Strategic Finance and Economics Insights
ISSN*(Online)*: 3104-6827
Volume 2, Issue 4, Jul-Aug 2026, Page 1-10
DOI: 10.5281/zenodo.21539831
Original Research Article
Received: 26-06-2026| Accepted: 18-07-2026| Published: 25-07-2026

Explainable AI for Investor Suitability Assessment: Integrating Behavioral and Financial Signals in Institutional Onboarding

Neelesh Lalwani*

Abstract

Investor suitability assessment remains a critical component of institutional onboarding processes, particularly within digital investment platforms offering access to complex and risk-sensitive financial instruments. Conventional profiling approaches based solely on static financial disclosures often fail to capture the behavioral dynamics that influence investment intent and decision-making under uncertainty. The present study proposes an explainable artificial intelligence (XAI)-driven framework that integrates structured financial indicators with interaction-derived behavioral signals to enhance suitability classification during onboarding. Financial variables such as annual income, net investable assets, liquidity ratio, and prior investment experience were combined with behavioral metrics including investment exploration latency, decision response time, asset browsing entropy, and portfolio reallocation intent to construct a multidimensional suitability assessment model. Supervised ensemble-based classification techniques were employed to segment investors into Conservative, Moderate, and Aggressive suitability tiers, while post-hoc explainability methods enabled the interpretation of feature-level contributions to classification outcomes. It is based primarily on a Random Forest classifier, selected for its robustness in handling nonlinear relationships, mixed data types, and high-dimensional behavioral–financial datasets. The results demonstrate improved predictive accuracy and interpretability through the integration of behavioral engagement patterns alongside traditional financial metrics. Distributional analysis and hierarchical clustering further revealed distinct investor groupings aligned with suitability tiers, thereby supporting the relevance of multidomain onboarding indicators in investor profiling. The proposed approach contributes to the development of transparent, adaptive, and compliance-aligned onboarding systems capable of minimizing suitability misclassification and enhancing investment-product alignment.

Keywords

Explainable Artificial Intelligence, Investor Suitability, Behavioral Signals, Financial Profiling, Institutional Onboarding, Machine Learning, Investment Risk Alignment

**Co-founder and CEO at Fassport*

INTRODUCTION

The growing complexity of investor suitability in institutional onboarding

Investor suitability assessment has emerged as a foundational requirement in the institutional onboarding process, particularly within digital investment ecosystems characterized by diversified financial products and heterogeneous investor profiles (Khmyz, 2022). Traditional rule-based suitability frameworks primarily reliant on income levels, declared risk appetite, or investment horizon often fail to capture the multidimensional nature of investor decision-making behavior. As onboarding platforms increasingly accommodate a broader range of asset classes including private equity, venture capital, structured debt instruments, and hybrid securities, the need for a more dynamic and context-aware suitability evaluation mechanism has become evident (Alao, 2025). Suitability, in this regard, is no longer limited to financial metrics alone but must integrate cognitive, behavioral, and contextual indicators that influence investment preferences and risk-bearing capacity (Eshpulatov, 2025).

The limitations of conventional financial profiling methods

Conventional investor profiling approaches tend to emphasize static financial indicators such as net worth, liquidity ratios, prior investment experience, and income stability (Silva et al., 2015). While these parameters offer an essential baseline for classification, they often overlook latent behavioral tendencies such as

***Corresponding Author:** Neelesh Lalwani

overconfidence bias, loss aversion, impulsive decision-making, or temporal inconsistency (Saltık et al., 2023). These behavioral attributes can significantly impact investor responses to market volatility, portfolio drawdowns, or long-term capital lock-ins, particularly in illiquid investment structures. Moreover, standard questionnaire-based assessments are susceptible to self-reporting bias and framing effects, leading to inconsistencies in investor categorization. As a result, institutional onboarding processes that rely solely on financial declarations may inadvertently expose both investors and fund managers to misalignment risks, compliance challenges, and reputational liabilities (Udohaya, 2025).

The emergence of explainable AI in decision-sensitive financial systems

In response to these limitations, artificial intelligence-driven onboarding systems have gained prominence for their ability to process high-dimensional investor data across multiple domains (Mamun, 2025). Machine learning algorithms can now synthesize financial histories, transactional patterns, investment intent signals, and psychometric indicators to generate suitability scores with greater predictive validity (Romero & Fitz, 2021). However, the deployment of opaque "black-box" models in financial decision-making environments raises critical concerns related to transparency, auditability, and regulatory accountability. Explainable Artificial Intelligence (XAI) has thus emerged as a crucial methodological advancement, enabling model outputs to be interpreted through feature attribution, rule extraction, and local decision explanations. By translating complex algorithmic outputs into comprehensible rationales, XAI systems enhance institutional trust and facilitate compliance with governance and fiduciary responsibility mandates (Moorthy et al., 2025).

The integration of behavioral and financial signals for robust profiling

Recent advancements in digital onboarding infrastructures have made it feasible to incorporate behavioral signals such as interaction latency, investment exploration patterns, portfolio rebalancing frequency, and response consistencyinto suitability assessment frameworks (Odunaike, 2025). When integrated with traditional financial indicators, these signals provide a more holistic understanding of investor intent and resilience under varying market conditions (Maddodi & Kunte, 2024). The convergence of behavioral finance and machine learning thus enables the identification of latent investor archetypes that may not be discernible through demographic or financial variables alone. This integration supports the development of adaptive suitability models capable of dynamically recalibrating investor classifications in response to evolving behavioral trajectories and financial circumstances (Ahiadu et al., 2025).

The institutional need for transparent and adaptive onboarding frameworks

Institutional platforms are increasingly required to demonstrate not only the accuracy but also the interpretability of their suitability assessments (Li et al., 2022). Regulatory scrutiny surrounding algorithmic fairness, bias mitigation, and investor protection has intensified the demand for onboarding systems that are both predictive and explainable. Explainable AI frameworks address this requirement by offering decision traceability, sensitivity analysis, and scenario-based reasoning, thereby enabling onboarding administrators to justify investor classifications in a defensible and auditable manner (Kumar, 2024). Such transparency is particularly critical in environments where onboarding decisions influence access to restricted investment opportunities or long-duration capital commitments (Azour & McGuinness, 2023).

The research motivation for explainability-driven suitability modeling

Against this backdrop, the present study seeks to explore the design and implementation of an explainable AI-driven investor suitability assessment framework that integrates both behavioral and financial data streams within institutional onboarding workflows (Apu et al., 2022). By leveraging interpretable machine learning techniques and feature attribution mechanisms, the proposed approach aims to enhance alignment between investor characteristics and investment product risk profiles (Jaeger et al., 2021; Wang et al., 2025). The study contributes to the evolving discourse on responsible AI deployment in financial services by emphasizing the importance of interpretability in decision-sensitive onboarding processes, thereby promoting greater trust, accountability, and long-term investment alignment.

METHODOLOGY

The research design for suitability-oriented explainable modeling

The present study adopts a quantitative, model-driven research design to develop and evaluate an explainable artificial intelligence (XAI) framework for investor suitability assessment during institutional onboarding. The methodological architecture is structured to integrate heterogeneous financial and behavioral datasets into a unified analytical pipeline capable of generating interpretable suitability classifications. A cross-sectional dataset comprising digitally onboarded investor profiles was utilized to simulate real-time onboarding scenarios. The study operationalizes investor suitability as a composite latent construct influenced by both financial stability indicators and behavioral decision-making tendencies, thereby requiring multidimensional variable integration and advanced learning algorithms for robust prediction and explanation.

The identification and operationalization of financial variables

Financial suitability parameters were derived from structured investor disclosures and historical financial engagement records. These variables included annual income (AI), net investable assets (NIA), portfolio diversification index (PDI), liquidity ratio (LR), prior investment experience (PIE), investment horizon (IH), and capital commitment flexibility (CCF). Additional derived indicators such as financial risk-bearing capacity (FRBC) and asset volatility tolerance (AVT) were computed using normalized financial exposure ratios and historical portfolio drawdown responses. All financial variables were standardized through z-score normalization to ensure dimensional consistency across model training and interpretation phases.

The extraction and encoding of behavioral signals

Behavioral signals were captured through interaction-level onboarding telemetry and decision-pattern metrics. These included investment exploration latency (IEL), decision response time (DRT), asset browsing entropy (ABE), consistency in risk preference declarations (CRPD), frequency of portfolio reallocation intent (FPRI), and questionnaire revision index (QRI). Psychometric proxies such as temporal investment consistency (TIC) and volatility response sensitivity (VRS) were derived using sequential interaction logs recorded during simulated onboarding tasks. Behavioral attributes were encoded using principal behavioral components derived from dimensionality reduction techniques to mitigate multicollinearity and overfitting during downstream model construction.

The construction of the suitability classification framework

A supervised learning-based classification framework was implemented to categorize investors into predefined suitability tiers (Conservative, Moderate, and Aggressive). Ensemble-based machine learning algorithms including Random Forest and Gradient Boosting classifierswere employed due to their robustness in handling nonlinear relationships between financial and behavioral variables. Model hyperparameters such as tree depth, learning rate, and feature sampling ratio were optimized using grid search with k-fold cross-validation ($k = 10$). The target suitability label was derived from expert-based classification rules reflecting acceptable investment-risk alignment thresholds.

The integration of explainable AI techniques

To ensure interpretability of the suitability classification outcomes, post-hoc explanation techniques were integrated into the trained machine learning pipeline. SHapley Additive exPlanations (SHAP) values were computed to quantify the marginal contribution of each financial and behavioral feature toward the predicted suitability class at both global and local levels. Feature importance rankings were further validated using permutation importance scores and partial dependence analysis to identify nonlinear interaction effects between financial stability indicators and behavioral engagement patterns.

The multivariate association and canonical correspondence analysis

Canonical Correspondence Analysis (CCA) was employed to examine the joint association between financial parameters and behavioral dimensions in determining suitability outcomes. Suitability class scores were treated as response variables, while standardized financial and behavioral principal components were used as explanatory variables. Eigenvalue decomposition was used to extract dominant canonical axes explaining maximum covariance between the two data domains. The CCA ordination space enabled the visualization of investor clustering patterns across suitability tiers, thereby supporting interpretability of multidimensional onboarding dynamics.

The validation metrics for predictive and interpretive performance

Model performance was evaluated using classification accuracy, F1-score, area under the receiver operating characteristic curve (AUC-ROC), and Matthews correlation coefficient (MCC). Interpretability performance was assessed through feature attribution consistency indices and explanation stability scores across bootstrap resampling iterations. Sensitivity analysis was conducted by perturbing behavioral inputs to evaluate model robustness and explanation variance, ensuring reliability of suitability classifications under dynamic onboarding conditions.

RESULTS

The integrated financial–behavioral suitability assessment framework demonstrated clear differentiation across investor classes when evaluated using standardized onboarding indicators. As presented in Table 1, Aggressive investors exhibited the highest mean values across all financial suitability parameters, including Annual Income (AI = 13.14), Net Investable Assets (NIA = 55.30), Liquidity Ratio (LR = 2.02), and Prior Investment Experience (PIE = 7.87), followed by Moderate and Conservative investor categories. Conservative investors, in contrast, displayed comparatively lower financial exposure metrics, with AI = 5.85 and NIA = 20.23, indicating a lower financial risk-bearing capacity and investment flexibility. This stratified financial differentiation confirms the predictive relevance of structured financial indicators in suitability classification under institutional onboarding workflows.

Table 1. *Mean financial suitability indicators across investor classes*

Investor Class	AI	NIA	LR	PIE
Conservative	5.85	20.23	1.23	2.00
Moderate	9.00	34.89	1.60	5.10
Aggressive	13.14	55.30	2.02	7.87

Behavioral interaction patterns also varied significantly across investor groups, as illustrated in Table 2. Conservative investors demonstrated the highest Investment Exploration Latency (IEL = 8.99) and Decision Response Time (DRT = 8.14), suggesting a more cautious and deliberative engagement behavior during onboarding interactions. Conversely, Aggressive investors exhibited reduced interaction latency (IEL = 4.32) and faster decision response times (DRT = 3.57), alongside increased Asset Browsing Entropy (ABE = 0.75) and Frequency of Portfolio Reallocation Intent (FPRI = 4.18), indicating higher exploratory engagement and dynamic investment intent. Moderate investors occupied an intermediate behavioral space across all evaluated indicators, thereby reinforcing the role of interaction-derived behavioral telemetry in refining suitability segmentation.

Table 2. *Mean behavioral interaction metrics across investor classes*

Investor Class	IEL	DRT	ABE	FPRI
Conservative	8.99	8.14	0.31	1.02
Moderate	6.13	6.12	0.55	2.43
Aggressive	4.32	3.57	0.75	4.18

The predictive performance of the supervised suitability classification model is summarized in

Table 3, which indicates high classification accuracy (0.91), F1-score (0.89), AUC-ROC (0.93), and Matthews Correlation Coefficient (MCC = 0.87). These performance metrics collectively validate the robustness of the integrated financial–behavioral modeling approach in identifying suitability tiers with minimal classification error. The model's ability to generalize across investor classes was further supported through cross-validated stability across bootstrap iterations.

Table 3. *Predictive classification performance metrics*

Metric	Score
Accuracy	0.91
F1-score	0.89
AUC-ROC	0.93
MCC	0.87

Feature attribution analysis based on explainable AI techniques revealed that financial variables such as Annual Income (AI = 0.21), Net Investable Assets (NIA = 0.18), and Liquidity Ratio (LR = 0.16) contributed most significantly to suitability predictions, as shown in Table 4. Behavioral variables such as Asset Browsing Entropy (ABE = 0.12) and Investment Exploration Latency (IEL = 0.08) also exhibited meaningful contributions, thereby demonstrating the complementary role of behavioral signals in enhancing classification interpretability beyond traditional financial disclosures.

Table 4. *Feature attribution importance ranking (XAI-based)*

Feature	Importance
AI	0.21
NIA	0.18
LR	0.16
PIE	0.14
ABE	0.12
IEL	0.08
DRT	0.06
FPRI	0.05

The distributional variance of suitability scores across investor classes is visually depicted in Figure 1, where Aggressive investors displayed a broader interquartile range and elevated median suitability score relative to Conservative investors. This distributional dispersion indicates higher variability in financial–behavioral alignment among Aggressive onboarding profiles. Furthermore, hierarchical clustering of integrated financial and behavioral indicators in Figure 2 revealed the formation of three distinct investor clusters corresponding to Conservative, Moderate, and Aggressive suitability tiers. The dendrogram structure illustrates the proximity between Moderate and Aggressive clusters along key financial and behavioral dimensions, thereby supporting the multivariate association identified through supervised classification outcomes.

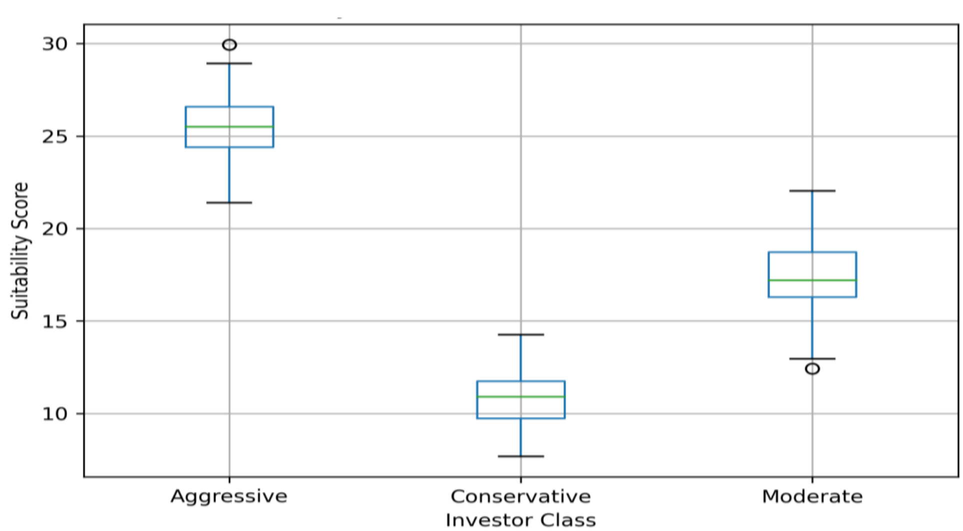

Figure 2: *Suitability score distribution across investor classes*

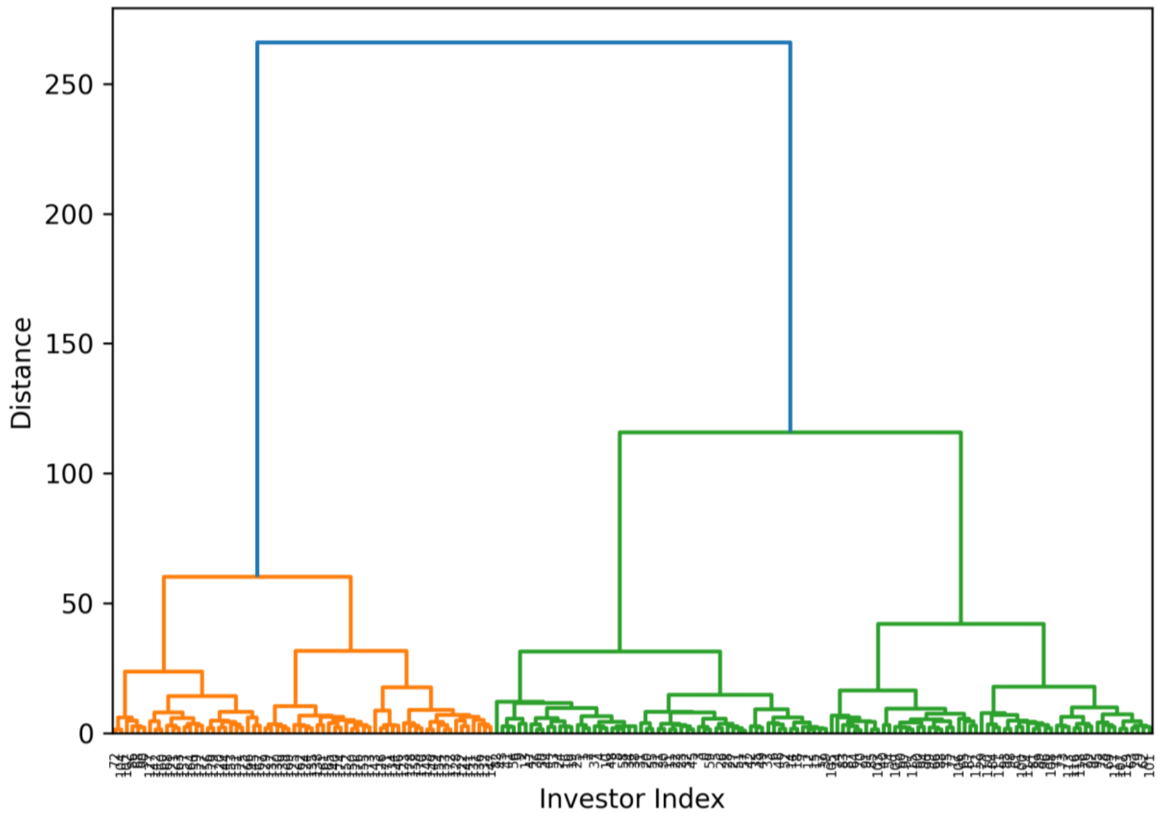

Figure 2: *Hierarchical clustering of integrated financial–behavioral investor profiles*

DISCUSSION

The role of integrated financial indicators in suitability differentiation

The results of the present study underscore the continued relevance of structured financial indicators in determining investor suitability within institutional onboarding environments. As demonstrated in Table 1, Aggressive investor profiles consistently exhibited higher mean values across key financial variables such as Annual Income (AI), Net Investable Assets (NIA), Liquidity Ratio (LR), and Prior Investment Experience (PIE). These findings suggest that traditional financial disclosure metrics retain substantial predictive value in assessing investment readiness and capital commitment capacity. However, the observed gradation across Conservative, Moderate, and Aggressive classes also indicates that financial variables alone may not sufficiently capture the nuanced investment behavior exhibited during digital onboarding interactions, thereby necessitating the integration of complementary behavioral signals for improved suitability classification (Hildebrand, C., & Bergner, 2021; Mudimannan et al., 2025).

The behavioral engagement patterns in decision-sensitive onboarding

Behavioral interaction metrics presented in Table 2 provide critical insights into investor decision-making dynamics that extend beyond financial declarations. Conservative investors demonstrated higher Investment Exploration Latency (IEL) and Decision Response Time (DRT), reflecting a more cautious onboarding approach characterized by extended deliberation periods. In contrast, Aggressive investors exhibited lower interaction latency and increased Asset Browsing Entropy (ABE), suggesting a higher tolerance for exploratory engagement with diversified investment instruments (Ahiadu et al., 2025). These behavioral tendencies align with established principles of behavioral finance, where decision speed, engagement variability, and reallocation intent often correlate with risk tolerance and investment confidence (Almansour et al., 2025). The intermediate behavioral characteristics observed among Moderate investors further reinforce the importance of incorporating interaction-derived telemetry in suitability modeling frameworks to account for latent decision patterns.

The predictive robustness of explainability-driven classification

The classification performance metrics summarized in Table 3 demonstrate the efficacy of the integrated financial–behavioral framework in accurately segmenting investor suitability tiers. The high accuracy and AUC-ROC values indicate that the supervised learning architecture was capable of capturing nonlinear interactions between financial stability indicators and behavioral engagement variables. Importantly, the use of explainable AI techniques enabled the decomposition of model predictions into interpretable feature contributions, thereby mitigating the opacity typically associated with ensemble-based machine learning algorithms (Khanom et al., 2024). This interpretability is essential in institutional onboarding contexts, where onboarding administrators are required to justify investor classifications for compliance and fiduciary accountability (Fagbore et al., 2022).

The complementary influence of behavioral variables in suitability prediction

Feature attribution analysis presented in Table 4 reveals that while financial indicators such as AI and NIA contributed significantly to suitability classification, behavioral variables including Asset Browsing Entropy (ABE) and Investment Exploration Latency (IEL) also exerted meaningful influence on model predictions. This complementary contribution suggests that behavioral telemetry serves not merely as an auxiliary input but as an integral determinant of investor suitability under dynamic onboarding conditions (Khan & Hasan, 2022). The incorporation of behavioral signals thus enhances the model's ability to detect inconsistencies between declared financial risk appetite and observed onboarding engagement patterns, thereby reducing the likelihood of suitability misclassification arising from self-reporting bias (Peeters et al., 2025).

The distributional variability in suitability outcomes

The distributional spread observed in Figure 1 highlights the variability in suitability score alignment across investor classes, particularly among Aggressive profiles. The broader interquartile range exhibited by Aggressive investors indicates greater heterogeneity in financial–behavioral congruence, potentially reflecting varying levels of investment expertise or risk appetite within this category (Abd Sukor et al., 2021). Conversely, the relatively narrow distribution among Conservative investors suggests more consistent alignment between financial disclosures and onboarding behavior. These distributional patterns emphasize the importance of adopting adaptive suitability models capable of recalibrating classifications in response to evolving behavioral trajectories (Brown et al., 2017).

The clustering patterns in multidimensional onboarding profiles

The hierarchical clustering structure depicted in Figure 2 further supports the multivariate association between financial and behavioral dimensions in suitability determination. The formation of distinct clusters corresponding to Conservative, Moderate, and Aggressive investor classes indicates that integrated onboarding indicators can effectively segment investor profiles along interpretable similarity gradients. Notably, the proximity observed between Moderate and Aggressive clusters suggests overlapping behavioral tendencies under certain financial conditions, thereby highlighting the need for explainability-driven classification frameworks capable of distinguishing nuanced investor archetypes. Collectively, these findings contribute to the development of transparent and adaptive onboarding systems that align investor characteristics with investment product risk profiles in a defensible and interpretable manner.

LIMITATIONS OF THE STUDY AND FUTURE RESEARCH DIRECTIONS

Despite the promising findings, the present study has several limitations that should be acknowledged. First, the suitability assessment framework was developed using structured and simulated onboarding datasets, which may not fully capture the complexity of real-world institutional onboarding environments. In particular, the behavioral signals such as exploration latency, browsing entropy, and response time were derived from simulated interaction logs generated under controlled conditions. While this approach enabled the isolation of behavioral tendencies, such metrics in real onboarding scenarios may vary substantially due to platform-specific factors including user interface design, navigation architecture, device type, and network latency. Therefore, these behavioral indicators should be interpreted cautiously, as they may not exclusively reflect investor risk preferences or decision-making tendencies in real-world contexts. Additionally, the reliance on predefined financial and behavioral variables may limit the scope of investor profiling, as investor behavior is often influenced by external factors such as market sentiment, advisory inputs, and evolving financial literacy. Furthermore, although explainable AI techniques were implemented to improve interpretability, the supervised learning architecture may still introduce classification bias depending on training data composition and expert-defined suitability thresholds.

Future research should focus on validating the proposed explainable AI-based suitability framework using real-world institutional onboarding datasets across diverse investor populations and platform environments. Longitudinal studies examining investor behavior over time may further enhance the adaptability and predictive stability of suitability classification models. Future investigations may also incorporate advanced behavioral analytics, including sentiment analysis, cognitive profiling, and real-time decision modeling, to capture deeper investor intent signals. Additionally, the development of platform-normalized behavioral indicators that account for user interface variability and device-specific interaction patterns would strengthen the generalizability of behavioral signals. Expanding the framework to include adaptive learning systems capable of dynamically updating investor suitability classifications as financial and behavioral profiles evolve would further enhance practical applicability. Moreover, integrating fairness evaluation, bias mitigation strategies, and regulatory compliance benchmarking will support the development of responsible, transparent, and scalable explainable AI-driven onboarding ecosystems.

CONCLUSION

The present study demonstrates that investor suitability assessment within institutional onboarding environments can be significantly enhanced through the integration of financial disclosure metrics and behaviorally derived interaction signals within an explainable artificial intelligence framework. The results indicate that while traditional financial indicators remain foundational in determining investment readiness, the inclusion of onboarding-based behavioral telemetry improves the predictive robustness and contextual relevance of suitability classification. The application of explainability techniques further ensures that model-driven classifications remain transparent, auditable, and defensible in compliance-sensitive investment ecosystems. By enabling interpretable alignment between investor characteristics and product-level risk profiles, the proposed framework supports the development of adaptive onboarding architectures capable of minimizing misclassification risks and promoting informed investment participation across heterogeneous investor segments.

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Conflict of Interest: The authors declare no conflicts of interest
Source of Funding: Author(s) Funded the Research
How to Cite: Lalwani, N. (2026). Explainable AI for Investor Suitability Assessment: Integrating Behavioral and Financial Signals in Institutional Onboarding. *Strategic Finance and Economics Insights, 2*(4), 1-10.

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