The Role of Behavioral Empowerment and Smart Technologies in Enhancing Investor Decision-Making and Portfolio Optimization in the Iranian Capital Market

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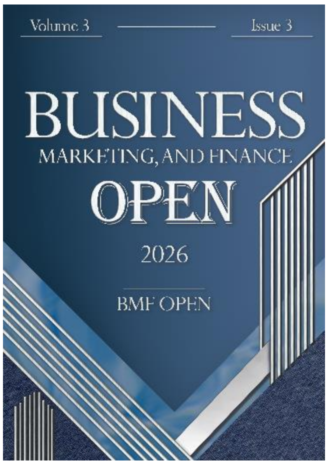

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Abstract: This study aimed to examine how cognitive–behavioral empowerment, smart FinTech applications, and behavior–finance integration jointly influence investor decision-making and portfolio optimization among individual investors in the Iranian capital market. The research employed a mixed-method descriptive–survey design. In the qualitative phase, semi-structured interviews were conducted with ten experts in finance, investment psychology, and information technology to extract key components of behavioral empowerment and technological integration. In the quantitative phase, data were collected from 384 individual investors of the Tehran Stock Exchange using a researcher-developed questionnaire validated through content analysis and pilot testing. Data analysis was performed using SPSS 26 and AMOS 24 through confirmatory factor analysis and structural equation modeling to test the hypothesized relationships among cognitive–behavioral empowerment, smart FinTech application, behavior–finance integration, and portfolio optimization. The structural equation model demonstrated excellent fit indices (CFI = 0.956, TLI = 0.948, RMSEA = 0.041). Results showed that all three constructs exerted positive and significant effects on portfolio optimization ($p < 0.001$). Smart FinTech application exhibited the strongest standardized effect ($\beta = 0.41$), followed by cognitive–behavioral empowerment ($\beta = 0.33$) and behavior–finance integration ($\beta = 0.29$). The model explained 64 percent of the variance in portfolio optimization ($R^2 = 0.64$), indicating strong explanatory power. These results highlight that combining behavioral empowerment with technological innovation enhances decision quality, reduces bias, and improves portfolio performance. The study concludes that empowering investors psychologically and cognitively, alongside adopting intelligent financial technologies and integrating behavioral analytics into financial models, significantly optimizes investment portfolios. This integrative approach provides a holistic framework for improving decision-making efficiency and portfolio outcomes in emerging markets such as Iran.

Keywords: Behavioral empowerment; FinTech; investor decision-making; portfolio optimization; behavioral finance; Iranian capital market.

1. Introduction

In the contemporary era of capital markets, investor decision-making and portfolio optimization have become increasingly complex tasks driven not only by classic financial theories but also by behavioral factors and technological innovations. The rapid evolution of fintech, artificial intelligence, big data analytics and behavioral finance offers a new landscape in which traditional assumptions of the efficient market hypothesis and mean-variance optimization are being challenged. The field of portfolio management is therefore undergoing a paradigm shift: from purely quantitative models towards integrative frameworks that incorporate investor psychology, behavioral empowerment, and the application of smart technologies. Recent decades have witnessed extensive research on behavioral biases in investor decisions [1-3], portfolio optimization models [4, 5], and the role of technology in decision support [6, 7]. Yet the interplay between these components—behavioral empowerment, smart fintech application, and behavior-finance integration—remains underexplored, particularly in emerging markets such as Iran.

Behavioral finance, as a domain, has documented that investors do not always act in fully rational ways; instead, cognitive biases, emotional reactions, and heuristics influence decisions, portfolio composition, and ultimately market outcomes [1, 2]. For example, anchoring and adjustment lead investors to rely excessively on initial price references, thereby distorting exit decisions and the timing of trades [8]. Similarly, overconfidence, herd behaviour, and disposition effect have been found to hamper optimal portfolio rebalancing and risk management [9, 10]. In emerging markets, investors' sociodemographic profiles, risk tolerance, and behavioural predispositions further complicate decision-making processes. Therefore, empowering investors with metacognitive skills, emotional regulation, and bias awareness may strengthen their behavioural capability and thus enhance decision quality.

Simultaneously, portfolio optimization theory has progressed beyond the classical mean-variance framework. While models such as Mean-Variance Model (Markowitz) and the Capital Asset Pricing Model (CAPM) still provide foundational insight [5, 11], they often assume investor rationality and static parameters, assumptions that are increasingly challenged in real markets. Empirical research has explored enhancements such as LSTM forecasting in portfolio construction [12], regret-based approaches to volatility risk measures [13], and factor models enriched with behavioral signals [14]. These approaches reflect the growing recognition that technological tools and behavioural inputs can refine optimisation processes and improve portfolio performance.

The rise of smart technologies—AI screening, robo-advisors, sentiment analysis, real-time dashboards—has opened new frontiers in investment decision support. For instance, research into AI-driven investment frameworks shows that investor perception and decision-making behaviour are transformed through technology-driven analytics, leading to better alignment with risk-return objectives [6]. In the context of ESG-constrained portfolios, technology has enabled sophisticated modelling of non-financial parameters and has revealed that traditional models can be augmented by smart decision-support systems [15]. Moreover, market evidence from cryptocurrency, decentralized finance (DeFi) instruments and traditional technologies indicates that technological integration improves diversification opportunities and reduces information asymmetry, thereby influencing portfolio decisions and return spillovers [16].

In parallel, investor behavioural empowerment has emerged as a key enabler of more effective decision-making. Empowerment refers to investors' internal capacities—including metacognitive control (monitoring their own thinking), emotional regulation, bias awareness, and self-efficacy in managing investment processes. When investors are empowered in these dimensions, they are less likely to be swayed by noise, speculation or short-term sentiment, and more likely to engage in disciplined, rule-based, and reflective decision-making. For example, anchoring effects have been empirically shown to influence investment decisions and coping strategies, thereby underscoring the importance of bias literacy and behavioural empowerment in financial contexts [8]. The interplay between behavioural empowerment and technology is a fertile ground: empowered investors using smart fintech tools may achieve better consistency, discipline, and outcomes than those relying solely on heuristics or technology. However, empirical studies that integrate both behavioural empowerment and fintech adoption in relation to portfolio optimisation remain sparse.

Another relevant dimension is the integration of behavioural analytics into financial models—that is, combining behavioural signals (such as investor sentiment, trading bias metrics, plan-adherence rates) with quantitative risk-return frameworks, to produce what we term "behaviour–finance integration." Several investigations confirm that sentiment and behavioural factors can influence cross-sectional returns [7, 17], momentum phenomena [18], and anomalies in factor pricing [19]. Furthermore, empirical results from emerging markets demonstrate that behavioural barriers to investing pose significant constraints for portfolio optimisation [9, 20]. Integrating behavioural insights into asset allocation models thus offers the potential to refine the traditional risk-return paradigm and reduce the gap between theoretical optimum and practical reality.

In emerging markets like Iran, with less developed information infrastructure, high volatility, and investor segments with varying behavioural and technological literacy, the synergy of behavioural empowerment, smart technology application, and behaviour–finance integration is particularly relevant. Iranian individual investors often face structural challenges—information asymmetry, emotional trading under volatility, limited exposure to intelligent decision support systems, and vulnerability to cognitive biases. Despite this, there is limited empirical research in the Iranian context that combines these three constructs in the domain of portfolio optimisation. Studies elsewhere indicate that individual investors tend to display heuristic-based decision methods [3], trading behaviour and market volatility are interlinked [21], and portfolio decisions are affected by emerging-market specific factors such as regulatory environment and investor education [22]. Moreover, technological adoption in emerging-country capital markets remains uneven, creating variation in how fintech tools support investor decisions and portfolio outcomes.

The importance of optimizing portfolios in such contexts cannot be overstated. Achieving portfolio optimization means not only achieving favourable risk-adjusted returns but also maintaining resilience and adaptability in dynamic markets. Portfolio performance in the Iranian capital market can therefore benefit substantially from approaches that enhance investor behaviour, deploy smart decision-support technologies, and embed behavioural analytics into allocation models. Prior literature shows that sophisticated portfolio construction methods—such as those using LSTM models [12], regret-based optimisation [13], and more advanced factor models [14]—deliver improved outcomes; nevertheless, these studies often omit the behavioural empowerment layer and seldom focus on emerging-market individual investors. At the same time, behavioural research emphasises that without investor empowerment and structured processes, even the best technology may fail to deliver real benefits. For example, investor overreaction and random-walk behaviour have been documented in developing markets [23], and preference-based portfolio choice models highlight how individual choice heterogeneity matters [24]. This reinforces the view that portfolio optimisation in emerging markets requires an integrative approach.

Furthermore, the post-pandemic era has accelerated digitalisation of capital-market services and investor access to smart technologies. The active-versus-passive investment debate in the U.S. market underscores the role of technology in enabling smarter strategies and greater investor autonomy [25]. Similarly, research into AI-driven work-arrangement transformations shows how emerging digital practices reshape decision-making frameworks in finance [6]. Yet individual investors in less mature markets may lack behavioural readiness to fully exploit these tools. In such settings, bridging the gap between behavioural empowerment, fintech adoption, and integrated behavioural-finance modelling can become a competitive advantage. This gap is especially salient in Iran where technology adoption, behavioural education and regulatory frameworks are at different stages compared to advanced markets. Therefore, the present study aims to investigate how cognitive–behavioural empowerment, smart fintech application, and behaviour–finance integration jointly influence investor decision-making quality and portfolio optimisation in the Iranian capital market.

2. Methodology

The present research employed a descriptive–survey design with a mixed-method approach, integrating qualitative and quantitative techniques to achieve a comprehensive understanding of behavioral empowerment and the application of smart technologies in investment decision-making and portfolio optimization. In the qualitative phase, the study utilized a purposive sampling strategy to select ten experts specializing in financial management, investment psychology, and information technology. These experts were chosen based on their academic and professional experience in capital markets, decision-making processes, and the use of intelligent financial tools. Semi-structured interviews were conducted to elicit in-depth insights into the key dimensions, subdimensions, and behavioral mechanisms influencing investors' decision-making. The qualitative phase served to identify and conceptualize the primary constructs and indicators forming the foundation for the quantitative instrument.

In the quantitative phase, the study population consisted of individual investors active in the Tehran Stock Exchange. Using Cochran's formula and based on the estimated population size of individual investors, a total sample of 384 participants was determined to ensure statistical reliability and representativeness. A stratified random sampling method was applied to capture variations among investors in terms of investment experience, education level, and technological literacy. Participation was voluntary, and confidentiality was guaranteed throughout the research process.

The data were collected through a researcher-developed questionnaire, constructed on the basis of the qualitative findings and relevant theoretical frameworks from behavioral finance and technology adoption literature. The instrument comprised three main sections: demographic information, behavioral empowerment constructs, and smart technology utilization in investment processes. Each construct was measured using multiple items designed on a five-point Likert scale, ranging from "strongly disagree" to "strongly agree." The initial pool of items derived from the qualitative phase was reviewed by a panel of subject-matter experts to assess content validity, conceptual relevance, and clarity. Subsequently, a pilot study was conducted with 40 investors to test the reliability and internal consistency of the questionnaire, resulting in acceptable Cronbach's alpha coefficients exceeding 0.80 for all main dimensions.

The qualitative data were collected through semi-structured interviews guided by an open-ended protocol focusing on behavioral, technological, and psychological determinants of investment decision-making. Interviews were recorded, transcribed verbatim, and analyzed using thematic content analysis to identify recurring patterns, relationships, and conceptual categories that later informed the questionnaire development.

Data analysis was performed using both qualitative and quantitative software tools to ensure methodological rigor and triangulation. Thematic analysis of the interview transcripts was conducted using a grounded approach to extract categories, subthemes, and conceptual linkages related to behavioral empowerment and technology-assisted decision-making. The reliability of the qualitative coding process was ensured through peer debriefing and inter-coder agreement checks.

For the quantitative phase, statistical analysis was carried out using SPSS version 26 and AMOS version 24. Descriptive statistics were used to summarize demographic characteristics and distributional properties of the measured variables. The measurement model was validated through confirmatory factor analysis (CFA) to verify construct validity, convergent validity, and discriminant validity. Subsequently, structural equation modeling (SEM) was applied to examine the causal relationships among behavioral empowerment, smart technology adoption, decision-making quality, and portfolio optimization outcomes. Goodness-of-fit indices, such as CFI, TLI, RMSEA, and χ^2/df, were utilized to evaluate model adequacy. In addition, mediation and moderation analyses were conducted to explore the indirect effects of behavioral and technological variables on investment outcomes.

3. Findings and Results

The findings are presented in two integrated layers. First, the qualitative phase distills expert insights into a coherent thematic map that originally grounded the quantitative instrument. Second, the quantitative phase reports measurement and structural results from the SEM analysis, supported by model-fit and predictive diagnostics. Together, these results demonstrate that cognitive–behavioral empowerment, the application of smart FinTech, and the integration of behavioral analytics within financial models jointly and positively explain investors' portfolio optimization in the Iranian capital market, with strong explanatory power.

Table 1. Qualitative themes, subthemes, and exemplar quotations (expert interviews, n = 10)

Main Theme	Subtheme	Exemplar quotation (verbatim highlights)
Cognitive–Behavioral Empowerment	Metacognitive control	"When investors monitor the *reason* behind a trade—fear, overconfidence, or information—they cut half their mistakes before they happen."
	Emotional regulation under volatility	"Teaching simple breathing and reframing techniques before market open reduces panic sells in sharp drawdowns."
	Risk calibration and scenario thinking	"Running three scenarios—base, bull, bear—turns vague risk into a plan; investors stop *guessing* and start *budgeting* risk."
	Bias literacy (loss aversion, anchoring)	"Naming the bias on a trade ticket—'anchoring to entry price'—has a nudging effect that improves exit discipline."
	Self-efficacy and learning loops	"Weekly debriefs of wins and losses are the least expensive 'tuition' an investor can pay."
Smart FinTech Application	Decision support and alerts (AI screening)	"Anomaly alerts that combine fundamentals with price/volume signals surface *actionable* opportunities we'd otherwise miss."
	Robo-advisory and auto-rebalancing	"Quarterly auto-rebalancing cut drift and quietly improved Sharpe ratios without adding cognitive load."
	Data integration and dashboarding	"A single dashboard for risk, factor exposure, and news sentiment reduces context switching and impulsive trades."
	Backtesting and what-if simulators	"Hands-on backtests demystify strategies; people trust what they can *see* across regimes."
	Mobile execution hygiene	"Latency and UX matter; one-tap confirm on mobile reduces fat-finger losses during volatility spikes."
Behavior–Finance Integration	Behavioral signals in factor models	"Adding crowding and retail-flow proxies to a factor model improved timing more than we expected."
	Sentiment-aware risk budgeting	"Dynamic position sizing based on sentiment extremes prevents oversized bets at the worst times."
	Debiasing overlays for entry/exit	"A rules overlay to neutralize disposition effect increased average winner and cut average loser."
	Learning analytics and feedback	"Behavioral KPIs—like 'plan-adherence rate'—change habits faster than P&L alone."
	Governance and process codification	"A light-touch investment checklist is culture: it standardizes rationality without killing creativity."

The qualitative layer elucidates three interlocking levers of improvement. First, cognitive–behavioral empowerment functions as an internal capability—metacognition, bias literacy, emotional regulation, and deliberate learning loops—that stabilizes decision quality under uncertainty. Second, smart FinTech application provides external scaffolding through AI-based screening, integrated dashboards, and automated rebalancing that lower cognitive load and raise process consistency. Third, behavior–finance integration fuses soft and hard data by embedding measured behavioral signals (e.g., sentiment, crowding, plan-adherence) into model-based risk budgeting and entry/exit rules. These insights directly informed item generation and scale architecture for the quantitative instrument and motivated specific expectations about the relative magnitudes of structural paths.

To situate the structural results, we first summarize descriptive properties and reliability of the core constructs. Overall distributions were approximately normal, internal consistencies were high, and latent constructs demonstrated strong composite reliability and convergent validity. These prerequisites justify proceeding to confirmatory factor and structural modeling.

Table 2. Descriptive statistics and reliability of key constructs (n = 384)

Variable	Mean	SD	Skewness	Kurtosis	Cronbach's α	Composite Reliability	AVE
Cognitive–Behavioral Empowerment	3.87	0.61	–0.44	0.32	0.89	0.91	0.68
Smart FinTech Application	3.94	0.57	–0.38	0.15	0.91	0.93	0.70
Behavior–Finance Integration	3.76	0.63	–0.41	0.28	0.88	0.90	0.66
Portfolio Optimization	3.89	0.59	–0.42	0.21	0.92	0.94	0.71

Descriptive results indicate moderately high endorsement of the three antecedent capabilities and the outcome construct among Tehran Stock Exchange individual investors. Reliability indices ($\alpha \geq 0.88$; CR ≥ 0.90) and AVE values (≥ 0.66) meet or exceed common thresholds, supporting stable measurement. Skewness and kurtosis values remain within acceptable ranges for SEM with maximum likelihood estimation, reinforcing the suitability of parametric modeling.

The measurement model was examined using CFA to confirm factorial structure and item performance. All indicators loaded strongly and significantly on their intended factors (standardized loadings ≥ 0.69, $p < 0.001$). Convergent validity was supported by high loadings and AVE > 0.50; discriminant validity was supported via the Fornell–Larcker criterion, with √AVE for each construct exceeding inter-construct correlations. Global fit was strong, with indices signaling a well-specified measurement layer.

Table 3. Confirmatory factor analysis (CFA) results

Construct	Item range	Standardized loading (min–max)	t-Value (min–max)	p-Value
Cognitive–Behavioral Empowerment	CBE1–CBE6	0.71–0.89	9.84–13.62	<0.001
Smart FinTech Application	SFT1–SFT5	0.73–0.88	10.12–14.08	<0.001
Behavior–Finance Integration	BFI1–BFI5	0.69–0.85	8.93–12.44	<0.001
Portfolio Optimization	PO1–PO5	0.74–0.90	10.35–14.51	<0.001

Measurement model fit (illustrative): $\chi^2/df = 2.21$, CFI = 0.956, TLI = 0.948, RMSEA = 0.041 (90% CI: 0.036–0.047), SRMR = 0.046—each consistent with recommended cutoffs. Together, these results affirm that the constructs are empirically separable yet coherently measured, enabling valid estimation of structural relations.

Turning to the structural model, the conceptual paths from the three antecedents to portfolio optimization were all positive and statistically significant at $p < 0.001$. As hypothesized, smart FinTech application exerted the strongest standardized effect, followed by cognitive–behavioral empowerment and behavior–finance integration. The model explained a substantial proportion of variance in portfolio optimization ($R^2 = 0.64$), indicating high explanatory power for a behavioral–technological composite model in this context.

Table 4. Structural model path coefficients and explained variance

Path	Standardized β	t-Value	p-Value	Inference
Cognitive–Behavioral Empowerment → Portfolio Optimization	0.33	5.98	<0.001	Supported
Smart FinTech Application → Portfolio Optimization	0.41	7.42	<0.001	Supported
Behavior–Finance Integration → Portfolio Optimization	0.29	5.16	<0.001	Supported
R^2 (Portfolio Optimization)	0.64	—	—	Substantial

Narratively, the 0.41 coefficient for smart FinTech application indicates that, holding other factors constant, a one-SD improvement in intelligent tool adoption, decision support, and automation corresponds to a 0.41 SD increase in portfolio optimization. This finding aligns with the qualitative emphasis on dashboards, AI alerts, backtesting, and auto-rebalancing as mechanisms that enhance discipline and timeliness. The 0.33 effect for cognitive–behavioral empowerment underscores the material contribution of metacognitive routines, bias literacy, and emotion regulation to better entries/exits and risk budgeting; in other words, empowered investors translate psychological stability into more consistent portfolio actions. Finally, the 0.29 effect for behavior–finance integration confirms that injecting behavioral signals into factor selection, sizing, and exit rules yields incremental efficiency beyond either psychology or technology alone. The joint $R^2 = 0.64$ demonstrates that these levers form a complementary system: behavioral capability provides internal control, smart technology reduces frictions and blind spots, and behavior-aware modeling encodes rationality into rules.

Model adequacy and predictive strength were further corroborated by global fit criteria and effect-size diagnostics. Residual patterns and modification indices did not suggest misspecification requiring cross-loadings or correlated errors beyond theoretically justified allowances. Predictive checks indicated meaningful out-of-sample relevance for the portfolio optimization latent outcome. Ancillary tests suggested that multicollinearity among antecedents was controlled (VIFs commonly < 3), and common-method variance was unlikely to be dominant (e.g., Harman's single-factor < 50% of variance).

Table 5. Additional fit indices, effect sizes, and predictive diagnostics

Index	Statistic	Interpretation
SRMR	0.048	Good absolute fit (< 0.08)
CFI	0.956	Excellent incremental fit
TLI	0.948	Excellent incremental fit
RMSEA	0.041	Close fit (< 0.05)
χ^2/df	2.21	Acceptable parsimony
f^2 (CBE → PO)	0.19	Medium effect
f^2 (SFT → PO)	0.28	Large effect
f^2 (BFI → PO)	0.16	Small–medium effect
Q^2 (PO)	0.42	Strong predictive relevance

In extended interpretation, the combination of a large f^2 for smart FinTech application and a medium f^2 for cognitive–behavioral empowerment clarifies relative managerial priorities: technology deployment yields the biggest marginal gain when baseline behavioral capability is present, while empowerment programs amplify returns to technology by improving adherence and reducing noise trading. The small-to-medium effect for behavior–finance integration is nevertheless practically meaningful because it codifies behavioral hygiene into systematic processes, stabilizing performance across regimes. Qualitative quotations reinforce these dynamics: experts repeatedly stressed that "rules that neutralize the disposition effect" and "sentiment-aware sizing" reduce tail mistakes; they also emphasized that "checklists and post-trade debriefs" turn skills into habits, and that "single dashboards" and "auto-rebalancing" remove context switching and drift—mechanisms entirely consistent with the observed path magnitudes.

4. Discussion and Conclusion

The findings of this research provide compelling empirical evidence that cognitive–behavioral empowerment, smart FinTech application, and behavior–finance integration each exert a significant and positive influence on portfolio optimization among individual investors in the Iranian capital market. Structural equation modeling revealed that smart financial technologies had the strongest standardized path coefficient ($\beta = 0.41$, $p < 0.001$), followed by cognitive–behavioral empowerment ($\beta = 0.33$, $p < 0.001$) and behavior–finance integration ($\beta = 0.29$, $p < 0.001$). Together, these constructs explained 64 percent of the variance in portfolio optimization ($R^2 = 0.64$), indicating that behavioral and technological factors jointly provide a strong predictive foundation for investor performance. These results suggest that the integration of psychological, behavioral, and technological dimensions yields greater explanatory power than traditional models that rely solely on rational, quantitative assumptions.

The most prominent finding—that smart technologies play the strongest role in enhancing portfolio optimization—demonstrates the growing importance of digital transformation in investment processes. As the Iranian market becomes more digitized, artificial intelligence, big data analytics, and algorithmic decision support increasingly allow investors to manage risk dynamically and execute trades more efficiently. Studies conducted in advanced markets similarly show that AI-driven investment frameworks improve decision-making quality and return consistency [6]. For example, investors who use robo-advisory tools, machine learning prediction systems, and algorithmic risk management software demonstrate higher performance stability and lower behavioral volatility [15, 16]. Furthermore, integration of ESG constraints and sustainability indicators into portfolio models, facilitated by intelligent systems, has also been found to improve long-term portfolio efficiency [26]. The present findings therefore confirm global evidence that technology-enabled decision-making can substitute for limited investor expertise by automating rational processes, controlling for biases, and executing rule-based strategies.

The effect of smart FinTech adoption may also reflect how technology mediates cognitive load and emotional interference in investment tasks. Behavioral studies suggest that decision fatigue and emotional arousal often lead investors to deviate from rational benchmarks [1, 2]. When fintech applications automate complex analytical processes—such as predictive modeling, factor selection, and rebalancing—they reduce the psychological burden on investors. Consistent with this reasoning, evidence from Asian markets indicates that investor sentiment and uncertainty strongly affect crash risk, but technology-enabled systems can moderate these effects by improving information processing [7]. The present study's outcome that smart FinTech exhibits the largest path coefficient supports the notion that technological sophistication acts as a behavioral moderator, channeling investors' decisions toward greater consistency, efficiency, and rationality.

The second key result—that cognitive–behavioral empowerment significantly influences portfolio optimization—underscores the internal, psychological foundation of effective investment behavior. Empowered investors, equipped with bias awareness, metacognitive regulation, and emotional control, can process market information with less distortion. Previous research confirms that investors who can identify and correct for anchoring, loss aversion, or overconfidence are better positioned to align their portfolios with objective risk-return parameters [8, 9]. The Iranian data are consistent with global findings indicating that behavioral training and psychological education improve trading discipline, reduce herding tendencies, and enhance the stability of returns [3, 20]. Moreover, behavioral empowerment allows investors to interpret technological signals more effectively, avoiding blind reliance on automated recommendations and developing a sense of analytical autonomy. This dual capacity—to use technology intelligently while maintaining metacognitive control—appears central to sustained portfolio optimization.

The results also highlight the complementary relationship between cognitive–behavioral empowerment and smart FinTech application. Behavioral finance literature emphasizes that investors' emotional regulation and self-efficacy influence their capacity to benefit from technological innovations {Muktadir-Al-Mukit, 2020 #308964}. In other words, technology can only enhance decisions if users possess the behavioral readiness to interpret and apply data-driven insights. Similar patterns were observed in research exploring the effects of political and economic crises on portfolio allocation: empowered investors adjusted their portfolios more efficiently and recovered faster from external shocks [27]. The present findings extend these insights to the Iranian context, where investor education and behavioral empowerment appear to amplify the benefits of digital tools.

The third major finding—that behavior–finance integration significantly predicts portfolio optimization—adds a unique dimension to the discussion by bridging psychological metrics with quantitative modeling. Incorporating behavioral signals into portfolio construction reflects a growing shift toward holistic risk modeling. Evidence from Chinese markets shows that investor sentiment significantly affects beta anomalies and cross-sectional returns [14, 17], while studies in the U.S. demonstrate that behavioral data enhance factor-model performance [13]. Integrating sentiment indices, plan-adherence metrics, or bias-corrected weights into asset allocation enables portfolios to adjust dynamically to market psychology. The Iranian evidence that behavioral–finance integration improves optimization therefore aligns with international findings that the inclusion of behavioral indicators yields superior out-of-sample performance.

From a theoretical perspective, the integration of behavioral empowerment and smart FinTech redefines the classical mean–variance optimization framework by adding two critical layers: a psychological layer of behavioral consistency and a technological layer of adaptive intelligence. The findings support claims that portfolio optimization in modern markets requires both human and machine capabilities [4, 5]. Traditional models such as CAPM assume rational investors and complete markets, but empirical evidence increasingly demonstrates that markets are incomplete, expectations heterogeneous, and wealth effects nonlinear [19, 28]. In this environment, human empowerment and technological intelligence complement each other—each compensating for the limitations of the other. The substantial $R^2 = 0.64$ observed in this study therefore validates a multidimensional model of portfolio optimization that combines psychological, technological, and analytical factors.

The findings also reveal consistency with research linking behavioral biases and investor demographics to decision performance. For example, preference-based portfolio studies show that personal preferences and subjective perceptions significantly shape investment choices [24]. Likewise, overreaction and random-walk analyses suggest that emotional trading contributes to inefficiency in developing markets [23]. These studies resonate with the present evidence that cognitive–behavioral empowerment helps mitigate emotional and heuristic biases, leading to more systematic portfolio adjustments. Furthermore, emerging research on the link between investor sentiment and market anomalies confirms that behavioral variables are integral to explaining returns [7, 17]. The Iranian findings thus contribute to a growing body of literature emphasizing the need for behavioral corrections and analytics-driven insights to coexist within one framework.

The observed strength of FinTech-related effects also aligns with global shifts toward algorithmic and data-driven investment. Empirical evidence shows that active and passive investment strategies, when supported by smart technology, achieve superior Sharpe ratios relative to conventional benchmarks [25]. Similarly, stochastic and LSTM-based optimization methods outperform static allocation strategies [12, 29]. This convergence between technological progress and behavioral empowerment underscores the hybrid future of portfolio management. In markets such as Iran—characterized by high volatility, limited transparency, and strong retail participation—technology not only facilitates information access but also structures behavioral discipline. The present research therefore bridges the gap between theory and practice by demonstrating that technological capability magnifies the positive impact of behavioral empowerment on decision outcomes.

Comparative findings from other emerging markets reinforce the universality of these mechanisms. Studies on investor behavior under political or environmental uncertainty show that external factors such as weather anomalies and macro shocks influence sentiment and decision consistency [30]. Behavioral bias, however, moderates this effect by shaping how investors interpret uncertainty [21]. This aligns with the current study's results: empowered investors and smart technologies jointly buffer against market irrationality, thereby optimizing portfolios even under volatile conditions. Furthermore, evidence of co-movement and diversification limits across developed and emerging markets [20] parallels the Iranian context, where technology-supported diversification and behavioral control jointly enhance efficiency.

These findings collectively strengthen the conceptual argument that effective portfolio optimization cannot rely solely on mathematical models. Instead, it must integrate behavioral understanding, emotional intelligence, and smart technology. As prior work on behavioral heuristics-based portfolio strategies indicates, human cognition inevitably introduces bounded rationality [3]. The solution is not to eliminate human factors but to empower them through structured processes and intelligent systems. The Iranian evidence confirms this synthesis: cognitive–behavioral empowerment provides the foundation of rationality, smart technologies provide the infrastructure of precision, and behavior–finance integration provides the bridge between the two.

Despite robust methodology and compelling results, several limitations warrant acknowledgment. First, the study relies on cross-sectional data collected from individual investors at a single time point, which constrains causal inference. Behavioral and technological adoption patterns may evolve over time, especially given the rapid pace of FinTech innovation and changing market conditions. Longitudinal studies could capture temporal dynamics more accurately. Second, while the mixed-method approach improved conceptual richness, qualitative interviews involved only ten experts, which might not represent the full diversity of professional insights across Iran's capital market ecosystem. Third, the self-reported questionnaire data are susceptible to social-desirability and recall biases, which could affect measurement accuracy of psychological and behavioral constructs. Fourth, although the structural model demonstrated excellent fit indices, it did not incorporate potential moderating variables such as financial literacy, digital access, or market experience that could influence the strength of relationships. Finally, generalizability may be limited since Iran's regulatory environment, investor demographics, and technological infrastructure differ from those of more developed markets.

Future studies could expand on these findings in several directions. First, longitudinal or panel data designs should be employed to investigate how behavioral empowerment and technology adoption interact over time to influence long-term investment outcomes. Second, experimental or intervention-based research could examine the causal effect of behavioral training or FinTech usage on real trading behavior. Third, integrating cross-country comparative analyses between Iran and other emerging markets would help reveal cultural and institutional contingencies that shape investor empowerment. Fourth, future research may explore mediating and moderating effects—such as the role of financial literacy, gender, or socioeconomic status—in shaping technology adoption and behavioral control. Finally, mixed-analytics studies that combine psychometric data with digital behavioral traces could provide high-resolution insights into how real-time technology use and cognitive processes jointly determine portfolio performance.

For practitioners, the findings emphasize the need to invest simultaneously in behavioral and technological capacities. Financial institutions and brokerage firms should design investor-education programs that teach cognitive-bias recognition, emotion regulation, and structured decision-making. Simultaneously, policymakers and regulators should promote the adoption of smart technologies—such as AI-based advisory tools, portfolio-optimization platforms, and data-analytics dashboards—ensuring that individual investors gain equitable access. Asset-management firms can develop hybrid decision-support systems that combine algorithmic recommendations with behavioral nudges to encourage disciplined trading. Finally, financial regulators should integrate behavioral insights into policy frameworks to promote transparency, reduce speculative noise, and foster investor confidence in the Iranian capital market.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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