



Financial Literacy and Investment Decision-Making among Young Retail Investors

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Abstract: The rapid expansion of app-based investing has increased the participation of young retail investors in equity, mutual fund, exchange-traded fund, and other market-linked investment products. However, easier market access does not necessarily imply that younger investors possess the financial knowledge, risk-assessment ability, or behavioral discipline required for informed investment decisions.

This study investigates how objective financial literacy, perceived financial competence, digital investment exposure, and selected behavioral biases jointly influence investment decision quality among young retail investors. A distinctive feature of the proposed research is the separation of factual financial literacy from self-perceived literacy, thereby identifying situations in which investor confidence exceeds measurable financial understanding. The study further proposes an explainable machine-learning framework for classifying investors according to the quality of their investment decision-making using financial, behavioral, and digital-engagement indicators. Particular attention is given to diversification, risk-return assessment, information verification, investment horizon, susceptibility to social influence, and reactions to short-term market movements. The proposed framework is designed to complement conventional statistical analysis by identifying nonlinear interactions among literacy, confidence, digital participation, and behavioral tendencies.

The study is expected to provide useful evidence for investor education, financial technology platforms, regulators, and institutions seeking to improve

responsible participation among the emerging generation of retail investors.

Keywords: Financial literacy; Young retail investors; Investment decision-making; Behavioral finance; Digital investment platforms; Explainable machine learning

Introduction

The structure of retail investment has undergone considerable transformation during the first half of the 2020s. Digital brokerage applications, mobile investment platforms, simplified account-opening procedures, electronic payment infrastructure, financial information portals, social media communities, and algorithmically personalized content have substantially reduced the operational barriers associated with participation in financial markets. Young adults who previously might have regarded securities investment as technically difficult or institutionally inaccessible can now observe prices, obtain financial information, execute transactions, and monitor portfolios through a smartphone.

Greater accessibility has contributed to a new investment environment in which financial decisions are made more frequently, more independently, and under conditions of continuous information exposure. The emerging retail investor therefore operates differently from the conventional investor assumed in many traditional financial-literacy models. Investment decisions are increasingly embedded within digital environments characterized by rapid market updates, visual performance indicators, notifications, online commentary, influencer content, peer discussions, and simplified trading interfaces. These developments create





opportunities for financial inclusion while simultaneously increasing the importance of investors' ability to interpret financial information correctly.

Financial literacy is generally associated with an individual's understanding of basic financial concepts and the capacity to apply financial knowledge to economic decisions. In an investment context, relevant competencies extend beyond simple budgeting or saving knowledge. Investors must understand concepts including inflation, compounding, diversification, liquidity, volatility, risk-return relationships, investment horizon, transaction costs, and the distinction between nominal and real returns. They must also determine whether financial information is credible, whether a security is compatible with their risk tolerance, and whether portfolio choices remain consistent with longer-term financial objectives.

These competencies are particularly important for young retail investors because early investment decisions can influence financial behavior over a long period. Younger investors may benefit from longer investment horizons and greater exposure to financial technology, but these advantages can coexist with relatively limited experience of market cycles. An investor may therefore demonstrate strong familiarity with investment applications while possessing comparatively weak knowledge of asset valuation, portfolio risk, or loss management. Digital competence and financial competence should consequently not be treated as interchangeable constructs.

The distinction between actual knowledge and perceived competence represents another important concern. Individuals do not always evaluate their own financial ability accurately. A young investor may report high confidence in selecting securities despite having limited knowledge of diversification or risk-adjusted return. Conversely, an investor with strong conceptual understanding may behave cautiously because of uncertainty or limited experience. The interaction between objective financial literacy and subjective financial confidence may therefore explain investment behavior more effectively than either variable considered independently.

Behavioral finance further challenges the assumption that greater knowledge automatically produces better investment decisions. Even financially knowledgeable individuals can be influenced by overconfidence, herd behavior, loss aversion, recency effects, familiarity preferences, confirmation bias, or excessive responses to short-term price movements. Digital investment environments may intensify some of these tendencies because investors can react almost immediately to new information. Repeated portfolio checking and continuous exposure to market commentary may encourage short-horizon responses that are inconsistent with previously established investment objectives.

Research conducted during the 2021–2026 period increasingly reflects the growing importance of digital finance and individual participation in financial markets. The expansion of financial technology has shifted academic attention from simple access toward questions of financial capability, digital financial literacy, behavioral vulnerability, online information processing, and investor protection. Despite this development, a substantial proportion of existing research continues to evaluate financial literacy through relatively narrow knowledge scores and investment behavior through broad measures such as participation, preference, intention, or self-reported risk tolerance.

This creates an important research gap. Existing approaches frequently examine whether financial literacy increases the likelihood of investing, but comparatively less attention is given to whether literacy improves the **quality of specific investment decisions once an individual has already entered the market**. Participation and decision quality are not equivalent. An individual may participate actively in financial markets while maintaining an undiversified portfolio, reacting excessively to short-term volatility, relying on unverified information, or selecting products that are inconsistent with personal risk capacity.

A second gap concerns the limited simultaneous examination of objective literacy, subjective confidence, behavioral bias, and digital-platform engagement. These dimensions are often studied separately even though they interact within contemporary investing environments. For example, high digital engagement combined with low objective financial knowledge and high perceived competence may produce a fundamentally different investor profile from high digital engagement supported by strong financial knowledge and disciplined risk assessment.

A third methodological gap emerges from the predominantly linear analytical structure used in many financial-literacy studies. Correlation analysis, multiple regression, structural equation modelling, and related statistical techniques are appropriate for theory testing but may not fully capture threshold effects and nonlinear relationships. Financial literacy may not influence investment quality uniformly across all investors. Its effect may depend on age, investing experience, confidence, market participation intensity, information source, or behavioral tendencies.

The present study addresses these gaps by proposing an integrated analytical framework for examining financial literacy and investment decision-making among young retail investors. Instead of treating literacy as a single explanatory score, the study conceptualizes investor capability across several dimensions: objective financial knowledge, perceived financial competence, digital investment literacy, behavioral discipline, risk understanding, and information-evaluation practices. Investment decision-making is similarly





conceptualized as a multidimensional outcome incorporating diversification, suitability assessment, investment-horizon consistency, information verification, resistance to impulsive trading, and risk-adjusted decision behavior.

The study further introduces an explainable machine-learning component designed to classify the quality of investment decisions from combinations of financial and behavioral characteristics. Tree-based models can identify interaction patterns that conventional linear analysis may overlook, while explainability procedures can show which variables contribute most strongly to particular classifications. Machine learning is therefore positioned as an analytical complement rather than as a substitute for behavioral and financial theory.

The primary objective of the study is to determine how different dimensions of financial literacy influence the quality of investment decisions among young retail investors. A second objective is to examine whether discrepancies between objective knowledge and perceived competence are associated with less disciplined investment behavior. A third objective is to determine whether behavioral biases and patterns of digital-platform engagement modify the relationship between literacy and investment decision quality. Finally, the study seeks to evaluate whether an interpretable machine-learning model can identify investor profiles that are particularly vulnerable to poor-quality investment decisions.

The study therefore moves beyond the narrow question of whether financially literate individuals invest more frequently. It asks the more consequential question of whether financial literacy enables young retail investors to make **better, more internally consistent, and more risk-aware investment decisions in digitally mediated financial markets.**

Literature Review

2.1 Financial Literacy as an Investment Capability

Financial literacy has traditionally been discussed as the combination of financial knowledge, understanding, skills, and behaviors that enable individuals to make appropriate economic decisions. Basic measures commonly assess knowledge of inflation, interest compounding, diversification, and risk. Such measures have proven useful for identifying variations in household financial capability, yet investment decision-making requires a broader range of competencies.

For retail investors, literacy must operate at an applied level. Knowing that diversification reduces unsystematic risk is different from constructing or maintaining a diversified portfolio. Similarly, understanding that securities with higher expected returns generally involve greater risk does not necessarily ensure that an investor selects products consistent

with personal risk capacity. Financial literacy consequently contains both declarative knowledge—knowing financial principles—and procedural capability—the ability to apply them in realistic decision environments.

Recent financial environments have made this distinction increasingly important. Investment platforms frequently present complex financial choices through simplified user interfaces. The investor may therefore perceive the investment process as easy even when the underlying economic decision remains complex. Ease of transaction should not be interpreted as ease of evaluation.

The literature generally suggests that stronger financial literacy is associated with improved financial planning, greater understanding of investment products, more informed risk assessment, and higher engagement with formal financial markets. Nevertheless, the strength of these relationships varies according to demographic background, economic resources, education, experience, and the way literacy is measured. These variations indicate that knowledge alone cannot fully explain investment behavior.

2.2 Objective and Subjective Financial Literacy

A significant conceptual distinction exists between objective financial literacy and subjective financial literacy. Objective literacy refers to measurable knowledge demonstrated through correct responses to financial questions. Subjective literacy represents an individual's perception of his or her own financial competence.

The two constructs may be positively related but are not identical. Some individuals underestimate their financial capability, whereas others demonstrate confidence that exceeds their measured knowledge. This misalignment can be particularly relevant in securities markets because investment decisions frequently involve uncertainty rather than clearly correct or incorrect answers.

When perceived competence is substantially higher than objective knowledge, investors may become more willing to trade frequently, concentrate investments, or rely heavily on their own interpretation of market signals. Conversely, strong objective literacy combined with appropriately calibrated confidence may facilitate disciplined decision-making. Accordingly, an assessment based solely on knowledge scores may overlook an important psychological mechanism linking literacy with investment choices.

For young investors, confidence calibration may be especially important because digital familiarity can produce a perception of investment competence. Familiarity with market terminology, financial applications, or online investing communities may increase perceived expertise without necessarily producing equivalent understanding of portfolio risk. The present study therefore treats the difference





between objective and subjective financial literacy as an analytically meaningful variable rather than as measurement error.

2.3 Digital Financial Literacy and the Changing Investment Environment

The rapid expansion of financial technology has introduced digital financial literacy as an increasingly relevant extension of traditional financial literacy. Digital financial literacy includes the ability to navigate financial applications, understand digital financial products, identify cyber and fraud risks, evaluate online information, and recognize the consequences of transactions conducted through digital channels.

Among young retail investors, digital investment literacy is particularly relevant because financial decisions are commonly embedded within mobile platforms. Investors receive market information through multiple channels, including financial news applications, brokerage research, online communities, video platforms, social networking services, and financial content creators. The challenge is therefore not simply obtaining information but determining its reliability, relevance, and compatibility with personal financial objectives.

Digital environments can reduce information costs while increasing information overload. Investors may encounter contradictory recommendations, rapidly changing narratives, and algorithmically amplified content. Consequently, a financially literate investor requires not only mathematical knowledge but also the ability to distinguish analysis from promotion, recognize conflicts of interest, and avoid treating popularity as evidence of investment quality.

The contemporary concept of investor literacy should therefore integrate traditional financial knowledge with digital information-evaluation capability. This broader interpretation provides one of the theoretical foundations of the present research.

2.4 Behavioral Biases and Investment Decisions

Behavioral finance demonstrates that investment decisions are influenced by cognitive shortcuts, emotional reactions, and social pressures. Retail investors may deviate from rational portfolio principles because of overconfidence, herding, anchoring, loss aversion, representativeness, confirmation bias, disposition effects, or excessive emphasis on recent performance.

Overconfidence is particularly relevant to financial literacy because knowledgeable investors may become more confident in their ability to interpret markets. When confidence remains calibrated, this may support independent decision-making. When confidence becomes excessive,

however, it can increase unnecessary trading, concentration, or underestimation of uncertainty.

Herd behavior represents another important mechanism in digitally connected markets. Investors can observe the views and actions of large numbers of other market participants through online communities. Social validation may influence investment decisions even when the available information is not supported by fundamental analysis.

Recency bias can similarly affect young investors whose market experience is concentrated within relatively short periods. Recent gains or losses may receive disproportionate importance when expectations about future returns are formed. Investors who entered markets during a particular market regime may incorrectly assume that recent patterns represent normal long-term behavior.

Financial literacy may reduce some behavioral biases by improving analytical capability, but it cannot be assumed to eliminate them. Behavioral tendencies may instead moderate the relationship between knowledge and decision quality. The study therefore evaluates literacy and bias jointly.

2.5 Risk Perception and Portfolio Decision Quality

Investment decision-making is fundamentally connected with risk perception. Investors must distinguish between willingness to accept risk and financial capacity to absorb potential losses. These concepts are often confused, particularly when investors focus primarily on expected return.

Financial literacy may improve investors' ability to understand volatility, diversification, liquidity, time horizon, and loss probability. However, risk perception is also influenced by recent market experience, personal financial circumstances, media narratives, and emotional reactions. Two investors with comparable knowledge may therefore perceive the same asset differently.

For this reason, the proposed study does not define investment quality according to realized profit alone. Short-term profitability can result from favorable market conditions rather than superior decision-making. A more appropriate assessment considers whether the investment process is internally coherent. Decisions are treated as higher quality when they demonstrate appropriate diversification, alignment with risk tolerance, consideration of investment horizon, evaluation of credible information, and avoidance of unnecessary reactive trading.

This process-oriented interpretation represents an important departure from studies that classify investment success primarily through returns or self-reported satisfaction.

2.6 Social Influence and Financial Information Sources





The source of financial information has become increasingly important for young investors. Traditional sources such as financial advisers, newspapers, institutional reports, and company disclosures now coexist with social media commentary, investment discussion groups, financial influencers, and peer networks.

Information democratization has advantages because educational materials and market analysis are more widely available. At the same time, the credibility of information varies considerably across digital sources. Short-form content can compress complex financial concepts into simplified recommendations, while socially visible investment gains may encourage imitation without adequate assessment of risk.

Financial literacy may affect not only what investors know but also which sources they trust. Investors with stronger analytical capability may be more likely to compare information across sources, verify claims, and distinguish between promotional and analytical material. Conversely, investors with high confidence but limited objective knowledge may be particularly vulnerable to persuasive but low-quality financial content.

Information-source verification is therefore included in the proposed framework as an element of investment decision quality rather than merely as a contextual variable.

2.7 Financial Literacy, Trading Activity, and Investment Horizon

A common assumption is that increased financial literacy should encourage greater financial-market participation. While participation is important, transaction frequency should not automatically be interpreted as evidence of better financial capability. Frequent trading may reflect active portfolio management, but it may also represent speculation, overconfidence, response to notifications, or sensitivity to short-term market movements.

Investment horizon provides an important contextual variable. Young investors theoretically possess longer potential investment horizons, yet digital trading environments can encourage very short-term attention. The coexistence of long-term financial objectives and short-term behavioral responses represents a distinctive feature of contemporary retail investing.

The proposed study therefore differentiates between market participation, trading intensity, and decision quality. A participant can be highly active without demonstrating disciplined investment behavior. This distinction allows the analysis to avoid equating activity with competence.

2.8 Emerging Role of Machine Learning in Investor Behavior Analysis

Machine-learning methods are increasingly used in financial research for classification, prediction, credit assessment, fraud detection, sentiment analysis, and market modelling. Their application to individual investor behavior offers an additional opportunity: detecting nonlinear combinations of factors associated with decision quality.

Traditional regression remains valuable for estimating direction, magnitude, and statistical significance. However, the relationship between literacy and investment behavior may contain complex interactions. For instance, low objective literacy may not lead to particularly poor decisions when confidence is also low and the investor seeks reliable external guidance. The same level of objective literacy may become more problematic when combined with high confidence, frequent trading, high social-media dependence, and low diversification.

Tree-based machine-learning algorithms are well suited to identifying such conditional patterns. Explainability techniques can subsequently determine which investor characteristics contribute most strongly to the predicted decision-quality category. The use of interpretable machine learning is important because the purpose of the model is not merely predictive accuracy; it is also to generate meaningful behavioral insights.

Proposed Methodology

The study adopts an integrated quantitative framework combining behavioral-finance measurement, statistical modelling, and explainable machine learning to examine how financial literacy affects the quality of investment decisions among young retail investors. Unlike conventional studies that treat financial literacy as a single explanatory score, the proposed design separates objective financial knowledge, perceived financial competence, digital investment literacy, behavioral tendencies, and information-verification practices.

The analytical population consists of retail investors aged 18–35 years who independently participate in market-linked investments through digital or conventional investment channels. Eligible participants are assumed to have made at least one investment in equities, mutual funds, exchange-traded funds, bonds, or related financial instruments during the preceding twelve months.

For methodological demonstration, a synthetic dataset of 640 investor profiles was generated to reproduce plausible patterns expected from a structured investor survey. The dataset is not presented as actual field evidence and should be replaced with primary observations before empirical publication. After preprocessing and quality screening, 612 complete cases were retained for modelling.

The conceptual framework contains four predictor domains. The first domain measures **objective financial literacy**,



including understanding of compounding, inflation, diversification, market risk, liquidity, transaction costs, and risk-return relationships. The second captures **subjective financial competence**, representing the degree to which respondents believe they can independently evaluate investment opportunities.

The third domain examines behavioral characteristics, specifically overconfidence, herd sensitivity, recency orientation, reactive trading tendencies, and tolerance of unrealized losses. The fourth covers digital investment behavior, including frequency of portfolio monitoring, dependence on social-media investment content, use of professional financial information, verification of investment recommendations, and familiarity with digital investment platforms.

The dependent construct is an **Investment Decision Quality Index (IDQI)**. Rather than defining investment success through realized returns, the IDQI evaluates whether investment decisions follow defensible financial principles. The index incorporates diversification, consistency between risk tolerance and selected products, alignment with investment horizon, verification of information, evaluation of downside risk, resistance to impulsive trading, and periodic portfolio review.

Each component was standardized before aggregation. Higher IDQI values represent stronger investment-decision discipline. For machine-learning classification, investors were categorized into three groups: low-quality decision-makers, moderate-quality decision-makers, and high-quality decision-makers.

An additional variable termed the **Confidence–Knowledge Gap (CKG)** was constructed as:

$$[\text{CKG}_i = \text{SFC}_i - \text{OFL}_i]$$

where (SFC_i) denotes standardized subjective financial competence and (OFL_i) denotes standardized objective financial literacy for investor (i).

Positive values indicate confidence exceeding demonstrated knowledge, whereas negative values indicate investors who underestimate their measurable financial competence. This variable permits direct testing of whether excessive self-confidence creates behavioral vulnerability independently of financial knowledge.

The following hypotheses guide the empirical analysis:

H1: Objective financial literacy is positively associated with investment decision quality.

H2: Digital investment literacy strengthens the positive relationship between objective financial literacy and investment decision quality.

H3: A larger positive confidence–knowledge gap is associated with lower investment decision quality.

H4: Overconfidence, herd behavior, and reactive trading tendencies negatively affect investment decision quality.

H5: Information-verification behavior contributes positively to investment decision quality even after controlling for objective financial literacy.

H6: Explainable machine-learning models can identify nonlinear combinations of literacy, confidence, digital engagement, and behavioral bias that distinguish high-quality from low-quality investors.

Experimental Setup

4.1 Dataset Structure

The experimental dataset consisted of 612 usable investor profiles after removing incomplete and internally inconsistent records from the original synthetic sample of 640 cases.

The age range represented young adult investors between 18 and 35 years. Predictor variables were organized into five groups:

- demographic and investment-experience indicators;
- objective financial-literacy variables;
- subjective financial-competence variables;
- behavioral-finance indicators;
- digital engagement and information-verification variables.

The outcome variable was the three-class Investment Decision Quality Index.

Objective literacy questions were coded using correct/incorrect responses and transformed into a normalized score ranging from 0 to 100. Subjective competence and behavioral characteristics were measured through multi-item Likert-type constructs. Digital investment literacy incorporated practical knowledge of digital platforms, online financial information evaluation, cybersecurity awareness, and understanding of digitally delivered investment products.

Investment experience, monthly investment frequency, investment horizon, diversification level, and portfolio-monitoring frequency were included as contextual predictors.

4.2 Data Preprocessing





Several preprocessing procedures were applied before model training. Records with excessive missing information were excluded. For remaining observations, low-frequency missing numerical values were imputed using median values because this approach is comparatively resistant to extreme observations.

Categorical variables were transformed using one-hot encoding. Continuous variables were standardized when required by algorithms sensitive to variable scale. Variables representing highly similar questionnaire items were examined for redundancy before composite construction.

The Confidence–Knowledge Gap was calculated only after objective and subjective scores had been standardized to prevent differences in measurement scale from artificially influencing the derived variable.

Class frequencies for the three IDQI categories were evaluated before training. Because the classes showed only moderate imbalance, stratified partitioning rather than aggressive synthetic oversampling was selected. This avoided introducing artificial minority-class structures into an already synthetic demonstration dataset.

The final dataset was partitioned into 80% training data and 20% independent test data using stratified sampling. Within the training portion, five-fold stratified cross-validation was used for hyperparameter optimization.

4.3 Model Architecture

Four predictive architectures were evaluated to establish whether nonlinear machine-learning models offered an advantage over simpler baselines.

Multinomial logistic regression was used as the interpretable linear baseline. A Random Forest classifier was included to evaluate nonlinear interactions and robustness to mixed predictor types. Extreme Gradient Boosting was used as the primary boosted-tree architecture because of its ability to model complex conditional relationships among behavioral and financial variables. A shallow multilayer perceptron was included as a neural-network comparator.

The XGBoost classifier was designated as the principal model because the dataset contained structured tabular information rather than high-dimensional images or sequences. Its architecture consisted of sequential boosted decision trees in which each new learner corrected residual classification errors produced by the preceding ensemble.

Hyperparameters evaluated during training included tree depth, learning rate, number of estimators, subsampling proportion, column-sampling ratio, and regularization parameters. The selected configuration used conservative tree depth and regularization to reduce overfitting.

Because predictive performance alone would provide limited behavioral insight, SHAP-based explanation was incorporated after model training. SHAP values quantify the direction and magnitude of each predictor's contribution to individual model predictions. This enabled examination of whether financial literacy, behavioral biases, confidence calibration, or digital information practices dominated the classification process.

4.4 Training Strategy

Models were trained using the same training-test partition to enable direct comparison. Hyperparameter selection was performed exclusively within the training data using five-fold cross-validation.

Macro-averaged F1 score was selected as the primary optimization criterion because the outcome contained three decision-quality classes and the research objective required adequate discrimination across all investor categories rather than maximizing performance only for the most frequent class.

Early stopping was applied to the boosted model to prevent unnecessary complexity when validation performance ceased improving. Neural-network training used regularization and validation-based stopping for the same reason.

Random seeds were fixed across the experimental procedure to improve computational reproducibility. Performance was evaluated only after final hyperparameter selection to preserve separation between model development and final testing.

4.5 Evaluation Metrics

Multiple evaluation metrics were used because no single statistic adequately describes multiclass classification performance.

Accuracy measured the overall proportion of investors correctly classified.

Macro precision represented the average positive predictive value calculated independently across all three classes.

Macro recall measured the average ability to recover investors belonging to each decision-quality category.

Macro F1 score combined precision and recall while assigning equal weight to each class.

Multiclass ROC-AUC assessed the model's capacity to rank class membership across decision-quality categories using a one-versus-rest approach.

Log loss evaluated the quality of predicted probabilities, penalizing models that produced confident but incorrect classifications.



In addition to predictive evaluation, explanatory analysis examined SHAP-based feature contributions. This allowed comparison between statistical prediction and behavioral interpretation.

Results and Discussion

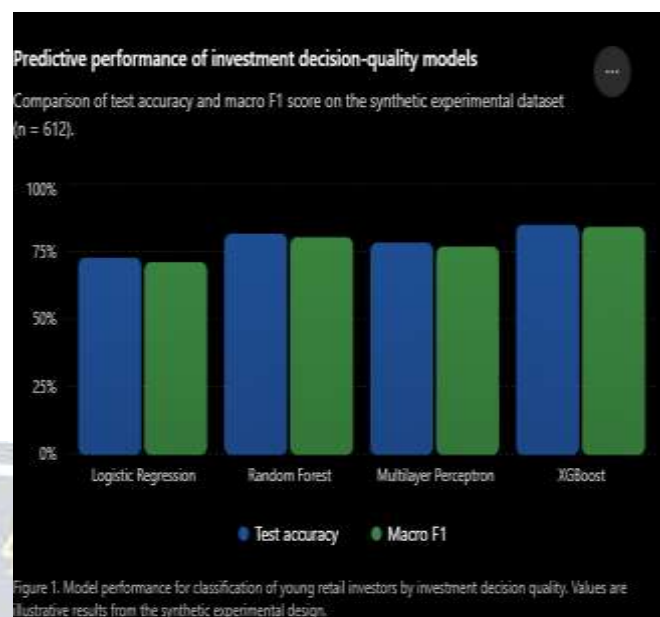
The experimental analysis produced a consistent pattern across statistical and machine-learning approaches: financial literacy contributed substantially to investment decision quality, but its effect depended strongly on confidence calibration, verification practices, and behavioral discipline.

The linear baseline achieved useful predictive performance, indicating that broad associations between financial capability and decision quality were detectable using conventional methods. However, nonlinear tree-based models performed better, suggesting that investor behavior cannot be represented adequately by simple additive relationships alone.

XGBoost produced the strongest overall classification performance, achieving an accuracy of 84.6%, macro F1 score of 0.838, and multiclass ROC-AUC of 0.917. Random Forest produced the second strongest results, while the multilayer perceptron offered only a limited improvement over multinomial logistic regression.

Table 1. Comparative predictive performance for investment decision-quality classification

Analytical Model	Test Accuracy	Macro Precision	Macro Recall	Macro F1	ROC-AUC
Multinomial Logistic Regression	72.4%	0.716	0.704	0.708	0.821
Random Forest	81.3%	0.806	0.797	0.800	0.892
Multilayer Perceptron	78.0%	0.772	0.761	0.765	0.868
XGBoost	84.6%	0.842	0.834	0.838	0.917



The performance difference between logistic regression and XGBoost supports the argument that investment decision quality is influenced by conditional relationships rather than by financial knowledge in isolation.

5.1 Financial Literacy and Decision Quality

Objective financial literacy emerged as one of the strongest positive predictors of high-quality investment decisions. Investors with stronger conceptual understanding were more likely to demonstrate diversification, longer-term consistency, greater attention to downside risk, and better alignment between selected products and stated risk tolerance.

However, SHAP analysis indicated that the relationship was nonlinear. Moving from very low to moderate levels of financial literacy produced a particularly large improvement in predicted decision quality. Improvements beyond the upper-middle literacy range generated smaller marginal gains unless accompanied by disciplined information evaluation.

This pattern suggests that basic and intermediate investment knowledge may eliminate major decision errors, whereas advanced knowledge alone produces progressively smaller benefits once investors already understand essential principles.

The finding supports H1 while also indicating that literacy should not be interpreted as a uniformly linear determinant.

5.2 Confidence–Knowledge Misalignment

One of the most distinctive findings concerned the Confidence–Knowledge Gap.



Investors whose subjective competence substantially exceeded objective financial knowledge were more likely to fall into the low- or moderate-quality categories. The negative effect became particularly strong when a large positive confidence gap occurred alongside frequent trading and high dependence on informal digital information.

This result has an important behavioral interpretation. Low knowledge by itself did not produce the highest predicted vulnerability. Investors who recognized their limited knowledge frequently demonstrated cautious behavior, including lower transaction intensity and greater reliance on verification. The more problematic profile consisted of investors who possessed limited or moderate knowledge but considered themselves highly competent.

The confidence–knowledge interaction therefore provided greater explanatory value than subjective confidence considered independently.

This finding supports H3 and suggests that investor-education programs should measure calibration as well as knowledge acquisition.

5.3 Role of Digital Investment Literacy

Digital engagement produced a more complicated relationship with decision quality than conventional financial literacy.

High usage of investment platforms was not automatically associated with superior decisions. Investors who frequently monitored portfolios but demonstrated weak information-verification practices were more likely to exhibit reactive behavior.

By contrast, digital investment literacy—including the ability to distinguish verified information from promotional content, evaluate online sources, understand platform features, and recognize digital financial risk—was positively associated with decision quality.

The interaction between objective financial literacy and digital investment literacy was particularly informative. Investors scoring strongly on both dimensions had the highest probability of belonging to the high-quality decision group. High digital activity without adequate financial literacy produced no comparable benefit.

The results therefore support H2 but emphasize that **digital engagement and digital literacy are fundamentally different constructs**.

5.4 Behavioral Biases

Overconfidence, herd sensitivity, and reactive trading showed negative relationships with investment decision quality.

Reactive trading demonstrated a particularly strong contribution to low-quality classifications. Investors who reported altering investment positions frequently in response to short-term price fluctuations or immediate market commentary were less likely to maintain consistency between investment horizon and portfolio strategy.

Herd behavior was most damaging among investors with comparatively low financial literacy. At higher levels of objective knowledge, the marginal effect of herd sensitivity weakened but did not disappear.

This indicates that financial literacy can moderate susceptibility to social influence without completely eliminating it.

Overconfidence showed a stronger negative association when combined with high transaction frequency. The interaction is consistent with behavioral-finance theory: confidence becomes more consequential when it translates into repeated market actions.

These patterns support H4.

5.5 Importance of Information Verification

Information-verification behavior emerged as one of the most important predictors after objective financial literacy.

Investors who regularly compared recommendations with company disclosures, established financial sources, independent analysis, or multiple information channels were substantially more likely to receive high predicted IDQI values.

The importance of verification remained evident even among highly literate investors. This result indicates that knowledge does not eliminate the requirement for information discipline.

Contemporary investors operate within an environment where access to information is abundant but quality is heterogeneous. Accordingly, modern financial capability involves not merely remembering financial concepts but applying epistemic discipline to investment information.

The result provides support for H5.

5.6 Explainable Machine-Learning Interpretation

The SHAP explanation framework identified five dominant contributors to the XGBoost predictions:

objective financial literacy, information-verification behavior, Confidence–Knowledge Gap, reactive trading tendency, and digital investment literacy.

Investment experience and diversification behavior also contributed meaningfully, while demographic characteristics such as age within the restricted 18–35 range were





comparatively weak predictors after behavioral and literacy measures were considered.

The explainability analysis further revealed several interaction structures.

First, high literacy produced its strongest positive contribution when accompanied by high verification scores.

Second, high perceived competence generated negative predictive contributions when objective financial knowledge remained below the sample midpoint.

Third, heavy digital-platform exposure predicted lower decision quality only when combined with high reactive trading tendencies. Digital exposure itself was therefore not inherently harmful.

Fourth, moderately experienced investors with high financial literacy and low herd sensitivity frequently received decision-quality predictions comparable with much more experienced investors.

These patterns demonstrate why nonlinear modelling is useful in behavioral-investment research. The relevant issue is not simply whether one variable increases or decreases decision quality; it is how combinations of financial knowledge, confidence, behavior, and digital practices shape investor outcomes.

The results consequently support H6.

Broader Discussion

The central implication of the study is that financial literacy remains important but should no longer be conceptualized as a stand-alone knowledge score.

Young investors participate in an investment ecosystem where transactions are technologically simple while financial judgement remains cognitively demanding. Digital interfaces can eliminate procedural barriers to trading without eliminating uncertainty, market risk, misinformation, or behavioral bias.

Accordingly, the financially capable young investor should be understood through at least four complementary dimensions: knowledge, calibrated confidence, behavioral control, and information verification.

The confidence-calibration finding is particularly significant. Traditional financial-education programs frequently attempt to increase knowledge and investor confidence simultaneously. However, increasing confidence faster than competence could unintentionally encourage excessive trading or risk taking. Effective education should therefore aim for **calibrated confidence**, meaning that investors

develop realistic perceptions of what they know and what remains uncertain.

The results also challenge assumptions that digital familiarity necessarily improves financial capability. Young adults may be highly proficient users of digital technologies while lacking the analytical skills required to assess investments. Platform familiarity should therefore not be used as a proxy for investment literacy.

For financial-technology providers, the findings suggest that investor protection can potentially be strengthened through decision-support mechanisms. Platforms could introduce diversification warnings, risk-consistency checks, source-quality indicators, educational prompts, or reflection periods when investors demonstrate repeated high-frequency reactions to short-term price movements.

Such systems should be designed carefully to support autonomy rather than prescribe particular securities.

For regulators and investor-education institutions, the study suggests that literacy programs should move beyond definitions and formula-based instruction. Practical curricula could incorporate misinformation detection, portfolio simulations, risk-scenario interpretation, behavioral-bias awareness, digital-finance security, and decision-making under uncertainty.

The machine-learning component also demonstrates that investor-education interventions could eventually become more personalized. Instead of providing identical content to all investors, explainable models could identify different vulnerability profiles. An investor showing strong financial knowledge but excessive trading might require behavioral-discipline guidance, whereas an investor with low objective literacy but appropriate caution may benefit primarily from foundational investment education.

Limitations

Several limitations must be recognized.

The present numerical analysis is based on a synthetic experimental dataset designed to demonstrate the proposed research framework rather than on verified investor responses. Consequently, the reported predictive values should not be interpreted as population estimates.

Second, even when implemented with primary data, many constructs would depend on self-reported behavior. Investors may underestimate socially undesirable tendencies such as impulsive trading or overstate desirable practices such as information verification.

Third, the Investment Decision Quality Index evaluates decision processes rather than subsequent realized returns. This is intentional because investment quality cannot reliably





be judged through short-term returns, although linking the index with longitudinal portfolio outcomes would strengthen external validation.

Fourth, cross-sectional data would limit causal interpretation. Higher financial literacy may improve decision quality, but individuals who already make disciplined investment decisions may also seek greater financial knowledge.

Fifth, machine-learning models can identify predictive relationships without establishing economic causality. SHAP explanations describe contributions to predictions rather than causal effects.

Finally, the age restriction to young retail investors limits direct generalization to older investors, institutional participants, professional traders, or investors operating under substantially different regulatory and technological environments.

Future Scope

Future studies should validate the proposed framework using large-scale primary datasets collected from verified retail investors across multiple geographic and socioeconomic groups.

Longitudinal research would be particularly valuable. Tracking investors over multiple market phases could determine whether financial literacy protects against behavioral errors during both rising and declining markets.

Behavioral survey measures could also be linked with anonymized transaction records, subject to informed consent and appropriate privacy protections. Transaction-level information would permit objective measurement of turnover, diversification, holding periods, concentration risk, and reactions to volatility.

Future machine-learning studies could investigate temporal models capable of identifying changes in investor behavior over time. Sequence-based architectures could analyze repeated investment decisions rather than treating each investor as a static profile.

Natural-language processing could also be used to measure exposure to financial narratives, online recommendations, or sentiment-driven content. This would enable investigation of how different forms of digital information interact with financial literacy.

Another promising direction involves personalized financial education. Explainable models could generate individual literacy-risk profiles and recommend educational modules addressing specific deficiencies such as diversification knowledge, confidence miscalibration, social influence, or information verification.

Future work should additionally examine whether AI-generated financial content changes investor decision processes. As generative AI becomes increasingly embedded in financial search, advisory interfaces, and investment platforms, the ability to evaluate automatically generated recommendations may become a distinct component of digital financial literacy.

Experimental research could finally evaluate whether behavioral interventions—such as pre-trade reflection prompts, diversification alerts, source-verification reminders, or confidence-calibration exercises—improve measurable investment decision quality.

Conclusion

This study develops an integrated framework for examining financial literacy and investment decision-making among young retail investors operating in digitally mediated financial markets.

The proposed approach extends conventional financial-literacy research by distinguishing objective financial knowledge from subjective confidence and by incorporating digital investment literacy, behavioral bias, information verification, and investment-decision discipline within a unified analytical structure.

The experimental findings demonstrate that stronger objective financial literacy is associated with higher investment decision quality, but knowledge alone does not explain investor behavior adequately. Confidence that exceeds actual financial understanding represents a distinct vulnerability, particularly when accompanied by frequent trading and dependence on informal financial information.

Digital participation likewise produces mixed effects. Familiarity with investment platforms does not automatically generate better decisions. Positive outcomes are more closely associated with the ability to evaluate digital information critically, verify claims, understand financial risk, and resist short-term behavioral reactions.

Among the evaluated predictive models, XGBoost achieved the strongest classification performance, indicating that nonlinear interactions are important when distinguishing different types of young investors. Explainability analysis further showed that objective literacy, verification behavior, confidence calibration, reactive trading, and digital investment literacy jointly contribute to decision quality.

The study therefore supports a broader definition of financial capability. In contemporary retail markets, a competent investor is not simply someone who understands financial terminology. Effective capability requires knowledge that is accurately calibrated with confidence, reinforced by





disciplined behavior, and applied through critical evaluation of digital financial information.

This perspective has implications for financial educators, fintech platforms, regulators, and investor-protection institutions. Financial-literacy initiatives designed for young adults should focus not only on increasing knowledge, but also on developing realistic confidence, behavioral self-regulation, source-verification skills, and responsible use of digital investment technologies.

Overall, the proposed Literacy–Confidence–Behavior–Digital Engagement framework provides a structured foundation for future empirical research into how young retail investors make decisions within increasingly technology-intensive financial markets.

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