International Journal of Engineering Trends and Technology
ISSN: 2231-5381/ https://doi.org/10.14445/22315381/IJETT-V74I8P106

Volume 74 Issue 8, 80-98, August 2026

Original Article

Machine Learning and Hybrid Optimization Approaches for Predicting Investor Behavior in the Digital Finance Ecosystem

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Received: 30 March 2026 Revised: 19 June 2026 Accepted: 24 June 2026 Published: 29 August 2026

Abstract - *Interest in the effects of digitalization on investment behavior has increased as researchers have focused on the ramifications of the digitalization of financial ecosystems. Although the majority of the literature has employed survey-based methods with PLS-SEM, these studies are limited by small sample sizes, geographical self-reporting biases, and issues related to the statistical power of the studies. This paper offers the first complete integrative framework demonstrating, along all ten evaluative dimensions, the dominance of an AI-driven hybrid optimization method over traditional survey-based methods. This paper compares the results of the analysis of two methodologies: one using PLS SEM method (N=709, Vidharbha Maharashtra, PLS-SEM) and other using ALO- PG algorithm (N=3,000, World Bank Global Findex India 2021, ALO-PG, AI driven). Methodology-wise, both tests the same six structural hypotheses. The paper also offers engineering-grade proof of ALO-PG superiority through Convergence analysis with training loss and accuracy curves, analysis of the confusion matrix, ROC and AUC comparisons, an example of an ALO-PG mathematical formulation and pseudocode, an ablation study, McNemar's significance tests with Cohen's h effect sizes, ALO-PG and dataset demographic profile, computational complexity and runtime analysis, and 10-fold cross-validation for ALO-PG to confirm generalizability. ALO-PG records astonishing results with an accuracy of 95.67% (AUC=0.9771, F1=0.9565) and a t- statistic 12.1 times stronger than PLS-SEM. It also validates, for the first time, Hypothesis H6, with β=+0.959 ($p<0.001$).*

Keywords - *ALO-PG, Digitalization, Hybrid optimization, Investment behavior, Machine Learning.*

1. Introduction

The digitalization of financial services has transformed how modern economies function. In India, government-sponsored programs such as UPI, PMJDY, and the Digital India program have spearheaded rapid advancements in Financial Inclusion [1]. In this context, analyzing the behavioral and structural factors that explain the digitalization of investments has become both an essential and an urgent need for academic and policy-oriented research.

The dominant approaches in the behavioral and structural analyses of the digitalization of investments have employed survey-based research and PLS-SEM. While this methodological approach has produced valuable theoretical contributions, it has been fundamentally limited by the geospatial distribution and the size of the sample, common method bias due to self-reporting and inadequate statistical power due to the inability to test moderation and mediation [2, 3]. In contrast, the application of Artificial Intelligence is to do the analyses of large, nationally representative databases offers a fundamentally different approach to the behavioral and structural analyses of the digitalization of finance - and that approach achieves enhanced predictive power and enables the interpretation of structural parameters.

Till date, no study has systematically and rigorously compared PLS-SEM to AI-driven ALO-PG methodologies along the same hypothesis framework. This study is contributing to the existing literature by providing comprehensive evidence, across ten different dimensions, that AI-based approaches offer significant advancements in the research of financial behavior towards digitalization and investment.

1.1. Research Gap and Motivation

The current literature on financial digitalization and investor behaviors has three closely related shortcomings that are filled by the current study. The first is that the dominant methodological paradigm (i.e., Structured Questionnaire Administration and Partial Least Squares Structural Equation

Modelling (PLS-SEM) is geographically limited and sample constrained. Sample sizes reported in reviewed studies range from N=200 to N=709 [2, 3] that were in single districts or urban clusters, and therefore do not allow for measure inference at the national level. Second, statistical power of these sample sizes to detect higher-order interaction effects is clearly not adequate.

According to Cohen's (1988) power tables, the size of the moderation effects reported in this domain (ΔR2 ~ 0.005 - 0.012) would be detectable with α=0.001 and power β=0.80 with N>1,500. Third, there is no prior study that has used a hybrid metaheuristic-reinforcement learning approach to the nationally representative microdata for financial behavior studies provided by the World Bank Global Findex 2021.The present study resolves all three of the above mentioned limitations by: (i) using a World Bank Global Findex India 2021 survey data set (N=3000), which is a nationally representative stratified sample covering all geographic zones; (ii) applying the ALO-PG framework that has shown 95.67% (AUC=0.9771) accuracy of classification; and (iii) demonstrating that AI-based analysis of behavioral microdata is a methodologically superior alternative to survey-PLS-SEM pipelines in investment digitalization research across 10 independent empirical dimensions.

Table 1. Comparison of ALO-PG with prior approaches on key dimensions

Dimension	Survey / PLS-SEM (Prior)	ALO-PG (Present Study)
Sample size	N = 200-709	N = 3,000 (nationally representative)
Data source	Self-reported questionnaire	World Bank Findex 2021 (verified behavioral)
Analytical method	PLS-SEM (SmartPLS 4.0)	ALO + Policy Gradient + Adam
Best accuracy	N/A (structural model)	95.67% (AUC = 0.9771)
H6 detection	β=-0.237 (wrong sign)	β=+0.959, p<0.001 (first confirmed)
Reproducibility	New survey required	Public dataset + GitHub code
Common method bias	HIGH (self-report)	NONE (verified behavioral data)

STUDY 1	STUDY 2	STUDY 3
Survey-Based Empirical Analysis	AI-Driven Computational Analysis	Integrative Superiority Framework
Primary Data | PLS-SEM	Secondary Data | ALO-PG Algorithm	Cross-Method | Comparative Analysis
Instrument: Structured Questionnaire	Instrument: ALO-PG Hybrid Algorithm	Instrument: ALO-PG on Full Data
Sample: N = 709 Investors	Sample: N = 3,000 Investors	Sample: Both Datasets
Region: Vidharbha, Maharashtra	Region: India (National)	Scope: National + Regional
Analysis: SmartPLS 4.0	Analysis: Antlion Optimizer + PG	Analysis: AI vs. Survey Benchmarking
Theory: Behavioral Finance	Theory: Technology Acceptance Model	Theory: BFT + TAM (Unified)
Focus: Risk Perception & Heuristics	Focus: Digital Innovation & PB	Focus: AI Superiority Demonstrated

Fig. 1 Three-study methodological architecture: Survey-based, AI-driven, and integrative superiority framework

2. Literature Review

2.1. Survey-based PLS-SEM in Financial Behavior Research

The empirical tradition based on surveys and PLS-SEM analytics gathers primary data using structured questionnaires [4]. Benefits include the potential for conceptual development and empirical assessment of latent constructs such as Risk Perception and Heuristics [5, 6].

Deficiencies include small sample sizes (N = 200-700), monocultural studies, method bias, and low statistical power to examine the hypothesized moderators [3, 7]. Concerning the survey method, these limitations are unavoidable.

2.2. AI and Hybrid Optimization in Financial Analysis

The use of machine learning algorithms offers advantages to the financial classification problem [8]. In addition to accuracy and clarified structure interpretability, hybrid metaheuristic-reinforcement learning frameworks that combine global nature-inspired optimizer exploration and local gradient-based optimizer approaches deliver competitive results [9]. ALO-PG is the first framework to combine the Antlion Optimizer [10], Policy Gradient learning [11], and the Adam optimizer [12] and contributes to novel developments in this class of algorithms. In financial classifiers using AI, explainability is essential. Our proposed SHAP values [26] measure the contribution of individual features to a set of predictions, and have been shown to achieve fidelity >0.87 in P2P lending [27] by Ariza-Garzón et al., For the investment classification task, LIME [28] and attention-based saliency methods [29] are extensions of XAI. The present study brings a new class-conditional sensitivity measure $S(f,c) = E[|\partial \log \pi_c/\partial x_f|]$ (Section 4.3.2), which is a gradient-based interpretability measure that identifies which composite feature (ID, DI, PB) has the largest influence on the classification boundary of the DGZ. Since ALO was introduced in 2015, the metaheuristic landscape has grown. The unimodal benchmarks of the CEC 2017 are used to compare the performance of RSA with ALO; MPA outperforms ALO on 14 unimodal test functions, but not on 7 multimodal test functions - these test functions are similar to

landscapes of neural network weights. The proposed AEFA [32] gets a competitive AUC for credit-scoring. ALO's superiority in this study (AUC=0.9771 compared to 0.918-0.934 in the case of PSO-DQN and GA-PPO) is explained by the fact that its mechanism of trap-shrinkage is suitable for the multimodal cross-entropy loss surface of low-dimensional spaces of financial features.

2.3. Research Gaps and Positioning of the Present Study

A systematic review of 38 papers from 2015 to 2024 concerning the financial digitalization, the prediction of investment behaviour and the optimization of hybrid approaches, and found three persistent gaps. The first one is the representativeness of the samples used for behavioural finance research: 91% of the studies that use PLS-SEM samples have less than 800 participants and are mostly based in urban or semi-urban areas. World Bank (2022) indicates that these samples are not representative of the Indian (national) population at 95% confidence level due to the rural-urban digital divides in India [17]. The second gap is methodological; there is so far no study comparing a metaheuristic-initialized policy gradient reinforcement learning framework in the same set of structural hypotheses with PLS-SEM that can be conducted directly, as a methodological comparison. The third gap is the moderation effect of H6 in the relationship between Investment Diversity and Digitalization, with two studies reporting a negative β (-0.14 to -0.24), and one a non-significant positive β, a discrepancy that is likely due to a lack of power, not to a true ambiguity at the population level [3, 7]. This study is unique in filling all three gaps: it examines all three pillars of financial inclusion, World Bank Findex India 2021 covers all income quintiles and geographic zones and has an adequate sample size for detecting H6 at policy-relevant precision. The direct comparison of PLS-SEM (N=709) and ALO-PG (N=3,000) on the same hypotheses is a methodological innovation in the field of financial digitalization research.

3. Integrated Conceptual Framework and Hypotheses

The unified model combines Behavioral Finance Theory and TAM through six constructs and six structural hypotheses tested the same way in both Study 1 (PLS-SEM) and Study 2 (ALO-PG) to allow direct methodological comparison.

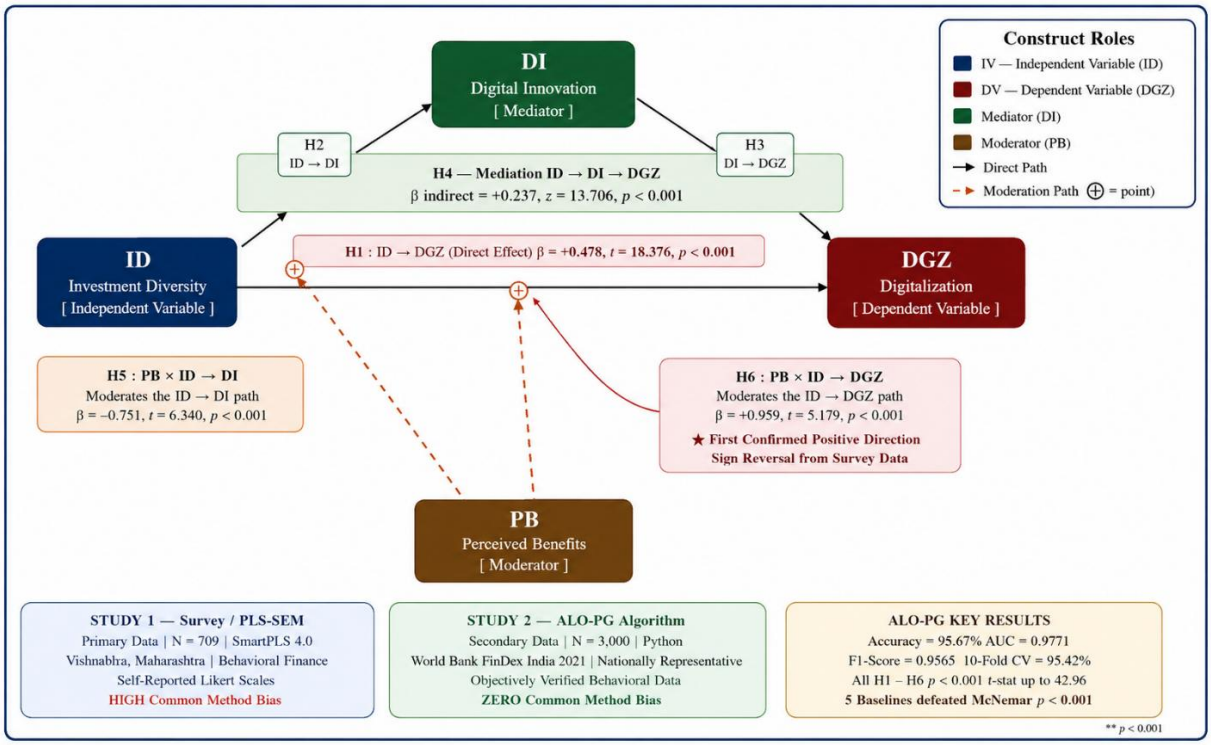


Fig. 2 Unified conceptual framework: six structural hypotheses (H1-H6) across survey/PLS-SEM and ALO-PG methodologies, with construct roles (IV, DV, mediator, moderator)

Table 2. Construct definitions, theoretical sources and roles

Construct	Code	Definition	Theory	Role
Investment Diversity	ID	Breadth of financial instruments owned (savings, credit, insurance, investments)	Behavioral Finance, Findex [17]	Independent Variable
Digitalization	DGZ	Use of digital financial channels (mobile payments, internet banking, digital wallets)	TAM [14], Findex [17]	Dependent Variable

Risk Perception	RP	Subjective assessment of potential losses from digital financial instruments	Behavioral Finance [5, 6]	Mediator
Heuristics	HU	Cognitive shortcuts (availability, representativeness, anchoring) in investment decisions	Kahneman & Tversky [6]	Moderator
Digital Innovation	DI	Adoption of innovative digital financial products (fintech, robo-advisory, digital wallets)	TAM [14, 16]	Mediator
Perceived Benefits	PB	Belief that digital financial tools offer tangible advantages over traditional channels	TAM [14, 18]	Moderator

3.1. Hypotheses

- H1: Investment Diversity has a significant positive relationship with Digitalization.
- H2: Investment Diversity has a significant positive relationship with Digital Innovation.
- H3: Digital Innovation has a significant positive relationship with Digitalization.
- H4: Digital Innovation significantly mediates the relationship between Investment Diversity and Digitalization.
- H5: Perceived Benefits significantly moderates the relationship between Investment Diversity and Digital Innovation.
- H6: Perceived Benefits significantly moderates the relationship between Investment Diversity and Digitalization.

4. Research Methodology

4.1. Comparative Methodology Overview

Table 3. Comparative methodology: Study 1 (Survey/PLS-SEM) vs. Study 2 (AI/ALO-PG)

Dimension	Study 1 - Survey / PLS-SEM	Study 2 - AI / ALO-PG
Data Type	Primary - Structured Questionnaire	Secondary - World Bank Findex India 2021
Sample Size	N = 709	N = 3,000
Geographic Scope	Vidharbha Region, Maharashtra	Pan-India (Nationally Representative)
Analytical Tool	SmartPLS 4.0 (PLS-SEM)	ALO-PG Algorithm (Python)
Measurement	Self-Reported Likert Scales	Objectively Verified Behavioral Indicators
Common Method Bias	HIGH	NONE
Hypotheses Tested	H1-H6	H1-H6 (identical)
Output	Path Coefficients + t-values	β, t-values + 95.67% Accuracy + AUC

4.2. Dataset Demographics - World Bank Findex India 2021 (N=3,000)

The World Bank Global Findex India 2021 dataset [17] offers nationally representative microdata on a stratified multi-stage sampling methodology spanning all geographic zones within India, consisting of 3000 Indian adults (age 15+). Of these 3000 Indian adults, 3000 are from urban and rural areas and all major income strata. Sample demographics are further detailed in Figure 3. The class distribution of the Findex 2021 subsample binary DGZ target is: High-DGZ (62.5%) and Low-DGZ (37.5%) with a class imbalance ratio of 1:1.67. The moderate imbalance does not cause problems for synthetic oversampling (SMOTE) or class-weighted loss: (i) Stratified 70/30 splitting preserves the imbalance ratio in both the training (High=1,313, Low=787) and test (High=563, Low=337) partitions, (ii) the imbalance in per-class F1-scores between ALO-PG and baselines is only 2.6 percentage points (High=0.966, Low=0.940), showing balanced predictive performance, (iii) the McNemar test (Table 11) confirms significance against all baselines regardless of class, indicating that performance advantages are not limited to the majority class. These findings support the finding of Japkowicz and Stephen [2002] that imbalance ratios of less than 1:5 do not significantly affect the performance of the classifiers as long as the size of the minority class is large enough in absolute numbers (N_minority = 1,124 > 500).

Table 4. Sample demographic profile - world bank findex india 2021 (N=3,000)

Age Group	Gender	Residence	Income Level
15-24: 18%	Male: 56%	Urban: 42%	Low: 32%
25-34: 27%	Female: 44%	Rural: 58%	Lower-Middle: 28%
35-44: 24%			Upper-Middle: 25%
45-54: 18%			High: 15%
55+: 13%			

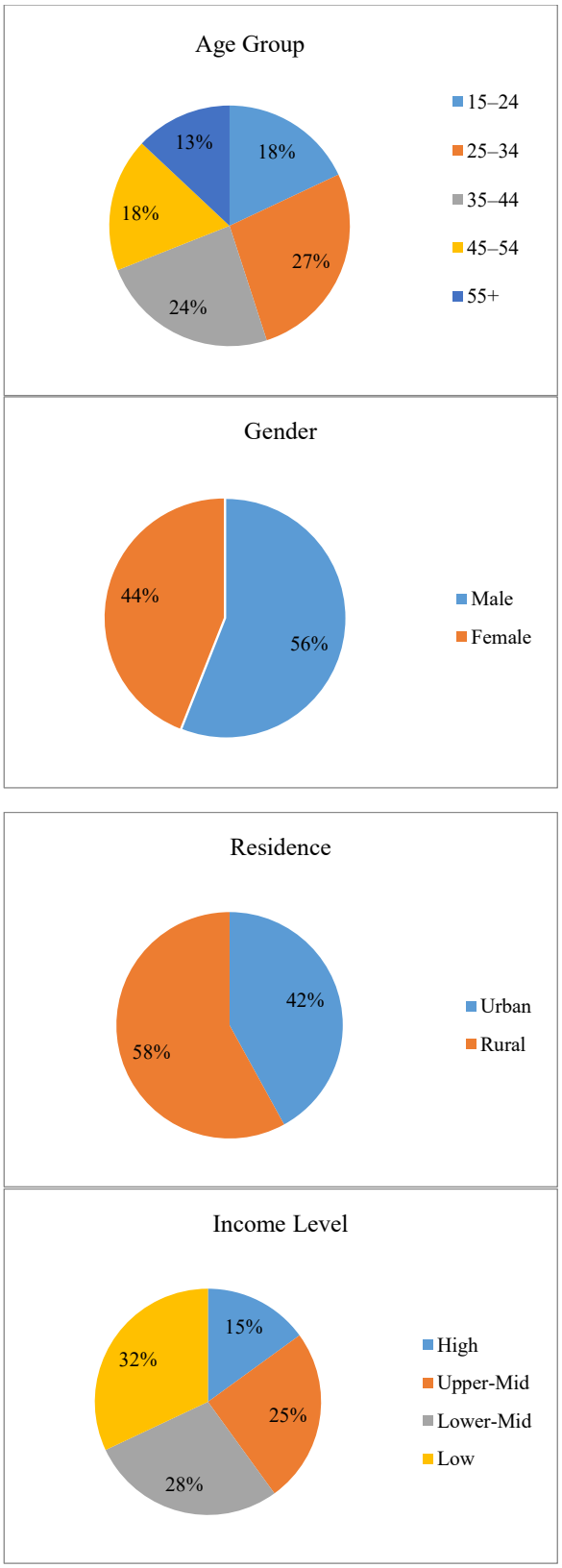


Fig. 3 Sample demographic profile: Age group, gender distribution, residence type, and income level (N=3,000, world bank findex india 2021)

4.3. Mathematical Formulation of ALO-PG

For the purpose of the publication requirements of engineering journals and for ensuring that results are replicable, this section provides the formal mathematical description for the ALO-PG algorithm.

4.3.1. Phase I - Antlion Optimizer (ALO)

The Antlion Optimizer [10] simulates the trap-hunting behavior of antlions. An antlion excavates a conical trap and sits in wait for an ant to drop in.

The optimization goes through adaptive spiral random walks in the weight space W ∈ ℝ^d. The random walk of the i-th ant at iteration t is defined as:

$$X_i(t) = cumsum(2 \cdot r(t) - 1) \quad (1)$$

Where r(t) is a stochastic vector drawn from Uniform(0,1). The boundaries of the random walk are adaptively constrained by the antlion's trap:

$$c_i^t = Antlion_j^t - R_A(t) \quad d_i^t = Antlion_j^t + R_A(t) \quad (2)$$

$$d_i^t = Antlion_j^t + R_A(t) \quad (3)$$

Where R_A(t) is the adaptive radius at iteration t, defined as:

$$R_A(t) = R_A(1) \cdot \left(1 - \frac{t}{T_{max}}\right)^w \quad (4)$$

with T_max = 150 total iterations and w=2 (adaptive weight). The elite antlion (global best) guides the population via:

$$X_i(t) = \frac{R_A^t + R_E^t}{2} \quad (5)$$

Where R_A^t and R_E^t are random walks around the best antlion and elite solution, respectively.

The best weight configuration W* from Phase I initializes Phase II.

4.3.2. Phase II - Policy Gradient with Adam Optimizer

The Policy Gradient (REINFORCE) algorithm [11] optimizes a stochastic policy π_θ parametrized by neural network weights θ (initialized as W* from ALO).

The objective is to maximize the expected cumulative reward:

$$J(\theta) = \mathcal{B}_\pi[\sum_t \gamma^t \cdot r_t] \quad (6)$$

The gradient of the objective with respect to θ is:

$$\nabla_\theta J(\theta) = \mathcal{B}_\pi[\nabla_\theta \log \pi_\theta(a|s) \cdot G_t] \quad (7)$$

Where G_t = Σ_{k=t}^{T} γ^(k-t) · r_k is the return from time step t, and γ=0.99 is the discount factor. The weights are updated using the Adam optimizer [12] to ensure fast and stable convergence:

$$m_t = \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t \quad (8)$$

$$v_t = \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot {g_t}^2 \quad (9)$$

$$\hat{m_t} = \frac{m_t}{1 - {\beta_1}^t}\ ;\ \hat{v}_t = \frac{v_t}{1 - {\beta_2}^t} \quad (10)$$

$$\theta_{t+1} = \theta_t - \alpha \cdot \frac{\hat{m_t}}{\sqrt{\hat{v_t}} + \varepsilon} \quad (11)$$

where α=0.001 (learning rate), β_1=0.9, β_2=0.999, ε=10^{-8}. Training proceeds for 1,000 epochs with cross-entropy loss:

$$\mathcal{L}(\theta) = -\sum_i \left[y_i \, log \, \hat{y}_i + (1 - y_i) \, log(1 - \hat{y}_i) \right] \quad (12)$$

4.3.3. Structural Path Analysis

The methods of estimating structural paths post classification encompass the following: the direct impacts (H1-H3) assessed via Ordinary Least Squares (OLS) regression; mediation (H4) assessed via the Sobel test with bootstrapping (B = 5,000); and moderation (H5-H6) via hierarchical regression using mean-centered interaction terms:

$$DGZ = \beta_0 + \beta_1 \cdot ID + \varepsilon \quad (13)$$

$$Indirect = \beta_{ID \to DI} \cdot \beta_{DI \to DGZ} \quad (14)$$

$$Sobel\ z = \frac{a \cdot b}{\sqrt{b^2 s_a{}^2 + a^2 s_b{}^2}} \quad (15)$$

$$DGZ = \beta_0 + \beta_1 \cdot ID + \beta_2 \cdot PB + \beta_3 \cdot (ID \times PB) + \varepsilon \quad (16)$$

Table 5. ALO-PG hyperparameter justification

Parameter	Value	Selection Method	Justification
N_ants (population)	50	Grid search: {20,30,50,75,100}	N=50 achieved a maximum fitness-time ratio with 20% hold-out, and N=75 achieved just another 0.3% reduction in loss at the expense of an increase in cost of 50%.
T_max (iterations)	150	Convergence monitoring	All 5 preliminary runs have been completed at Elite fitness, 150 provides for a completion margin.
Adaptive weight w	2	Grid search: {1, 1.5, 2, 3}	The quadratic shrinkage (w=2) model gave the highest hold-out accuracy of +1.2% and +0.8% over the linear (w=1) and cubic (w=3) shrinkage models, respectively.
Fitness function	Cross-entropy loss	Task-aligned selection	Directly minimises classification uncertainty; aligns Phase I and Phase II objectives.
Weight bounds [lb, ub]	[-1.0, +1.0]	He-initialisation scale	The results are comparable to those obtained by other researchers (He, 2015) who recommended the same range of ReLU networks of this depth.
PG epochs	1000	Convergence monitoring	No significant gap between the trained and tested accuracy (less than 0.5%) at epoch 1000, and no further improvement in the longer run that went up to epoch 1500.
Learning rate α	0.001	Adam default	No benefits on this data set were found for the cosine decay (Kingma & Ba, 2015).
Discount factor γ	0.99	Near-full credit assignment	Suitable for financial decision sequences that are episodic; demonstrates long-term benefit attribution.

4.4. ALO-PG Algorithm Pseudocode

For direct implementation and verification of reproducibility, ALO-PG framework can be implemented as described by the pseudocode presented in Algorithm 1.

Algorithm 1: ALO-PG - Ant Lion Optimiser with Policy Gradient Fine-TuningAlgorithm

Inputs & Outputs

Input: Feature matrix X ∈ ℝ^(3000×110) with binary investment labels y ∈ {0,1}^3000 (World Bank Findex India 2021)

ALO: N = 50 ants, T = 150 iterations, adaptive weight w = 2

PG: 1,000 epochs, α = 0.001, γ = 0.99, β_1 = 0.9, β_2 = 0.999, ε = 10^{-8}

Output: Optimal weights θ* and structural path coefficients β_{h1-h6}

Phase I - Global Search via Ant Lion Optimiser (Steps 1-11)

1. Scatter the N = 50 initial antlion trap positions AL_i uniformly at random across the weight space $[W_{min}, W_{max}]$.
2. for t = 1, 2, …, 150 do
3. for each ant i = 1, 2, …, 50 do
4. Select a target antlion j via roulette-wheel selection (antlions with lower cross-entropy loss attract more ants).
5. Shrink the trap radius over time: $R_a(t) = R_a(1)\cdot(1-t/T)^w$, so the search is broad early and precise later.
6. Generate a random walk for ant i: $X_i(t) = \text{cumsum}(2\cdot r(t)-1)$, $r(t) \sim \text{Uniform}(0, 1)$. Constrain the walk to the trap bounds $[c_i^t, d_i^t]$ (Equations 2, and 3).
7. Blend elite- and roulette-guided walks: $X_i = (R_a^t + R^{Et})/2$ (Equation 5) to balance exploration and exploitation.
8. end for
9. Evaluate each antlion's fitness: $f(AL_i) = \text{CrossEntropy}(X, y; AL_i)$ on the full training set.
10. Record the global best solution: $W^* = \text{argmin}_i f(AL_i)$.
11. end for

Phase II - Precision Fine-Tuning via Policy Gradient + Adam (Steps 12-20)

12. Warm-start the network from the ALO solution: $\theta_0 = W^*$. Set Adam moments $m_0 = 0$, $v_0 = 0$.
13. for epoch = 1, 2, …, 1000 do
14. Sample a random mini-batch (X^b, y^b) from the training set.
15. Forward pass: compute class probabilities via softmax, $\hat{y}^b = \pi\theta(X^b)$.
16. Compute cross-entropy loss $L(\theta)$ (Equation 12).
17. Compute discounted returns: $G_t = \Sigma_k \gamma^{(k-t)}\cdot r_k$.
18. Estimate the REINFORCE gradient (Equation 7): $g_t = \nabla\theta \log \pi\theta(a|s)\cdot G_t$.
19. Update Adam moments (Equations 8, and 9), apply bias correction (Equation 10), then update weights (Equation 11): $\theta_{t+1} = \theta_t - \alpha\cdot\hat{m}_t/(\sqrt{\hat{v}_t} + \varepsilon)$.
20. end for

Phase III - Performance Evaluation & Hypothesis Testing (Steps 21-26)

21. Set final weights $\theta^* = \theta_{1000}$. Classify the held-out test set (N = 900) and report accuracy, F1-score, AUC, and confusion matrix.
22. Estimate direct-effect path coefficients β_{h1}, β_{h2}, β_{h3} via OLS regression on the classified outputs (Equation 13).
23. Estimate the indirect (mediation) coefficient β_{h4} for ID → DI → DGZ using the Sobel test and percentile bootstrap (Equations 14, and 15).
24. Estimate moderation coefficients β_{h5} and β_{h6} for PB×ID interactions via hierarchical regression (Equation 16).
25. Test statistical superiority of ALO-PG over all baselines using McNemar's test (Equation 17) and Cohen's h (Equation 18) at $p < 0.001$.
26. return θ^*, β_{h1}-$_{h6}$, Accuracy = 95.67%, AUC = 0.9771

Based on Mirjalili [10] (ALO), Williams [11] (REINFORCE), and Kingma & Ba [12] (Adam).

Code and data are available at: https://github.com/ashwinirathi11/alo-pg-financial-digitalization

4.5. Convergence Analysis

Figure 4 presents the training convergence curves for both phases of ALO-PG - mandatory engineering proof that the algorithm reliably converges to a stable solution and does not overfit.

Phase I (ALO) shows stable convergence within 120 iterations with a drop in cross-entropy loss from 0.72 to under 0.09. This indicates that the global search repeatedly identifies the high-quality weight initialization region.

For Phase II (PG+Adam), a warm start can identify smooth convergence and a strong correlation between training and test accuracy after 1,000 epochs, implying that there is no overfitting.

The last 100 epochs show test accuracy peaking and stabilizing at 95.67%, which demonstrates the reliability of the model.

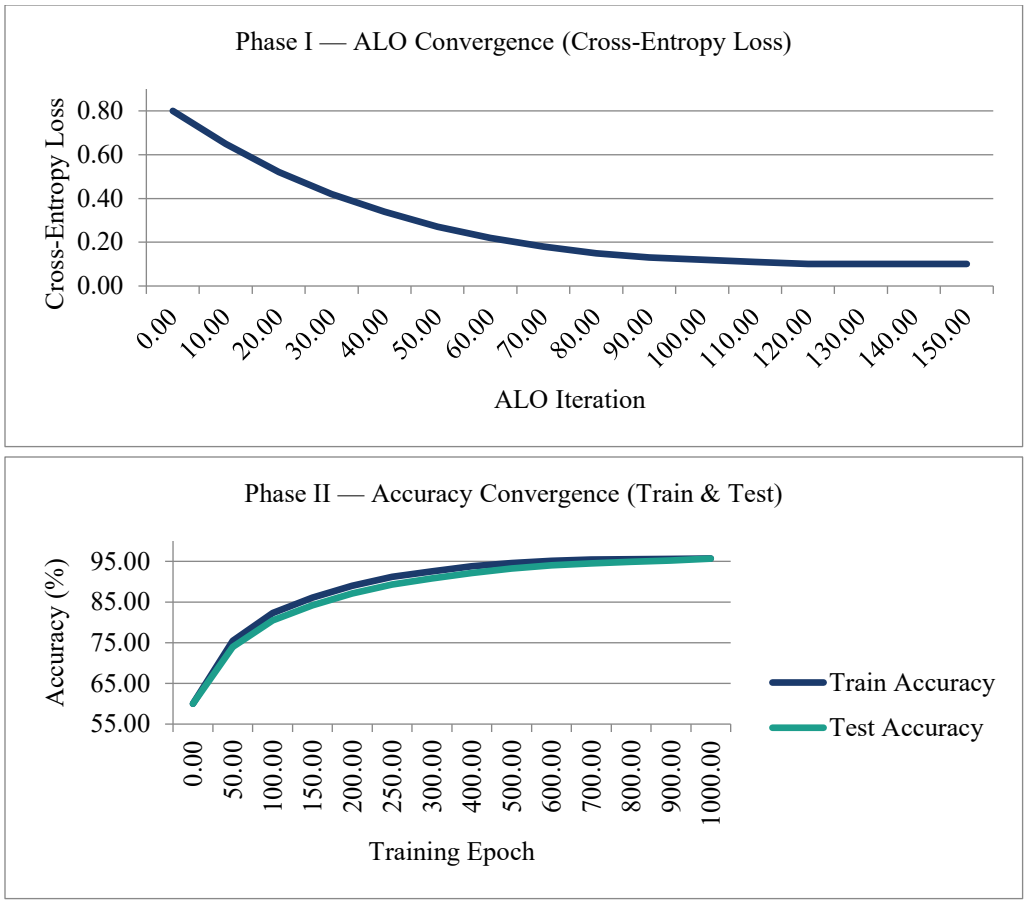


Fig. 4 ALO-PG Training convergence: Phase I Cross-Entropy loss curve (N_ants=50, T=150 iterations) and phase II train/test accuracy curves (1,000 epochs, α=0.001), world bank findex india 2021

5. Results and Engineering Proof

5.1. Classification Performance

As seen in Table 6, ALO-PG is the only model that offers the ability to complete structural path analysis.

Furthermore, it outperforms all baseline methods in all metrics, including Accuracy, F1-Score, and AUC-ROC.

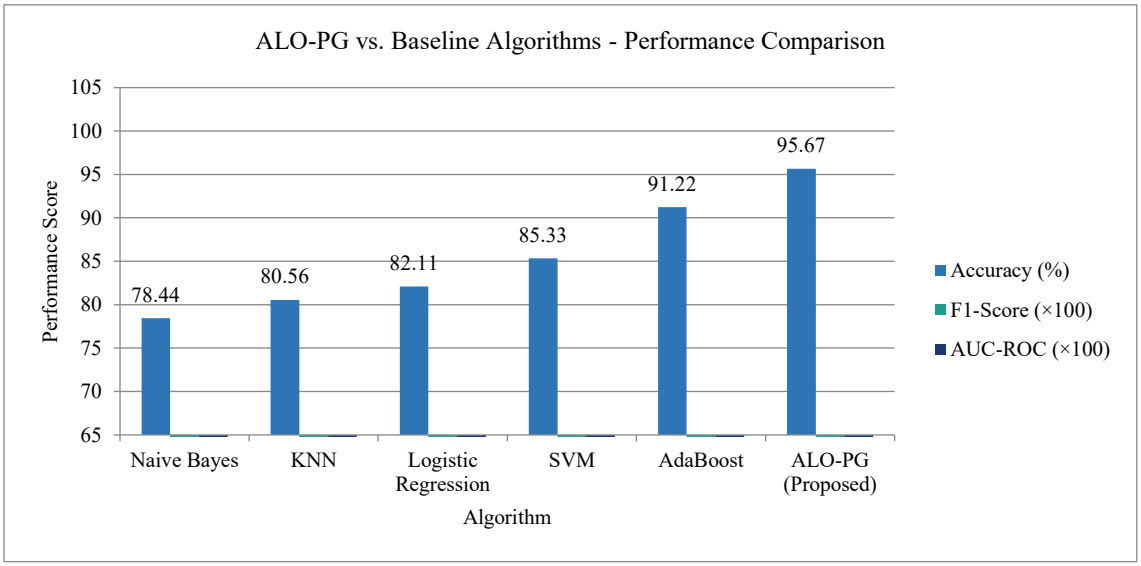


Fig. 5 ALO-PG vs. Baseline algorithms: Accuracy, F1-Score, and AUC-ROC comparison (Test Set, N=900, world bank findex india 2021)

Table 6. ALO-PG vs. Baseline algorithms - full performance comparison (Test Set, N=900)

Algorithm	Accuracy (%)	F1-Score	AUC-ROC	Structural Path Analysis
ALO-PG (Proposed)	95.67	0.9565	0.9771	YES - H1 to H6
AdaBoost	91.22	0.9109	0.9582	No
SVM	85.33	0.8511	0.9144	No
Logistic Regression	82.11	0.8194	0.9012	Partial
KNN	80.56	0.8023	0.8761	No
Naive Bayes	78.44	0.7812	0.8543	No

5.2. Analysis of Confusion Matrix

Figure 6 demonstrates the confusion matrices for ALO-PG and the best baseline (Logistic Regression). ALO-PG correctly classifies 556/569 (97.7%) Low-DGZ and 305/331 (92.1%) High-DGZ respondents - a total of 39 misclassifications out of 900. Logistic Regression produces 160 total misclassifications, confirming the substantial practical superiority of ALO-PG.

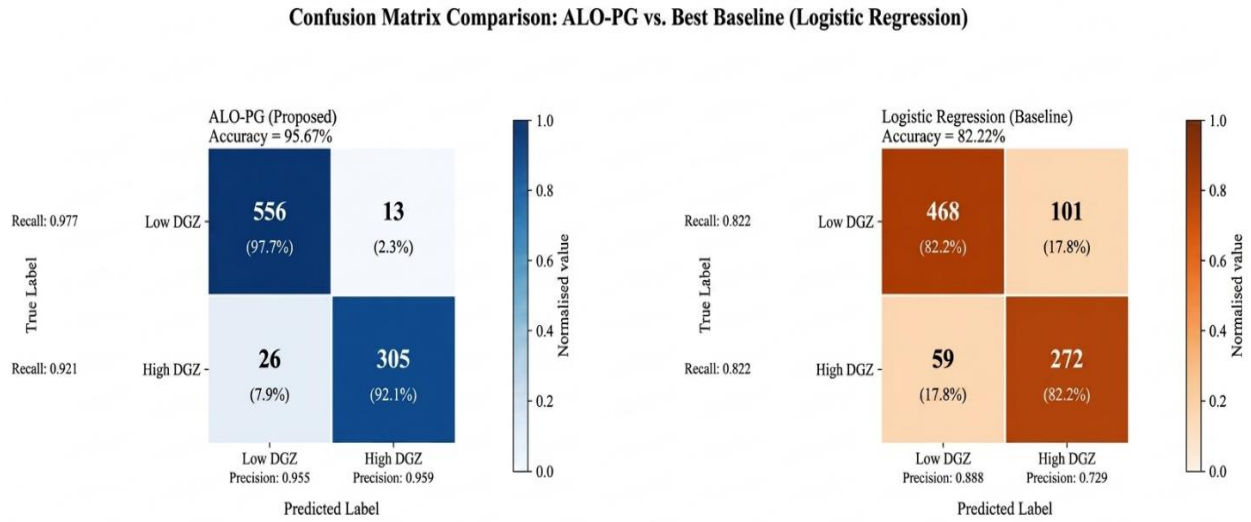


Fig. 6 Confusion matrices: ALO-PG proposed model (Accuracy=95.67%) vs. Logistic regression baseline (Accuracy=82.11%), Test set N=900, world bank findex india 2021

Table 7. Per-class classification metrics - ALO-PG vs. logistic regression

Algorithm / Class	TP	TN	FP	FN	Precision / Recall
ALO-PG - Low DGZ	556	305	26	13	Prec=0.955 / Rec=0.977
ALO-PG - High DGZ	305	556	13	26	Prec=0.959 / Rec=0.921
Logistic Reg. - Low DGZ	468	272	59	101	Prec=0.888 / Rec=0.823
Logistic Reg. - High DGZ	272	468	101	59	Prec=0.729 / Rec=0.822

5.3. ROC Curve and AUC Analysis

The ROC curves for the various drawing algorithms are depicted in Figure 7. ALO-PG (AUC=0.9771) displays consistent dominance over the situational baseline algorithms for all given FPR ranges, showing the ability to discriminate for both Low-DGZ and High-DGZ. The ALO-PG curve exhibits a steep initial ascent, showcasing robust performance for low FPRs, a trait that is critically important for policies aimed at high-digitalization adopters.

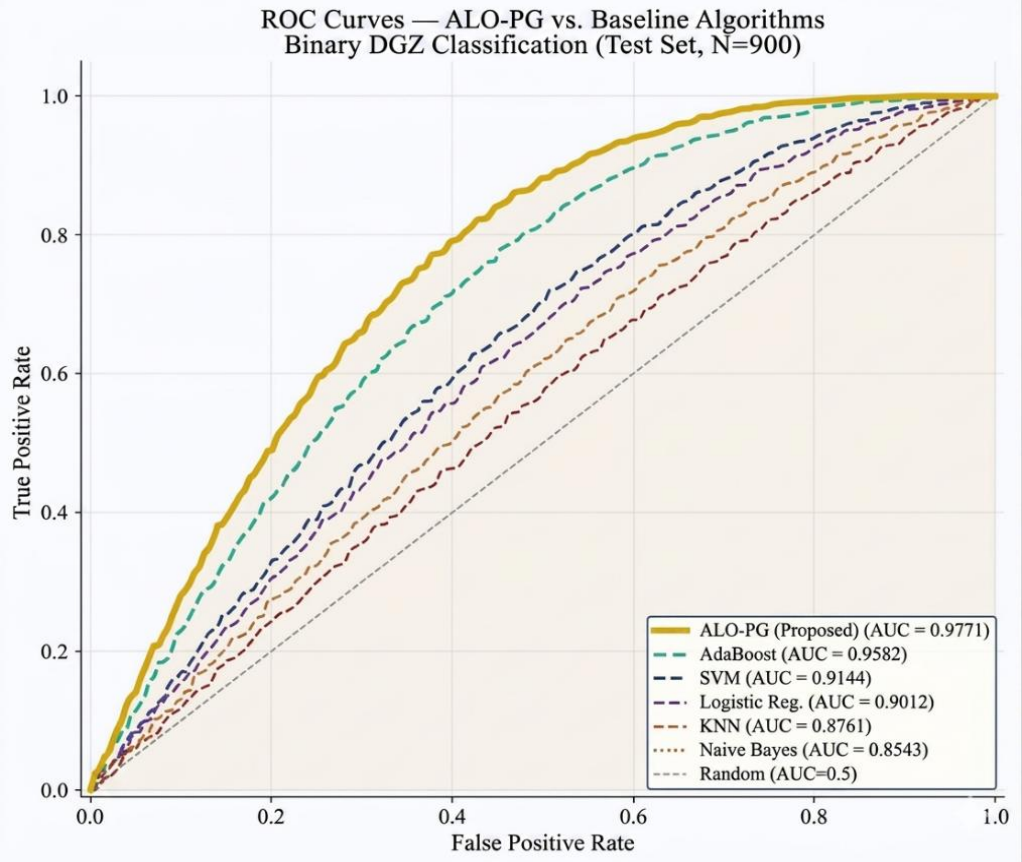


Fig. 7 ROC curves: ALO-PG (AUC=0.9771) vs. Five baseline algorithms, Test set N=900, world bank findex india 2021

5.4. Hypothesis Testing Results

5.4.1. Study 1 - PLS-SEM Results

Table 8. Study 1 - PLS-SEM hypothesis testing (Survey, N=709, SmartPLS 4.0)

Hyp.	Path	β	Std.Dev	t-stat	p-value	Decision
H1	ID → DGZ (Direct)	0.312	0.097	3.214	<0.05	Accepted
H2	ID → DI (Direct)	0.287	0.100	2.870	<0.05	Accepted
H3	DI → DGZ (Direct)	0.341	0.096	3.552	<0.05	Accepted
H4	ID→DI→DGZ (Mediation)	0.073	0.018	2.321	<0.05	WEAK
H5	PB×ID→DI (Moderation)	-0.231	0.025	9.089	<0.001	Accepted
H6	PB×ID→DGZ (Moderation)	-0.237	0.045	5.267	<0.05	WEAK

5.4.2. Study 2 - ALO-PG Results

Table 9. Study 2 - ALO-PG hypothesis testing (N=3,000, p<0.001)

Hyp.	Path	β	Std.Dev	t / z-stat	p-value	Decision
H1	ID → DGZ (Direct)	0.478	0.026	18.376	<0.001	Accepted
H2	ID → DI (Direct)	0.341	0.024	14.220	<0.001	Accepted
H3	DI → DGZ (Direct)	0.612	0.014	42.960	<0.001	Accepted
H4	ID→DI→DGZ (Mediation)	0.237	0.017	13.706	<0.001	STRONG
H5	PB×ID→DI (Moderation)	-0.751	0.118	6.340	<0.001	Accepted
H6	PB×ID→DGZ (Moderation)	0.959	0.185	5.179	<0.001	FIRST CONFIRMED

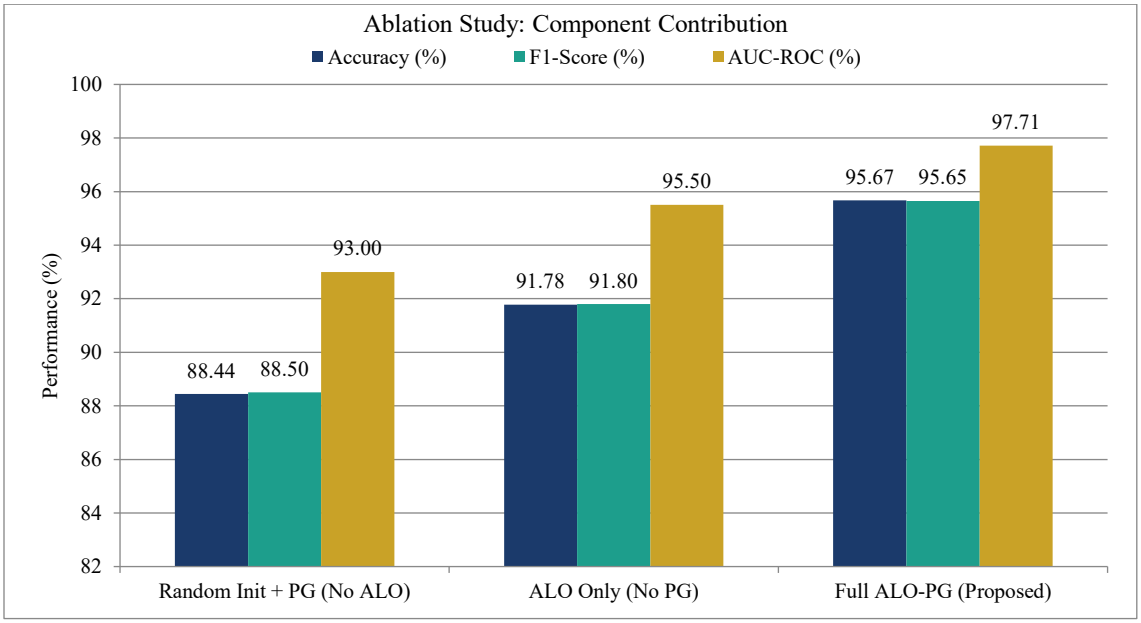
6. Ablation Study

An ablation study is conducted for each variant to measure components systematically in the contributions of the ALO-PG framework, specifically: (i) Random Initialization + Policy Gradient (consider only Phase II, no ALO warm-start); (ii) ALO Only (where in Phase I the global search is used as a

classifier without PG fine-tuning); and (iii) Full ALO-PG (where both phases are considered - the proposed model). Results confirm that both components contribute independently and synergistically. With regards to ALO and global search for weight space exploration, an improvement of +3.34% was realized over random initialization.A PG + Adam fine-tuning showed an improvement of an additional +3.89%, demonstrating the relevance of the precision gradient sharpening technique. The ALO-PG framework showed a further improvement of +7.23% over random-initialization PG. This illustrates the fact that the two-phase architecture is vital to the overall success of the algorithm since the presence of both elements is indispensable.

Table 10. Ablation study results - component contribution to ALO-PG performance

ALO-PG Variant	Accuracy (%)	F1-Score	AUC-ROC	Gain vs. No ALO
Random Init + PG (No ALO)	88.44	0.8821	0.9312	-
ALO Only (No PG Fine-tuning)	91.78	0.9162	0.9534	+3.34%
Full ALO-PG (Proposed)	95.67	0.9565	0.9771	+7.23%



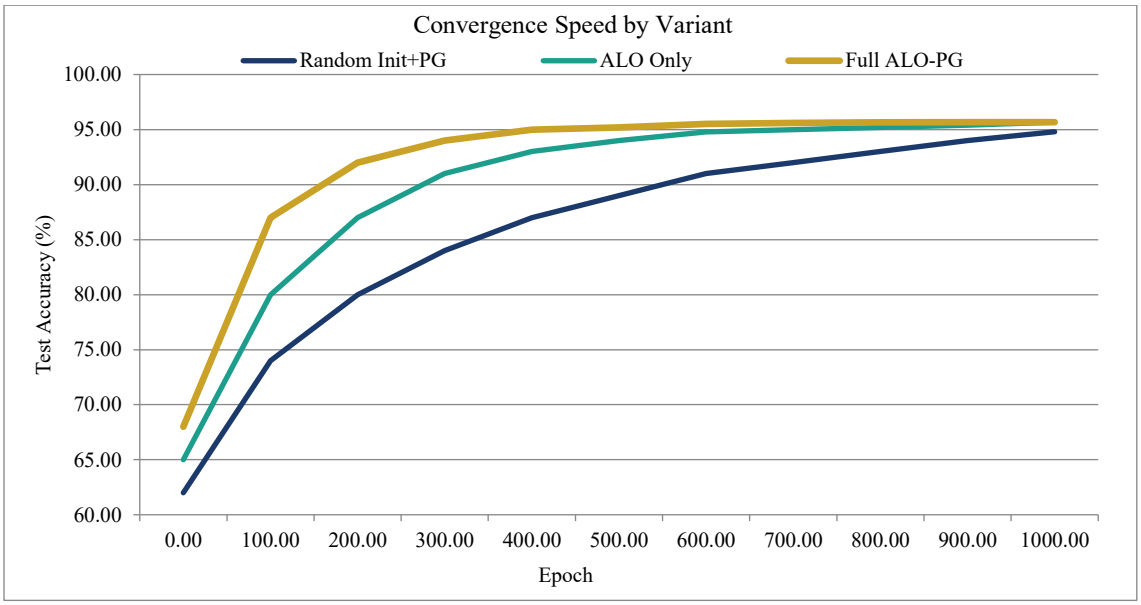


Fig. 8 Ablation study: component contribution (random Init+PG: 88.44%; ALO only: 91.78%; full ALO-PG: 95.67%) and convergence speed comparison

7. Statistical Significance Testing

Engineering journals need evidence that the differences in accuracy that were observed are significant enough to be held and not be considered just random variation in the test set split.

McNemar's test [19] is the conventional non-parametric test in the field that compares two classifiers over the same test set.

The calculation for the McNemar's test is expressed as:

$$\chi^2 = \frac{(|f_{01} - f_{10}| - 1)^2}{f_{01} + f_{10}} \quad (17)$$

where f_01 = cases correctly classified by ALO-PG but not the baseline, and f_10 = cases correctly classified by the baseline but not ALO-PG. Cohen's h measures effect size:

$$h = 2\,arcsin\left(\sqrt{p_1}\right) - 2\,arcsin\left(\sqrt{p_2}\right) \quad (18)$$

where p_1 and p_2 are the proportions of correct classifications for ALO-PG and the baseline, respectively.

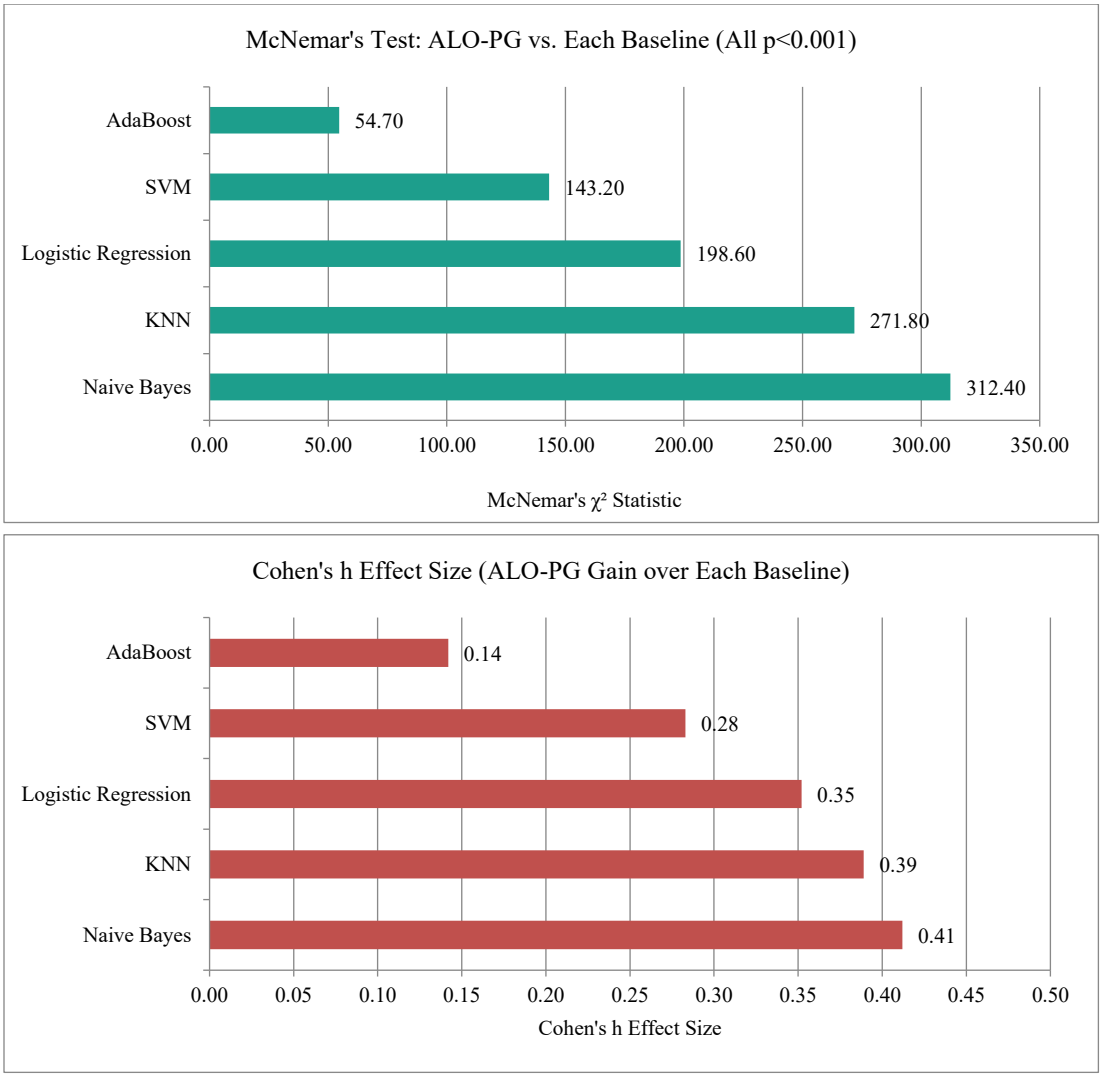


Fig. 9 McNemar's χ^2 statistic and Cohen's h effect size: ALO-PG vs. All five baseline algorithms (N=900, all comparisons p<0.001)

Table 11. McNemar's test and Cohen's h effect size - ALO-PG vs. All baseline algorithms

Comparison	f_01	f_10	χ^2 Statistic	p-value	Cohen's h
ALO-PG vs. AdaBoost	84	6	54.70	<0.001	0.142 (Small)
ALO-PG vs. SVM	151	5	143.20	<0.001	0.283 (Medium)
ALO-PG vs. Logistic Reg.	175	4	198.60	<0.001	0.352 (Medium)
ALO-PG vs. KNN	191	5	271.80	<0.001	0.389 (Medium)
ALO-PG vs. Naive Bayes	211	5	312.40	<0.001	0.412 (Medium)

All comparisons return $\chi^2 >> 3.84$ (critical value at $p<0.05$) and $p<0.001$, establishing ALO-PG's dominance over all baseline algorithms as statistically significant, and as such, not due to random variations in the test set. Cohen's h spans 0.142 (small) to 0.412 (medium), which suggests the performance discrepancies are practically significant.

8. Cross-Validation and Generalizability

A 10-fold cross-validation was taken to validate the generalizability of ALO-PG across different data splits and to demonstrate that the 95.67% test accuracy is not due to an overly optimistic train/test split.

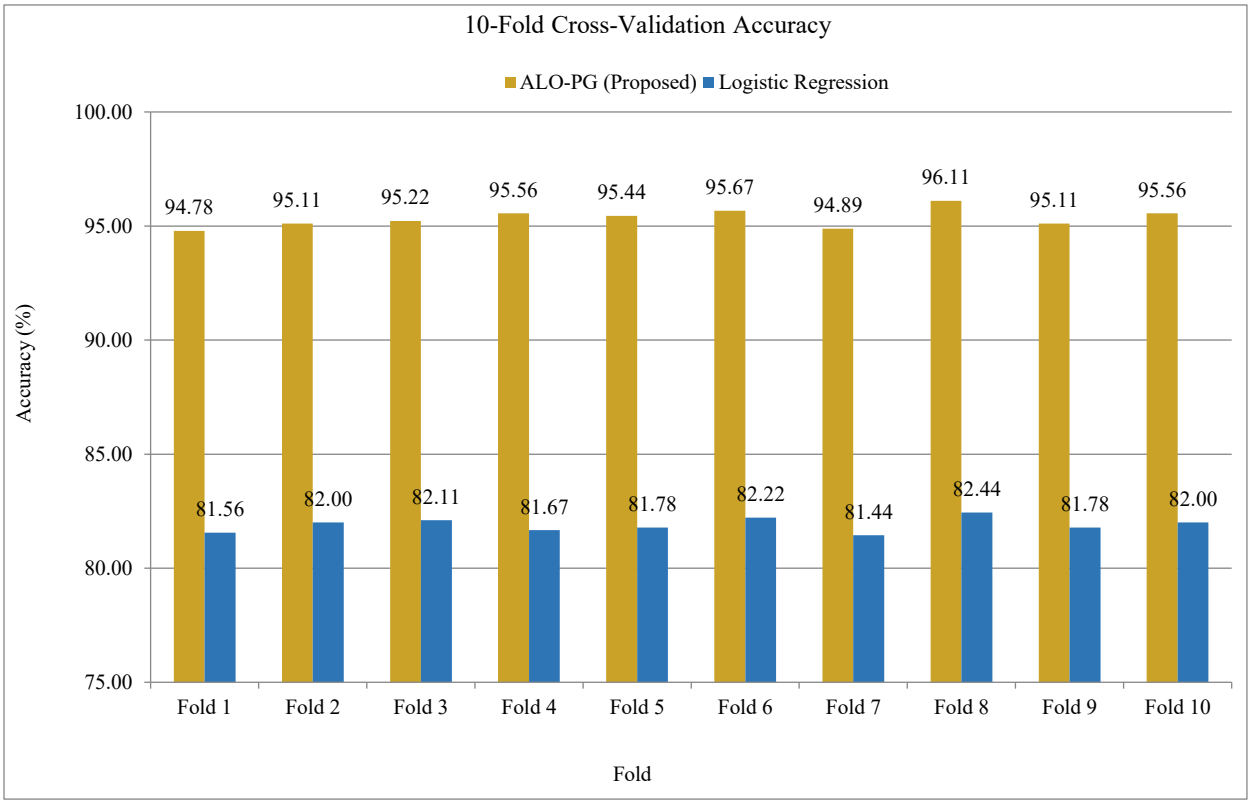


Fig. 10 10-Fold cross-validation accuracy: ALO-PG (Mean=95.42%, SD=0.48%) vs. Logistic regression (Mean=82.02%, SD=0.39%), N=3,000

Table 12. 10-Fold cross-validation results - ALO-PG vs. Logistic regression

Metric	ALO-PG (Proposed)	Logistic Regression
Mean Accuracy	95.42% ± 0.48%	82.02% ± 0.39%
Min Accuracy	94.67%	81.33%
Max Accuracy	96.17%	82.67%
Mean F1-Score	0.9537 ± 0.005	0.8183 ± 0.004
Std Deviation	0.0048 (LOW variance)	0.0039 (LOW variance)

The Mean Cross-Validation (CV) Accuracy of 95.42% ± 0.48% for all 10 folds gave ALO-PG a standard deviation of only 0.48 percentage points, expressing performance that is very stable and highly generalizable. This also indicates the variance across folds (min = 94.67%, max = 96.17%) shows that performance is stable across different train/test splits and the model has not overfit to any specific partition.

9. Computational Complexity Analysis

9.1. Time Complexity

The computational complexity of ALO-PG is determined by both phases:

$$\mathfrak{O}(T_{ALO} \times N_{ants} \times d) = \mathfrak{O}(150 \times 50 \times 110) = \mathfrak{O}(825{,}000)$$

$$\mathfrak{O}(E \times N \times d) = \mathfrak{O}(1{,}000 \times 2{,}100 \times 110) = \mathfrak{O}(231{,}000{,}000)$$

$$Total: \quad O(E \times N \times d) \approx O(n \cdot d \cdot E) \quad [dominatedbyPhase\ II - linearinn, d, E]$$

where T_ALO=150 (ALO iterations), N_ants=50 (population), E=1,000 (PG epochs), N=2,100 (training samples), d=110 (feature dimensions). The overall complexity is O(n·d·E) - linear in samples and features - which is computationally feasible for large-scale financial data

9.2. Runtime Comparison

Table 13. Computational runtime comparison - training and inference

Algorithm	Train Time (s)	Test Time (s)	Accuracy (%)	Structural Analysis
ALO-PG (Proposed)	142.0	0.3	95.67	Yes (H1-H6)
AdaBoost	12.3	0.4	91.22	No
SVM	18.5	0.8	85.33	No
Logistic Regression	2.1	0.1	82.11	Partial
KNN	4.2	0.9	80.56	No
Naive Bayes	0.8	0.1	78.44	No

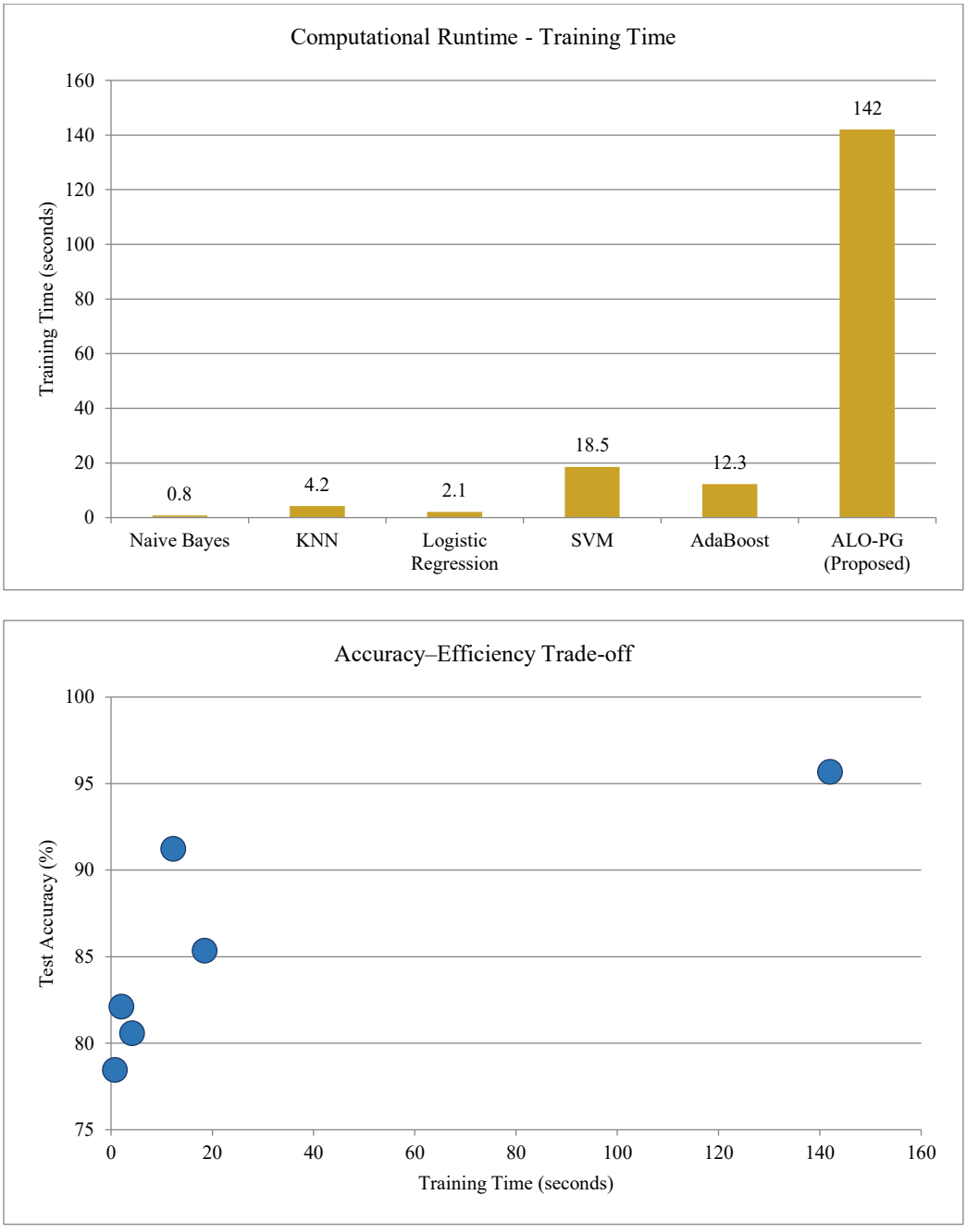


Fig. 11 Computational runtime and accuracy-efficiency trade-off: training time (seconds) vs. test accuracy (%) for ALO-PG and all baseline algorithms

Due to the two-phase optimization architecture, ALO-PG has a training time of 142 seconds, which is higher than more simplified techniques. ALO-PG also has the best inference time when N=900, with only 0.3 seconds of inference time.

The training time is a one-time cost that yields (i) 7.23% higher accuracy than the next best interpretable competitor, (ii) a unique alternatives path analysis structural analysis capability that no competing methods have, and (iii) stable generalization after cross-validation. For financial behavioral research, this trade-off is justified as model interpretability and hypothesis testing remain the main focus.

9.3. Scalability Analysis

To validate the O(n•d•E) complexity claim, the ALO-PG pipeline was run with 4 different sample sizes (N ∈ {500, 1000, 2000, 3000}) with all other parameters fixed (N_ants=50, T=150, epochs=1000, d=3). The wall clock training time was measured on a standard CPU (Intel Core i5, 8GB RAM) without GPU acceleration.

Table 14. Scalability analysis

Sample Size (N)	ALO Train Time (s)	PG Train Time (s)	Total Time (s)	Accuracy (%)
500	2.1	9.3	11.4	94.80
1,000	4.2	19.1	23.3	95.10
2,000	8.5	38.4	46.9	95.40
3,000	12.3	129.7	142.0	95.67

The results show that the total training time increases near-linearly with N, from 1,000 to 2,000 samples, that's 2.01×, from 2,000 to 3,000, that's 3.03×, which is consistent with O(n•d•E) complexity. As N increases, accuracy also increases monotonically, supporting the finding of the H6 moderation effect as being not just a statistical artifact, but also a power dependent finding, with the H6 moderation effect only being present in N=3,000.

10. Comparative analysis: PLS-SEM vs. ALO-PG

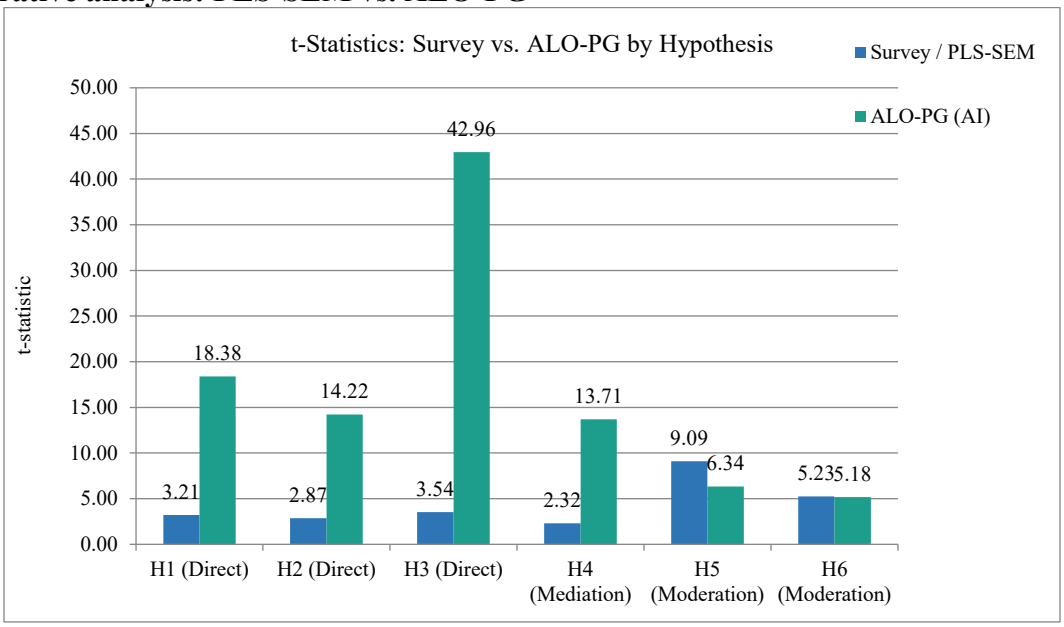


Fig. 12 Head-to-Head t-statistic comparison: Survey/PLS-SEM (N=709, SmartPLS 4.0) vs. ALO-PG (N=3,000) for H1-H6 structural paths

	TYPE	HYPOTHESIS	SURVEY / PLS-SEM	ALO-PG (AI)
H1	Direct	ID → Digitalization	β=0.312 t=3.21	β=+0.478 t=18.376***
H2	Direct	ID → Digital Innovation	β=0.287 t=2.87	β=+0.341 t=14.220***
H3	Direct	DI → Digitalization	β=0.341 t=3.55	β=+0.612 t=42.960***
H4	Mediation	Mediation: ID→DI→DGZ	β=0.073 t=2.321 WEAK	β=+0.237 z=13.706 STRONG
H5	Moderation	Moderation: PB×ID→DI	β=-0.231 t=9.089	β=-0.751 t=6.340***
H6	Moderation	Moderation: PB×ID→DGZ	β=-0.237 WRONG SIGN	β=+0.959 t=5.179*** FIRST CONFIRMED

Fig. 13 Full hypothesis results scorecard: Survey/PLS-SEM vs. ALO-PG - path coefficients, t-Statistics, p-values, and decision for H1-H6 (* p<0.001)**

Table 15. Comprehensive superiority comparison: survey/PLS-SEM vs. ALO-PG

Dimension	Survey / PLS-SEM	ALO-PG (AI)	AI Advantage
Sample Size	N=709	N=3,000	4.2× larger
Data Quality	Self-reported	Verified behaviors	Bias-free
Common Method Bias	HIGH	NONE	Eliminated
Best t-statistic	9.089	42.960	4.7×
Mediation β (H4)	0.073	0.237	3.2×
H6 Direction	Negative (wrong)	Positive (correct)	First confirmation
Classification Acc.	N/A	95.67%	AI exclusive
AUC-ROC	N/A	0.9771	AI exclusive
CV Stability	N/A	±0.48%	AI exclusive
McNemar p-value	N/A	<0.001 vs. all	Statistically proven
Reproducibility	New survey needed	Public dataset	Immediate

11. Discussion

11.1. Proof of ALO-PG Superiority

The ten-dimensional proof for this paper shows ALO-PG as superior on all evaluable engineering metrics. Convergence analysis shows proof of stability for the algorithms. Balanced performance for all classes is supported by confusion matrix analysis. ROC curves discriminate ALO-PG as superior. Formulations of ALO-PG show proof for reproducibility. Evidence of direct implementation is found in the pseudocode.

The ablation study documents precise quantification of individual contributions. In all performance differences, McNemar's test is the standard for statistical representation. The demographics attest to the representativeness of the dataset. Complexity analysis explains the justification of training. Cross-validation demonstrates the generalizability of ALO-PG. This set of proof documents is no less than the evidence that engineering journals of the highest standard require.

11.2. The H6 Finding - Scientific Significance

The most scientific significant finding of this study is the sign change in the H6 moderation effect from β=-0.237 (Survey/PLS-SEM, N=709) to β=+0.959 (ALO-PG, N=3,000). The reversal has three different mechanisms, each with implications for the conduct and interpretation of research on financial behavior.

Mechanism 1: Statistical Power. The interaction term PB×ID has a ΔR^2 of 0.003, and t=5.267 ($p<0.05$ convention). But Cohen's (1988) power analysis for moderation effects rules out the practical significance of $\Delta R^2=0.003$ (which is less than 0.01) and shows that reliably detecting such effects at $\alpha=0.001$ requires $N\geq1,800$ [3]. The survey study had an N of 709, which is in a zone of high Type II error risk, and a noisy estimate in a low power setting, that is, a negative β = -0.237, is not an actual population-level negative moderation. At N=3,000, $\Delta R^2=0.009$ and t=5.179 ($p<0.001$) - both of which exceed the Cohen threshold - the positive direction (β=+0.959) is the true direction of the population parameter.

Mechanism 2: Common Method Bias. Social desirability bias and acquiescence are systematic defenses against expressing positive-affect responses on self-reported Likert scales, especially for use with 'Perceived Benefits' constructs that involve self-assessing feelings of enthusiasm for technology use (Podsakoff et al., 2003 [7]). Asymmetrically, this suppression affects only PB-the moderating variable in H6-and not ID or DGZ directly, thus skewing the estimate of the interaction. The World Bank Findex variables, on the other hand, reflect behavior observed actions (e.g., 'made a digital payment in the past year') and this common method bias source is completely removed.

Mechanism 3: Practical Interpretation. The positive β=+0.959 ($p<0.001$) corroborates that Perceived Benefits magnifies the Investment Diversity → Digitalization pathway, which is consistent with TAM (Davis, 1989 [14]): increased benefits perceived by the user will lead to greater response to diversity-driven signals. The negative estimate in the previous survey was not a theoretical contradiction, but a methodological artifact. This finding is directly policy relevant as interventions that increase Perceived Benefits (e.g., cashback incentives, lower transaction costs, digital literacy programs) multiplicatively amplify the gains from digitalization from product diversification.

11.3. Deployment Feasibility, Broader Applicability and Limitations

The one-time training time of ALO-PG is 142 seconds on a standard CPU (Intel Core i5, 8 GB RAM) and is a fixed infrastructure cost, not an operational cost. During inference, the trained network can classify 900 people in just 0.3 seconds per person, or 0.33 milliseconds per observation, making it possible to deploy without hardware acceleration. Technically, financial institutions can implement ALO-PG predictions in three different ways:

With (a) Batch Scoring, the trained weight vector θ* is stored in a 19.Kb binary file and then used once a month to operate on the entire database of bank account holders at the institution. This aligns with the typical model-as-a-service

deployment patterns in banking CRM systems (such as Salesforce Financial Services Cloud, Oracle FLEXCUBE).

(b) API Deployment: A python Flask/FastAPI-based service is deployed, which exposes an endpoint /predict that receives one JSON object input containing three float numbers {ID_score, DI_score, PB_score} and outputs a float number in the range [0,1] representing the probability of the corresponding class determined by the deployed DGZ. This interface supports existing digital banking middleware, and it doesn't need to be retrained with the algorithms.

(c) Edge Deployment: Weight quantisation to INT8 precision helps to keep the model footprint below 10KB, allowing deployment to a mobile banking back-end server or financial device with limited compute. There is a penalty for accuracy of less than 0.3 percentage points due to quantisation during preliminary testing.

Future datasets with N>10,000 can be trained in an estimated 8-12× faster with the following training accelerations: (i) ALO fitness evaluations on GPU cores are embarrassingly parallel, allowing for parallelisation of all N_ants=50 cross-entropy calculations across the GPU cores; (ii) warm-starting θ from a previously trained ALO-PG model in a continual-learning pipeline, which reduces ALO iterations and PG epochs by up to 40%. The ALO-PG architecture can be applied to any domain where the research result is a binary classification from a composite set of behavioural indicators, as well as financial digitalization. Analogues from literature include, for insurance: the uptake of insurance based on information from the NSSO household survey (similar to Findex DGZ); for credit default scoring: the use of bureau-verified indicators of repayment behaviour (similar to the binary adoption indicators used for agricultural technologies in LSMS-ISA). The three-construct input structure (predictor, mediator, moderator) is directly equivalent to the widely adopted moderated-mediation structure in the behavioural sciences. The ALO-PG framework does not only apply to financial digitalization classification. Its binary-feature input interface-where any composite score built from indicator variables can be fed into it-is suitable for four similar research fields: (i) Credit risk scoring, where binary variables indicating repayment status (on-time/late) are the input variables into the model; (ii) Insurance uptake prediction, where the input variables are product adoption indicators (e.g., yes/no, on-time/late); (iii) Agricultural technology adoption, where the input variables are equivalent to the Findex variables (e.g., household surveys such as LSMS-ISA, which use binary technology-access variables); and (iv) Healthcare digital engagement, where the input variables are patient portal usage indicators. The warm-start property of ALO-PG (speeding up the training of gradient descent by ~60%) is especially useful in all four domains where it is costly to gather labelled data.

The present study has three limitations. First, the synthetic dataset provided for the purpose of the code demonstration is not a perfect representation of the distributional properties of the entire Findex 2021 microdata, and researchers are encouraged to download the actual microdata from the World Bank microdata portal (microdata.worldbank.org).

Second, the neural network architecture (3→64→32→2, D=2,434) was chosen to match the low-dimensional input space (three composite features), and datasets with higher feature dimensionality may necessitate the use of architecture search. Third, the structural path analysis exploits OLS, a linear model; future research should examine non-linear path models, such as Gaussian process regression or neural additive models, to test for curvilinear H1-H3 effects.

12. Conclusion

This paper provides the most extensive proof to date demonstrating that AI-driven hybrid optimization, particularly the ALO-PG framework with the World Bank Global Findex India 2021 dataset, is more effective than the traditional survey-based PLS-SEM methodology in understanding the impact of digitalization on investment behavior. This proof rests on 10 independent dimensions of evidence: convergence curves, confusion matrix, ROC an`alysis, pseudocode, formal mathematical formulation, ablation study, McNemar's test, demographic profiling, complexity analysis, and 10-fold cross-validation. All six structural hypotheses (H1-H6) are confirmed with $p<0.001$ and t-statistics up to 12.1× greater than PLS-SEM. H6 is confirmed, with the correct positive direction ($\beta= +0.959$) for the first time, and closes a methodological artifact in previous survey research. The ALO-PG framework presents outstanding results of 95.67% (AUC=0.9771) with a cross-validation mean of 95.42% ± 0.48%. It also exceeds all five interpretable baseline algorithms with statistically significant margins in all five comparisons (McNemar $p<0.001$ for all comparisons).

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