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# Predicting Gen Z Investment Perception Through Digital Financial Literacy and Ipo Awareness: an Interpretable Ai Framework

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**ABSTRACT**

This study develops an interpretable artificial intelligence framework for predicting Investment Perception among Generation Z using Digital Financial Literacy, IPO Awareness, Technology Innovativeness, Trust, Financial Attitude, and Digital Financial Self-Efficacy. A secondary survey dataset comprising 426 respondents was analyzed through comparative machine learning, hyperparameter optimization, stacking ensemble modelling, SHAP-based interpretation, repeated cross-validation, bootstrap uncertainty assessment, and ablation analysis. Five baseline algorithms, including Logistic Regression, SVM-RBF, Random Forest, XGBoost, and Gradient Boosting, were evaluated before the optimized learners were incorporated into a stacking ensemble. The proposed model achieved cross-validated accuracy of 0.707, F1-score of 0.780, ROC-AUC of 0.749, and MCC of 0.397. On the held-out test set, accuracy was 0.640, F1-score was 0.726, and ROC-AUC was 0.686. SHAP analysis identified Digital Financial Self-Efficacy as the strongest global predictor, followed by Trust and IPO Awareness. IPO Awareness accounted for 15.06% of global SHAP importance and demonstrated positive incremental predictive value in the ablation analysis. Digital Financial Literacy remained relevant to individual predictions but showed comparatively limited unique incremental contribution. Overall, the findings demonstrate the value of interpretable ensemble modelling for understanding Generation Z investment perception and provide transparent, data-driven insights for financial educators, investment platforms, and fintech stakeholders.

**Keywords:** Digital Financial Literacy; IPO Awareness; Generation Z; Investment Perception; Interpretable AI.

## Introduction

The way younger people are accessing capital markets, and assessing investment opportunities, has been revolutionized by digital investment platforms, mobile financial apps, and technology-driven financial services. Generation Z is especially significant in this change as they have high exposure to digital financial information, online investment platforms, and technology-mediated financial products. The use of digital financial services is not guaranteed to lead to informed financial evaluation or continued participation. Financial literacy, financial experience, and risk tolerance are still significant factors for investment-related responses in Generation Z (Tubastuvi et al., 2024). The behavioral and financial aspects also influence the investment opportunities and financial products assessment of younger investors (Hamijaya & Ida, 2024). In primary-market settings, the attitudes of retail investors toward IPOs also suggest that their IPO awareness and perceptions affect investment decision making (Arora et al., 2024).

Therefore, Digital Financial Literacy (DFL) is an essential skill in today's investment landscape. It builds on financial literacy, adding the capacity to access, understand, evaluate and use financial information via digital means. Investment behavior of Generation Z has been linked to financial literacy (Lieanto & Kohardinata, 2025), and financial attitudes and financial literacy have also been linked to how people assess investment opportunities (Utami et al., 2025). Recent evidence also suggests that DFL is applicable for investment decision making in fintech-based environments (Candera et al., 2026). Financial knowledge can be combined with psychological and behavioral traits and affect the way Generation Z assesses equity investment opportunities (Selvamani et al., 2026).

In the context of this study, Investment Perception is the attitude of Generation Z in assessing the opportunities and investment products in financial matters. It is conceptually different from investment intention which is a willingness or plan to engage in investment behavior. It is also different from financial attitude which encompasses general evaluative tendencies towards financial management and decision making, and from investment awareness which is more related to knowledge, familiarity and access to information related to investments. This is significant as it shows that perception is different from the related antecedent characteristics of awareness and attitudes.

Although there is growing literature on the investment behaviour of Generation Z, there are major conceptual and methodological gaps. The focus of previous studies has been mainly on financial literacy, financial investment decisions, financial behavior, attitudes, or intentions regarding financial investment. There has been less focus on the combined predictive power of the Digital Financial Literacy, IPO Awareness, Technology Innovativeness, Trust, Financial Attitude, and Digital Financial Self-Efficacy in an integrated Investment Perception framework. Existing studies also mostly focus on statistical relationships rather than predictive assessment out of sample. Thus, the capacity of the financial and behavioral constructs to predict reliably in nonlinear and interacting situations has not been well studied.

An alternative approach is machine-learning techniques, which focus on prediction-based generalization and enable multiple predictors to be assessed concurrently. But in finance applications model opacity is still a significant issue. The limitation can be overcome by using Explainable Artificial Intelligence (XAI) through enhancing transparency and uncovering the influence of individual predictors on model outputs (Weber et al., 2024). Thus, XAI methods can be used for predictive modelling and interpretable financial decision support (Černevičienė & Kabašinskas, 2024).

For this reason, this study aims to create an interpretable AI framework to predict Investment Perception among Generation Z based on six financial, behavioural and technology constructs. The study evaluates several machine-learning algorithms, creates a stacking ensemble, and combines SHAP interpretation and ablation analysis. This method separates the global feature importance from incremental predictive contribution. The investment-awareness-related indicators are used to operationalize IPO Awareness, and interpreted as a proxy construct not a direct measure of IPO participation.

The study pursues three objectives:

- To examine the reliability, descriptive characteristics, and interrelationships of the financial and behavioral constructs associated with Investment Perception.
- To develop and compare baseline, optimized, and stacking-based machine-learning models for Predicting Investment Perception among Generation Z.
- To explain and evaluate the incremental predictive contributions of Digital Financial Literacy and IPO Awareness using SHAP and ablation analysis.

## 2. Literature Review

Given the increasing shift of investment activities to mobile apps, digital brokerage platforms and technology-based financial services, Digital Financial Literacy (DFL) has taken center stage. For Generation Z, it's not enough to have access to digital platforms to participate in these environments. The person will also need to be able to analyse financial information, assess investment options and use financial knowledge to make decisions. Sawitri et al. (2024) emphasized the need for financial literacy and financial inclusion to influence the investment decisions of Generation Z. Likewise, Saptyana (2024) found that the financial technology, financial literacy, lifestyle, and financial behavior have a significant effect on investment decision making. The results indicate that the concept of digital financial capability is not a standalone construct of knowledge but exists within a larger system of behaviors and perceptions.

This view is also echoed by recent studies on the relationship between financial ability and investment assessment. In the study, Pratama and Artini (2025) found that financial literacy has an interaction effect with risk-taking and financial satisfaction in determining the investment decisions of Generation Z. Additionally, Fenny and Purba (2026) found that Digital Financial Literacy was relevant to the investment behavior of Generation Z. More directly, Hidayat and Sumunar (2026) linked financial literacy and financial technology with perceptions towards stock investment. Taken together, these studies suggest that DFL can shape the perception of investment opportunities, the evaluation of information, and the evaluation of financial products among younger investors. The Investment Perception can then be seen as a product of the processing and application of digitally delivered financial information, in part.

A further dimension of explanation comes from financial confidence and attitudes. Digital Financial Self-Efficacy is the confidence in conducting financial activities in technology-mediated environments. Financial self-efficacy was related to investment interest for Generation Z by Johan and Azarian (2025) and financial management behavior, e-trust, and investment decisions were linked to financial self-efficacy by Khorimah et al. (2025). Financial Attitude, on the other hand, is a person's attitude towards financial planning, evaluation and decision making. Oen and Natsir (2025) showed that personal financial factors affect the investment choices of Generation Z, while Judijanto et al. (2024) highlighted the importance of financial education and risk tolerance in determining the behavior of investors. The results suggest that perceived investment opportunities might be influenced by confidence and attitudes and by financial capability.

In digitally mediated investment environments, the concepts of Trust and Technology Innovativeness are also applicable. Trust helps to minimize uncertainty among people when dealing with a fintech platform or online financial service. Trust is a crucial element in the investment decision-making process of Generation Z in fintech as identified by Adinugroho (2025). Technology Innovativeness can also impact the perception of new investment systems, especially if digital interfaces, automated services and new technologies are part of it. Ningrum et al (2025) highlighted the evolving capital market context in which Generation Z makes investment decisions, and Yusup and Gunawan (2024) showed the effectiveness of predictive methods in analyzing financial literacy, investment interest, and risk tolerance. All of these studies indicate that the psychological and technology-related traits should be incorporated into a more comprehensive Investment Perception framework.

Another key element is investment awareness. It is a reflection of the level of knowledge on investment products, availability of information and understanding of opportunities. Nareswara and Putra (2024) determined that financial literacy, investment motivation, and risk tolerance were correlated with the investment interest. In primary-market settings, awareness in relation to IPOs could be more important, as investors need to consider company information, the nature of the offering, the anticipated returns, and the risks involved. Arora et al. (2024) found that the attitudes and perceptions of retail investors have a significant role in investment decisions pertaining to IPOs. IPO Awareness is, however, relatively under-researched in predictive research targeting Generation Z, especially when compared to financial literacy, trust, self-efficacy, attitudes and technology related traits.

Machine-learning techniques offer a chance to analyze these interrelated factors in ways beyond association analysis. Nonlinear algorithms and ensemble models can capture complex interactions among financial, behavioral and technological predictors. But the predictive performance of a model is not sufficient to explain the influence of individual variables on the model output. The importance of explainability in financial applications was highlighted by Černevičienė and Kabašinskas (2024), who noted that it enhances transparency and interpretability. Similarly, Weber et al. (2024) pointed out that explainability is crucial for financial applications to boost transparency and interpretability.

The literature thus shows two main gaps. First, the concepts of DFL, IPO Awareness, Trust, Technology Innovativeness, Financial Attitude and Digital Financial Self-Efficacy are rarely combined in a single predictive model, specifically on Generation Z Investment Perception. Second, the existing studies focus on explanatory associations, instead of out-of-sample prediction and interpretable ensemble modelling. To fill these gaps, the present study combines the six constructs in a comprehensible machine-learning framework and uses SHAP analysis and ablation testing to separate the global importance of the features from the incremental importance of the features in the model's prediction.

## 3. Methodology

### 3.1 Research Design

This study was quantitative, secondary data, out of sample predictive modelling design, which was used to study Investment Perception of Generation Z. The analytical framework combined construct assessment, statistical diagnostics, supervised machine learning, ensemble learning, explainable artificial intelligence, and robustness testing to a reproducible workflow. The aim was predictive, not causal. Thus, the analysis was limited to discrimination, classification performance, generalization to novel observations, contribution of features, and model stability. Six constructs were used to explain the study: Digital Financial Literacy (DFL), IPO Awareness (IPOA), Technology Innovativeness (TI), Trust (TRUST), Financial Attitude (FA), and Digital Financial Self-Efficacy (DFSE). Investment Perception (IP) was specified as the outcome construct. The modelling strategy involved comparing algorithms from different methodological families such as linear, kernel, bagging and boosting. Optimizations and stacking of models with complementary performance profile were then carried out. This design allowed for the comparison of individual learners and the ensemble as a system within a common evaluation framework.

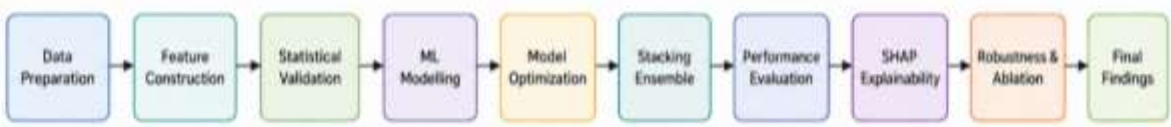


**Figure 1. Workflow of the proposed interpretable AI framework for Predicting Investment**

**Perception among Generation Z.**

### 3.2 Dataset Collection and Construct Operationalization

The empirical analysis was conducted on a publicly available dataset of investment applications for Generation Z created by Tan and Tjhin (2025) and released on 18 March 2025 (Version 1) (DOI: 10.17632/273p5pc7hd.1). The sample consisted of 426 respondents and 48 original variables related to the demographic characteristics, digital financial attributes, behavioral characteristics, investment-related responses, and multi-item Likert-scale measures. After an examination of the structure of the measures, seven analytical constructs were developed. DFL had four items, IPOA had four items, TI had four items, TRUST had three items, FA had six items, DFSE had five items, and IP had five items. Construct level scores were calculated by taking the arithmetic mean of the items at the respondent level.

The dependent construct in the predictive model was Investment Perception, defined as the respondents' general attitude of evaluation for investment applications and financial products. The construct was utilized as a predictor of actual investment behavior instead of a measure of the same. IPO Awareness was applied to a specific operational qualification. No scale specific to IPO was included in the source data set. IPOA was therefore developed based on indicators that are related to investment awareness, which include investment knowledge, access to investment information, knowledge about financial products, and perceived financial capability. It was therefore interpreted as a proxy for awareness of IPOs and not as a measure of participation in IPOs or specific knowledge about IPOs.

### 3.3 Data Preprocessing and Measurement Assessment

Data preprocessing was done prior to the development of the models so as to ensure consistency of the data and reduce information leakage in the analysis. The data set was checked for duplicate observations, missing values, out-of-range responses on the Likert scale and invalid data types. Items for each of the relevant measures were transformed to numeric data and combined into construct level mean scores. Cronbach's alpha was used for internal consistency. In addition, corrected item-total correlations and alpha-if-item-deleted statistics were examined to determine whether any individual items negatively impacted scale reliability. Special attention was paid to TRUST as it had relatively low internal consistency. None of the TRUST items were dropped due to lack of improvement in the overall reliability coefficient.

The mean, standard deviation, observed range, skewness and kurtosis were used to construct distributions. To determine bivariate relationships between constructs, Pearson correlation coefficients were calculated. Variance Inflation Factors from auxiliary regressions with an intercept were used to assess multicollinearity of predictors.

The continuous IP composite was binarised with an empirical median of 3.40 for classification modelling. No external validation of the cut-off point for the operationalized Investment Perception construct was found, so a distribution-based cut-off was used, which was the median. Those who had IP scores less than 3.40 were categorized as Class 0 (Lower Investment Perception) while those who scored 3.40 or above were categorized as Class 1 (Higher Investment Perception). This left a target of 181 Class 0 and 245 Class 1 observations. The analytical sample was divided to maintain class proportions with an 80:20 stratified train-test split. A fixed random state of 42 was used for stochastic procedures. The held-out test set was not used in model selection and hyperparameter optimization. Only DFL, IPOA, TI, TRUST, FA and DFSE were selected as predictors. The target leakage problem was avoided by excluding the IP composite and its individual components from the feature matrix.

### 3.4 Predictive Modelling and Ensemble Development

The following five supervised classifiers were tested first: Logistic Regression, Support Vector Machine (radial basis function kernel), Random Forest, XGBoost and Gradient Boosting. The model set included linear decision functions, nonlinear kernel methods, bagging and gradient-based boosting. For scale-sensitive algorithms (Logistic Regression and SVM-RBF), feature standardization was added to the pipelines. Tree-based learners were fitted without standardization. Repeated stratified cross-validation was used to estimate baseline performance within the development sample to provide reliable estimates across resampling.

Gradient Boosting and SVM-RBF were selected for hyperparameter tuning given their complementary performance in the initial experiments. In terms of class sensitive performance, SVM-RBF outperformed Gradient Boosting in recall, F1 score and MCC, while in terms of discrimination, Gradient Boosting outperforms SVM-RBF. Hyperparameter tuning was conducted using Tree-structured Parzen Estimator search algorithm of Optuna. Only development data was used for tuning and ROC-AUC was chosen as the main optimization objective as it measures the discrimination of the ranking over a range of classification thresholds.

The optimized Gradient Boosting and SVM-RBF models were then combined in a stacking ensemble.

Logistic Regression was used as the level-1 meta-learner and both algorithms were used as level-0 base learners. To minimize leakage between stacking levels, out-of-fold class-probability estimates were provided to the meta-learner from the base learners. The stacking ensemble was then compared to baseline models and tuned individual models, using the same evaluation criteria.

### 3.5 Performance Evaluation, Explainability, and Robustness

These evaluation metrics were chosen: Accuracy, Precision, Recall, F1-score, ROC-AUC, Specificity, and Matthews Correlation Coefficient. The primary discrimination measure was ROC-AUC, and F1-score and MCC were highlighted as measures that offer further insights into classification balance. Specificity was reported for the lower-Perception class to quantify identification performance.

A prespecified multi-criteria ranking framework that included cross-validated ROC-AUC, F1-score, MCC, accuracy and recall guided final model selection. Complementary evidence of generalization was obtained from held-out test performance. The composite ranking index was not interpreted as a probability, effect size, or percentage measure of predictive performance and was only used for comparative model selection.

Model interpretation was performed for the predicted probability of the higher-IP class with model-agnostic permutation SHAP. Global feature importance was quantified by mean absolute SHAP values and dependence analysis was performed for IPO Awareness and Digital Financial Literacy. The contributions of the predictors to the model outputs were evaluated using SHAP, and the incremental predictive value was evaluated using the ablation analysis.

Stratified five-fold cross validation repeated 10 times was used to evaluate the robustness. Selected metrics were quantified by bootstrap resampling of performance estimates on a repetition level. The full six-predictor model was compared with three reduced models: the model without IPO Awareness, the model without Digital Financial Literacy, and the model with both IPO Awareness and Digital Financial Literacy. No causal relationships were inferred from any of the model outputs, but rather predictive associations were made.

## 4. Results

### 4.1 Sample Characteristics and Measurement Assessment

A total of 426 Generation Z respondents made up the final analytical sample. Most participants were aged 21–27 years (73.71%), while 26.29% were aged 15–20 years. The majority of the respondents were male (66.43%) and females (33.57%) with the highest number of respondents having a bachelor's degree (49.53%). The reliability of the constructed instruments was generally satisfactory with Cronbach's alpha ranging from 0.700 to 0.870. The item-deletion diagnostics for the items suggested retaining all three for the trust scale, which had the lowest reliability ($\alpha = 0.629$).

**Table 1. Descriptive Statistics and Reliability of the Study Constructs**

| Construct | Items | Mean | SD | Cronbach's α |
|---|---|---|---|---|
| Digital Financial Literacy (DFL) | 4 | 2.982 | 0.532 | 0.700 |
| IPO Awareness (IPOA) | 4 | 2.847 | 0.597 | 0.766 |
| Technology Innovativeness (TI) | 4 | 2.484 | 0.788 | 0.830 |
| Trust (TRUST) | 3 | 3.129 | 0.509 | 0.629 |
| Financial Attitude (FA) | 6 | 3.167 | 0.563 | 0.870 |
| Digital Financial Self-Efficacy (DFSE) | 5 | 3.106 | 0.613 | 0.826 |
| Investment Perception | 5 | 3.210 | 0.594 | 0.830 |

The descriptive results indicate that Financial Attitude, Investment Perception, Trust, and Digital Financial Self-Efficacy exhibited comparatively higher mean scores, whereas Technology Innovativeness showed the lowest mean among the examined constructs.

### 4.2 Correlation and Multicollinearity Assessment

Investment Perception was positively related to all six predictors. Digital Financial Self-Efficacy showed the strongest correlation with IP ($r = 0.659$, $p < .001$), followed by Financial Attitude ($r = 0.616$, $p < .001$), Digital Financial Literacy ($r = 0.595$, $p < .001$), IPO Awareness ($r = 0.593$, $p < .001$), Trust ($r = 0.563$, $p < .001$), and Technology Innovativeness ($r = 0.195$, $p < .001$). There was also a moderate correlation between DFL and IPO Awareness ($r = 0.589$, $p < .001$). VIF values were between 1.062 and 2.336 and were below the conventional level, indicating that there was no problematic multicollinearity among the six predictors.

**Table 2. Correlation Matrix and Variance Inflation Factors**

| Construct | DFL | IPOA | TI | TRUST | FA | DFSE | IP | VIF |
|---|---|---|---|---|---|---|---|---|
| DFL | 1.000 | | | | | | | 2.054 |
| IPOA | .589*** | 1.000 | | | | | | 2.118 |
| TI | .164*** | .212*** | 1.000 | | | | | 1.062 |
| TRUST | .508*** | .513*** | .144** | 1.000 | | | | 1.600 |
| FA | .627*** | .598*** | .196*** | .516*** | 1.000 | | | 2.102 |
| DFSE | .625*** | .662*** | .219*** | .534*** | .628*** | 1.000 | | 2.336 |
| IP | .595*** | .593*** | .195*** | .563*** | .616*** | .659*** | 1.000 | — |

*Note. **p < .01; **p < .001.

The overall correlation structure among the constructs is illustrated in Figure 2.

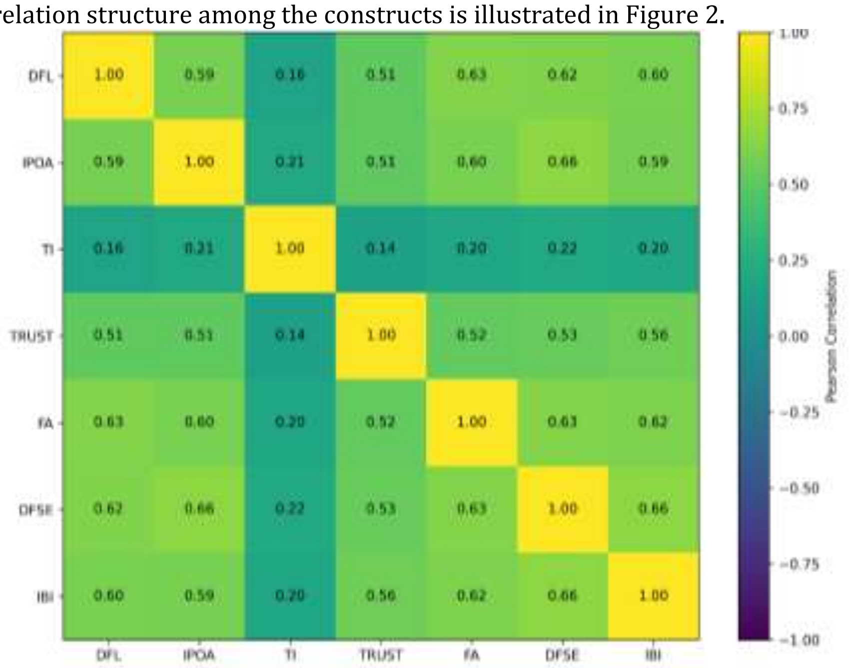


**Figure 2. Correlation structure among the study constructs.**

### 4.3 Baseline Machine-Learning Performance

Five baseline classifiers were tested using the repeated stratified cross-validation and then tested with the held-out sample. XGBoost achieved the best cross-validated ROC-AUC (0.742), followed by Gradient Boosting (0.741) and Logistic Regression (0.739). SVM-RBF, on the other hand, had the highest cross-validated accuracy (0.699), F1-score (0.791), and MCC (0.415). Random Forest had the highest held-out accuracy (0.674), ROC-AUC (0.684) and MCC (0.324) while SVM-RBF had the highest held-out F1-score (0.762).

**Table 3. Performance of Baseline Machine-Learning Models**

| Model | CV Accuracy | CV F1 | CV ROC-AUC | CV MCC | Test Accuracy | Test F1 | Test ROC-AUC | Test MCC |
|---|---|---|---|---|---|---|---|---|
| Logistic Regression | 0.678 | 0.750 | 0.739 | 0.327 | 0.616 | 0.692 | 0.682 | 0.198 |
| SVM-RBF | 0.699 | 0.791 | 0.671 | 0.415 | 0.651 | 0.762 | 0.653 | 0.317 |
| Random Forest | 0.655 | 0.720 | 0.710 | 0.280 | 0.674 | 0.736 | 0.684 | 0.324 |
| XGBoost | 0.681 | 0.735 | 0.742 | 0.340 | 0.616 | 0.692 | 0.671 | 0.198 |
| Gradient Boosting | 0.679 | 0.737 | 0.741 | 0.332 | 0.651 | 0.722 | 0.677 | 0.272 |

The corresponding ROC curves for the baseline classifiers are presented in Figure 3.

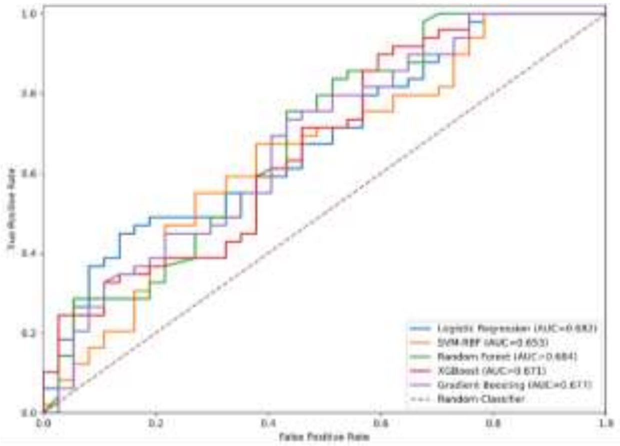

**Figure 3. ROC curves of the baseline machine-learning models on the held-out test sample.**

### 4.4 Optimized Models and Proposed Stacking Ensemble

After the baseline evaluation, Gradient Boosting and SVM-RBF were chosen for optimization due to their complementary predictive properties. Tuned Gradient Boosting had the highest cross-validated ROC-AUC for all the optimized individual models (0.758), and Tuned SVM-RBF had the highest recall (0.977), F1-score (0.793), and MCC (0.422).

The cross validated accuracy, recall, F1-Score, ROC-AUC, MCC of the proposed stacking ensemble were 0.707, 0.902, 0.780, 0.749 and 0.397 respectively. On the held-out test sample, it achieved an accuracy of 0.640, F1-score of 0.726, ROC-AUC of 0.686, and MCC of 0.244.

**Table 4. Performance of Tuned Models and the Proposed Stacking Ensemble**

| Model | CV Accuracy | CV Recall | CV F1 | CV ROC-AUC | CV MCC | Test Accuracy | Test F1 | Test ROC-AUC | Test MCC |
|---|---|---|---|---|---|---|---|---|---|
| Tuned Gradient Boosting | 0.695 | 0.863 | 0.765 | 0.758 | 0.367 | 0.616 | 0.703 | 0.692 | 0.192 |
| Tuned SVM-RBF | 0.705 | 0.977 | 0.793 | 0.743 | 0.422 | 0.628 | 0.738 | 0.663 | 0.223 |
| Proposed Stacking Ensemble | 0.707 | 0.902 | 0.780 | 0.749 | 0.397 | 0.640 | 0.726 | 0.686 | 0.244 |

The proposed stacking ensemble achieved the best overall balance of discrimination, classification performance and held-out generalization under the prespecified multi-criteria selection framework. The composite ranking index was only used as a model selection tool and not interpreted as a predictive performance percentage or effect size. Figures 4 show the architecture of the ensemble and its comparative performance.

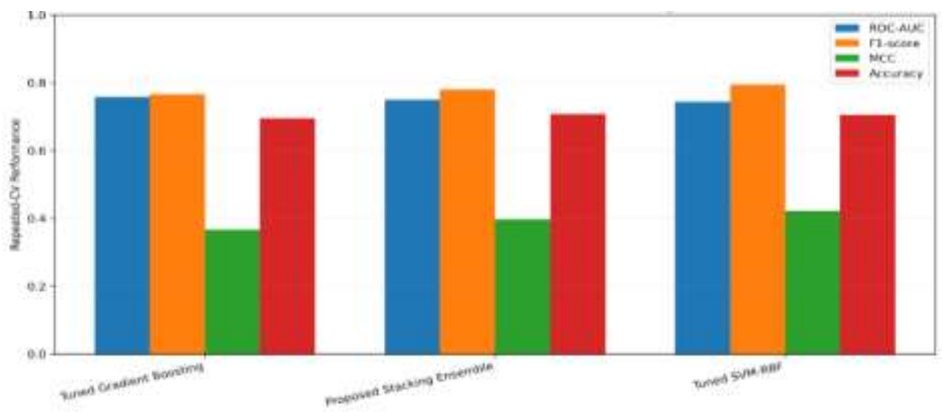

**Figure 4. Comparative performance of the optimized individual learners and proposed stacking ensemble.**

### 4.5 Explainability of the Final Predictive Model

Permutation-based SHAP analysis was used to quantify the contribution of each predictor to the model's probability of higher Investment Perception. The global importance of the Digital Financial Self-Efficacy was the highest with 34.33% of the total mean absolute SHAP contribution, followed by Trust (22.03%) and IPO Awareness (15.06%). Technology Innovativeness, Financial Attitude and Digital Financial Literacy contributed 11.13%, 9.81% and 7.64% respectively. These values are relative to the predictive importance in the model and are not to be interpreted as causal effects.

**Table 5. Global SHAP Importance of Predictors**

| Rank | Predictor | Mean \|SHAP\| | Relative Importance (%) | Feature-SHAP Correlation |
|---|---|---|---|---|
| 1 | Digital Financial Self-Efficacy | 0.0726 | 34.33 | 0.935 |
| 2 | Trust | 0.0466 | 22.03 | 0.954 |
| 3 | IPO Awareness | 0.0319 | 15.06 | 0.945 |
| 4 | Technology Innovativeness | 0.0235 | 11.13 | 0.954 |
| 5 | Financial Attitude | 0.0208 | 9.81 | 0.895 |
| 6 | Digital Financial Literacy | 0.0162 | 7.64 | 0.902 |

The global distribution of SHAP contributions is presented in Figure 5.

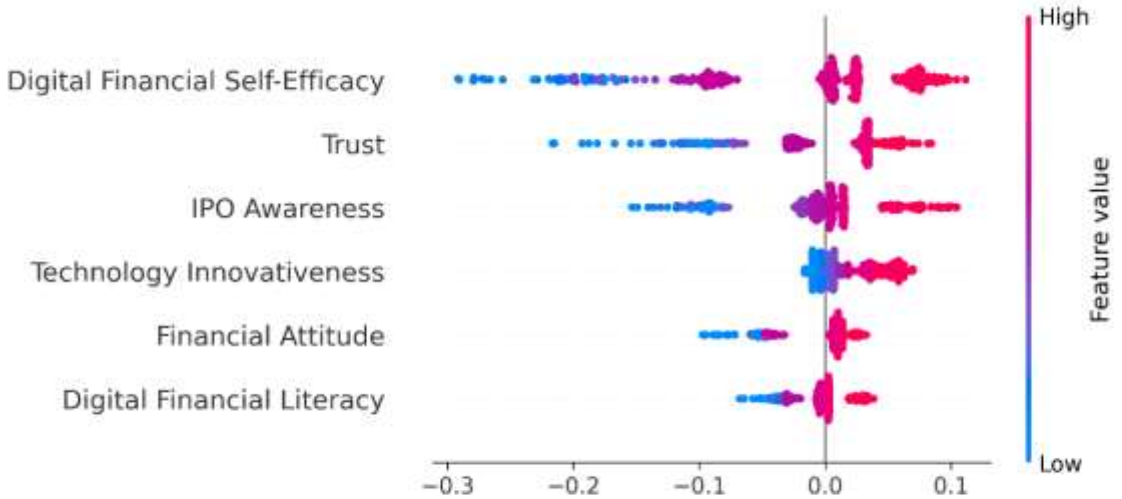


**Figure 5. SHAP summary plot showing the magnitude and direction of predictor contributions to higher Investment Perception.**

The two focus financial constructs exhibited different kinds of prediction. The SHAP importance of IPO Awareness was about double that of Digital Financial Literacy in the world. Individuals who were less than the median IPO Awareness had a mean SHAP contribution of −0.0380, while those who were at or above the median had a mean SHAP contribution of 0.0262. DFL was similar in direction but smaller in positive contribution at or above the median at 0.0063.

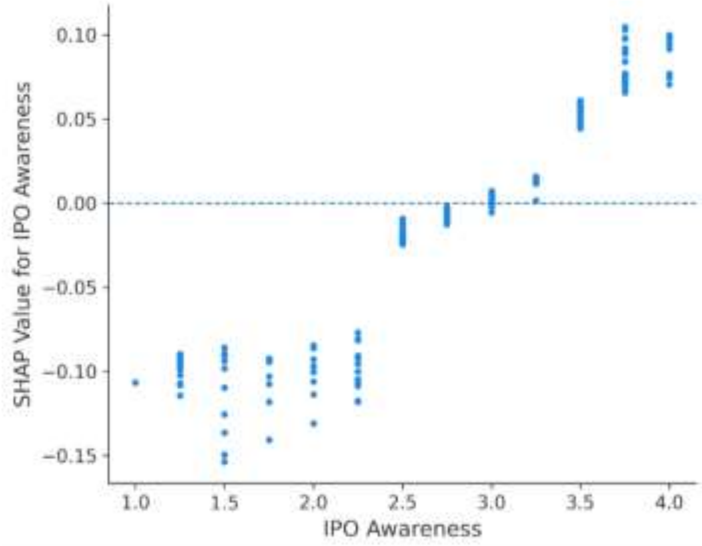


**Figure 6. SHAP dependence of IPO Awareness on the predicted probability of higher Investment Perception.**

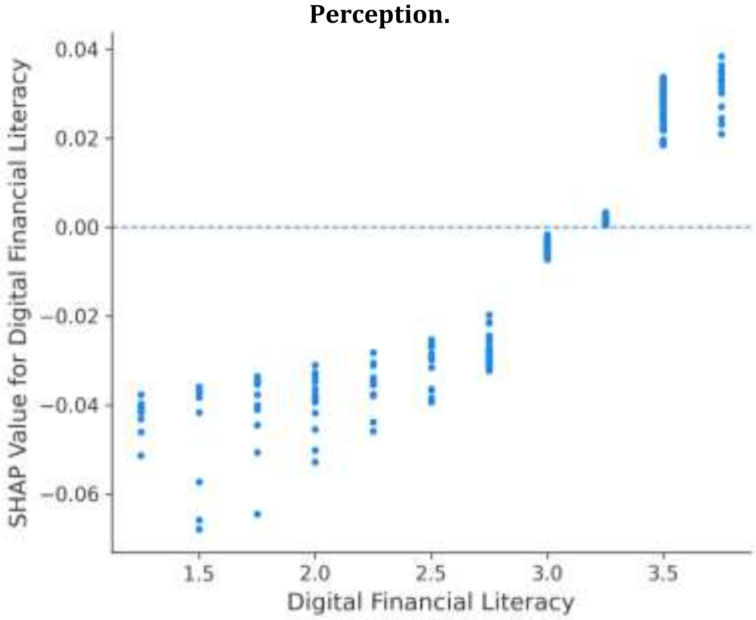


**Figure 7. SHAP dependence of Digital Financial Literacy on the predicted probability of higher Investment Perception.**

### 4.6 Robustness and Uncertainty Assessment

Five-fold stratified cross-validation was performed ten times to assess the robustness of the model after selection. The mean ROC-AUC, F1-score, accuracy, and MCC for the final stacking ensemble were 0.734, 0.764, 0.685, and 0.349, respectively. Recall was also high (0.889), while specificity was lower (0.408), which means that higher-Perception respondents were more easily identified.

**Table 6. Repeated Cross-Validation and Bootstrap Robustness of the Final Model**

| Metric | Mean | SD | Bootstrap 95% CI |
|---|---|---|---|
| ROC-AUC | 0.734 | 0.052 | 0.730–0.738 |
| F1-score | 0.764 | 0.029 | 0.761–0.767 |
| Accuracy | 0.685 | 0.038 | 0.680–0.689 |
| MCC | 0.349 | 0.091 | 0.340–0.359 |
| Recall | 0.889 | 0.055 | — |
| Specificity | 0.408 | 0.085 | — |

Bootstrap confidence intervals for the principal repeated cross-validation metrics are presented in Figure 8.

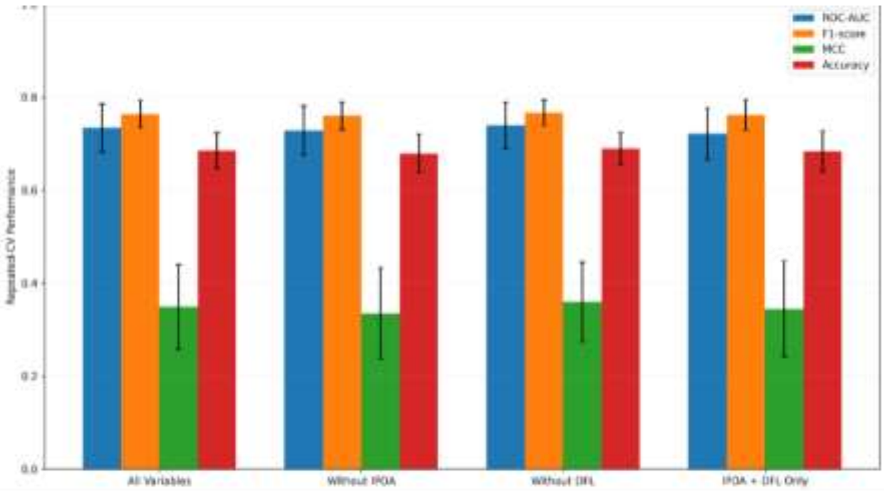


**Figure 8. Bootstrap confidence intervals for the principal repeated cross-validation performance metrics of the final model.**

### 4.7 Ablation Analysis

To assess the unique contribution of IPO Awareness and Digital Financial Literacy over the other variables, the study used the method of ablation analysis. Removing IPO Awareness reduced ROC-AUC from 0.734 to 0.728, F1-score from 0.764 to 0.760, MCC from 0.349 to 0.335, and accuracy from 0.685 to 0.679. The uniform decreases for all these metrics suggest that the IPO Awareness helped the full model in a predictive sense.

On the other hand, exclusion of DFL resulted in slight improvements in several performance parameters such as ROC-AUC (0.734 to 0.740) and MCC (0.349 to 0.359). This does not mean that DFL was not important, as the SHAP analysis showed it was important for individual predictions. Rather, the ablation analysis suggests that its unique incremental value was small when all the other financial, behavioral and technology-related predictors were simultaneously modelled.

**Table 7. Ablation Analysis of Predictor Configurations**

| Model Configuration | ROC-AUC | F1 | MCC | Accuracy | Recall | Specificity |
|---|---|---|---|---|---|---|
| Full model | 0.734 | 0.764 | 0.349 | 0.685 | 0.889 | 0.408 |
| Without IPO Awareness | 0.728 | 0.760 | 0.335 | 0.679 | 0.884 | 0.402 |
| Without DFL | 0.740 | 0.766 | 0.359 | 0.689 | 0.888 | 0.420 |
| IPO Awareness + DFL only | 0.721 | 0.762 | 0.345 | 0.684 | 0.880 | 0.419 |

The comparative performance of the four predictor configurations is illustrated in Figure 9.

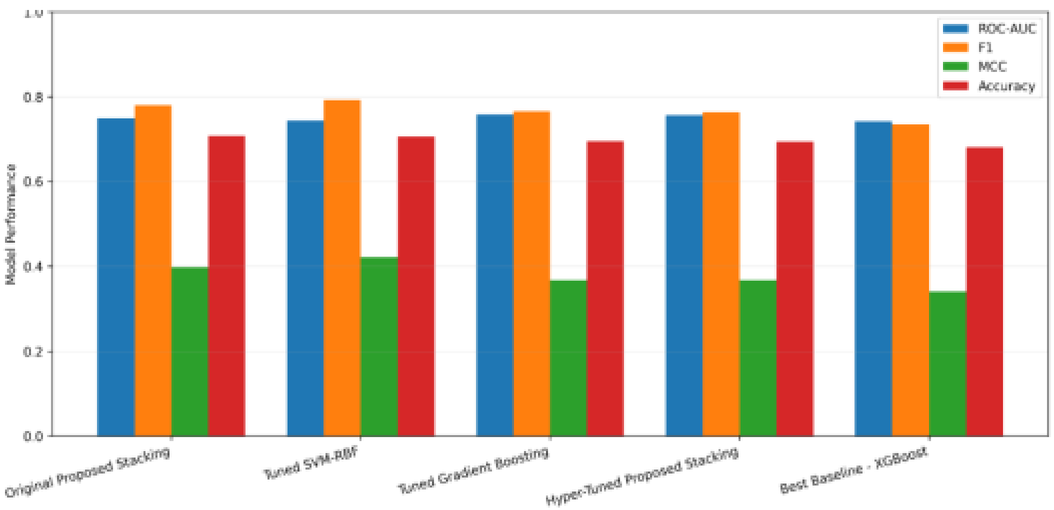


**Figure 9. Ablation analysis comparing predictive performance under alternative predictor configurations.**

## 5. Discussion

The results suggest that the financial, behavioral and technological factors are interrelated to Investment Perception for Generation Z. Digital Financial Self-Efficacy and Trust were the top two global predictors identified by SHAP analysis, followed by IPO Awareness. This indicates that trust in technology-mediated financial environments and confidence in conducting financial activities digitally are important factors for differentiating respondents with higher Investment Perception. This greater contribution compared to Digital Financial Literacy could suggest that experience and perceived trustworthiness of digital financial environments carry more discriminative information than knowledge-based capability. IPO Awareness also had a positive incremental contribution in the ablation analysis and was ranked third in global SHAP importance.

The remaining predictors were modelled simultaneously and Digital Financial Literacy had a relatively low SHAP contribution and low incremental contribution to the model. But it doesn't mean that DFL isn't relevant. Rather, its predictive information might be similar to other constructs like Digital Financial Self-Efficacy, Financial Attitude, Trust, and investment awareness. This is in line with previous research that found financial capability to be a complement to psychological and behavioral traits, rather than separate. Johan and Azarian (2025) highlighted financial self-efficacy as a key factor influencing the investment interest of Generation Z, and Adinugroho (2025) pointed out that trust is a crucial factor in investment decisions involving fintech. The relevance of DFL is also in line with the results of Fenny and Purba (2026) and Pratama and Artini (2025) who found that financial literacy was associated with investment-related behavior.

The results from the SHAP and ablation are complementary. While ablation assesses the loss of predictive power from removing a predictor from the model, SHAP quantifies the strength of the contribution of a predictor to the model's outputs for each observation. IPO Awareness was consistent in both analyses. Removing it had an impact on ROC-AUC, F1-score, MCC and accuracy, suggesting that it provided predictive information that was not provided by the other variables. This result aligns with the findings of Arora et al. (2024) who emphasized the role of investors' attitudes and perceptions in IPO decision making.

The best overall balance in terms of modelling was obtained by the stacking ensemble based on the pre-defined multi-criteria selection framework. The ROC-AUC was relatively low, suggesting moderate discrimination, while the relatively higher recall and F1-score suggested better identification of respondents belonging to higher-Perception class. The lower specificity was reflective of relatively poor classification of lower-Perception respondents. The stacking, repeated validation, SHAP interpretation, and ablation analysis therefore goes beyond predictive accuracy, and contributes to transparent financial AI modelling (Weber et al., 2024).

The results are relevant for fintech platforms, financial education providers, and capital-market institutions, especially to enhance digital financial self-efficacy, trust, and investment awareness among younger investors. Interpretation should be made with caution, however, due to the nature of cross sectional secondary data, moderate sample size, proxy-based IPO Awareness construct, and held-out validation from the same source population. Future studies must use direct IPO-specific measures, larger and more heterogeneous samples, longitudinal designs, independent external validation, and calibrated and/or cost-sensitive models to increase measurement precision, specificity and external validity.

## 6. Conclusion

This study has designed an interpretable AI model for predicting Investment Perception among Generation Z with the medium of Digital Financial Literacy, IPO Awareness, Technology Innovativeness, Trust, Financial Attitude, and Digital Financial Self-Efficacy. The results indicate that financial, behavioral, and technology factors are interwoven and that predictive variation in Investment Perception is linked to this interwoven combination. Digital Financial Self-Efficacy was the top global predictor followed by Trust and IPO Awareness. Ablation analysis also revealed that the information from IPO Awareness was also informative and didn't need to be considered along with the other variables. Digital Financial Literacy made a contribution to individual predictions, but its incremental contribution was relatively small when the other constructs were taken into account simultaneously. The proposed stacking ensemble was the best overall balance within the pre-defined multi-criteria evaluation framework. It was tested using repeated stratified cross-validation, held-out testing, bootstrap uncertainty assessment, SHAP interpretation, and ablation analysis. The model showed moderate discrimination and higher recall than specificity, but it offered a transparent and repeatable method to perform predictive analysis of Generation Z Investment Perception. The main contribution of the study is the combination of interpretable ensemble learning and financial, behavioral, and tech predictors and the ability to differentiate between global feature importance and incremental predictive contribution. The results also show the predictive power of IPO Awareness in the modelling framework. Since there was no measure available in the dataset specific to IPOs, investment-awareness-related indicators were used as proxies for IPO Awareness. Future research should use direct measures of the IPO process, larger and more diverse samples, longitudinal designs, and external validation of the models to increase measurement precision, predictive generalizability, and model robustness.

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