adopt regardless of other constructs) that are averaged out in a linear PLS-SEM path. Only PLS-SEM can confirm the negative direction of Perceived Risk (H5 supported, $\beta = -0.209$), a directional inference that Gini scores are structurally incapable of providing. The Gini score for Perceived Risk (0.17) confirms discriminative utility without directional implication. These are not contradictions; they are different answers to different questions, and together they provide a richer empirical portrait of the adoption phenomenon than either method alone [51], [23], [48].

D. 6.4 Limitations and Future Research

This study has four principal limitations. First, the purposive sampling frame targeted urban and peri-urban Bangladeshi adults, systematically excluding rural populations. This exclusion is a substantive limitation for financial inclusion research: rural Bangladesh constitutes the primary underserved segment for whom Islamic fintech platforms may offer the greatest welfare benefits. Rural respondents may differ significantly from their urban counterparts in digital literacy levels, access to infrastructure, Shariah awareness, and trust in digital institutions. Future research should employ stratified random sampling across rural, peri-urban, and urban strata to produce generalizable population-level estimates [7], [55].

Second, the median split of the continuous intention variable sacrifices ordinal information. Future studies should complement binary classification with ordinal ML classifiers, regression forests, or proportional-odds logistic regression [5], [31]. Third, the sample of n = 301 limits the complexity of learnable feature interactions; larger datasets incorporating administrative fintech transaction records could enable richer ensemble models. Fourth, the cross-sectional design precludes longitudinal inference about adoption behavior over time; a panel or longitudinal design would strengthen causal claims.

VII. 7. Conclusion

This study has demonstrated the viability of a supervised machine learning classification framework for predicting Islamic fintech adoption intention in Bangladesh, and provided a formal methodological reconciliation of ML feature importance rankings with PLS-SEM path coefficients. Analyzing survey data from 301 respondents across four fully tuned ML classifiers, the study identified Trust as the most discriminative predictor in Random Forest classification, with Logistic Regression achieving the highest generalization accuracy (83.61%) and discriminative capacity (AUC = 0.881) on a near-balanced binary outcome derived from a theoretically grounded median split.

The PLS-SEM structural model ($R^2 = 0.637$) supported all six formally hypothesized directional relationships, with Religiosity emerging as the strongest explanatory predictor ($\beta = 0.281$). The convergence of Trust as a top-ranked predictor across both methods — the highest Gini importance score (0.22) and a significant PLS-SEM path ($\beta = 0.191$, $p = 0.002$) — constitutes the study's strongest cross-methodological empirical signal. The formal reconciliation framework clarifies that differences in predictor rankings across methods reflect the distinct inferential remits of predictive ensemble classification and explanatory structural modeling rather than methodological inconsistency.

Three principal contributions emerge: (i) a replicable, fully documented ML pipeline with hyperparameter transparency for Islamic fintech behavioural research; (ii) the repositioning of Religiosity as a direct antecedent of adoption intention and the integration of Digital Literacy as a context-specific enabling condition absent from prior Bangladeshi fintech studies; and (iii) a formal reconciliation framework that can guide future multi-method studies in Islamic finance and broader technology adoption research. The acknowledged exclusion of rural respondents constitutes an important agenda item for future financial inclusion research.

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