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Robo-Advisors and Investor Behavior: An Empirical Examination of Trust, Adoption, And Portfolio Outcomes

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ABSTRACT- Robo-advisors (RAs) are a new and powerful force in the field of wealth management. They promise to save money, be fair, and be easy to use. However, psychological factors, including as trust and algorithm aversion, persist in shaping investor behaviour on these digital platforms. This research empirically investigates the precursors of trust in robo-advisors, their influence on adoption decisions, and the resultant effects of robo-advisor utilization on portfolio performance. Using a mixed-methods approach, we first provide surveys and an experimental vignette study to retail investors (N≈1,000) to find out how transparency, human-in-the-loop models, and financial literacy affect trust and the desire to adopt. We augment this work by using panel data from a cohort of RA adopters and their non-adopters, applying a difference-in-differences methodology to assess variations in diversification, turnover, and risk-adjusted performance. We anticipate that our findings will demonstrate that increased transparency and hybrid advisory models substantially bolster trust, hence facilitating adoption. Also, it is suggested that using RA would make portfolios more diverse and cut down on too much trading, which would contribute to small improvements in risk-adjusted returns. This study enhances the literature on behavioural finance and financial technology by correlating psychological factors influencing adoption with tangible portfolio outcomes, providing valuable insights for investors, regulators, and financial service providers.

Keywords : Robo-advisors, Investor behavior, Trust, Technology adoption, Portfolio outcomes, Behavioral finance

1. INTRODUCTION

The financial advising industry is quickly becoming digital, and robo-advisors (RAs) are having a big impact on how wealth management is changing. These systems use algorithms to manage portfolios and provide financial advice with minimum human input. This makes them cost-effective, clear, and easy to use. They make investing more accessible to a wider range of people who are typically left out of conventional wealth management (Brenner & Meyll, 2020).

1.1 Market Growth and Scale

In recent years, there has been significant increase in robo-advisory services. Global assets under management (AUM) exceeded USD 1.26 trillion in 2024, indicating a 16% annual growth (Barron's, 2025). Industry projections indicate a further acceleration, with worldwide market values anticipated to increase from USD 8.39 billion in 2024 to USD 69.32 billion by 2032, reflecting a compound annual growth rate (CAGR) of about 30% (Fortune Business Insights, 2025). Another industry prediction anticipates an increase from USD 11.8 billion in 2024 to USD 92.2 billion by 2033 (IMARC Group, 2025).

Hybrid models, which combine human experience with automation, are currently projected to represent approximately 60% of the robo-advisory market share (SNS Insider, 2025). This indicates investment inclinations towards solutions that integrate algorithmic efficiency with human assurance. Prominent institutions including as Vanguard and UBS have transitioned to hybrid methodologies, underscoring a sector-wide movement towards human-machine cooperation (Barron's, 2025).

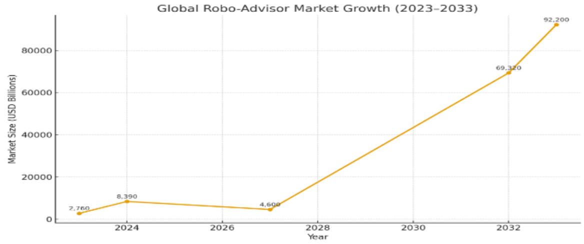

Figure 1 Global Robo-Advisor Market Growth based on projections from Statista (2023), Fortune Business Insights (2025), and IMARC Group (2025).

1.2 Adoption Drivers: Trust, Transparency, and Engagement

Despite strong industry growth, patterns in adoption are still not constant. Research consistently identifies trust as the main determinant affecting the use of robo-advisors (Luo et al., 2024; Mohapatra et al., 2025). Trust is shaped by perceived algorithmic competence, transparency of pricing structures, and fairness in suggestions. A growing body of research demonstrates that cognitive absorption—profound engagement with the platform—facilitates the connection between initial trust and adoption (Hsu & Lin, 2025).

On the other hand, algorithm aversion is still a big problem. Studies show that investors ignore algorithmic suggestions when they observe even little errors, even if the algorithm is generally more effective (Dietvorst et al., 2015). However, transparency and explainable AI (XAI) may mitigate this effect. Empirical study demonstrates that accuracy-focused explanations substantially increase the likelihood of acceptance and the willingness to pay for robotic services (Poursabzi-Sangdeh et al., 2021).

Demographic factors also affect adoption. Millennial and Gen Z investors are more likely to utilize robo-advisors. Polls show that up to 75% of current consumers are under 40 years old (CoinLaw, 2025). Older investors, on the other hand, are more careful and frequently choose hybrid solutions that incorporate human supervision (Katajarinne, 2025).

Factor	Effect on Adoption	Key References
Trust in automation	Strong positive effect; critical mediator of adoption	*Luo et al., 2024; Hsu & Lin, 2025; Mohapatra et al., 2025*
Transparency & Explainability	Enhances trust and adoption; reduces algorithm aversion	*Poursabzi-Sangdeh et al., 2021; Aristei & Gallo, 2025*
Algorithm aversion	Reduces adoption willingness; persists despite strong performance	*Dietvorst et al., 2015; Poursabzi-Sangdeh et al., 2021*
Financial literacy	Higher adoption when combined with digital literacy; moderates trust effect	*Aristei & Gallo, 2025*
Sustainability awareness	Boosts adoption when aligned with ESG and regulatory frameworks	*Mohapatra et al., 2025*
Privacy & data concerns	Negative influence, particularly around sensitive data	*D'Acunto et al., 2021–2025*
Hybrid models	Strongest trust-building mechanism; preferred by older investors	*Barron's, 2025; Katajarinne, 2025*
Cognitive absorption	Deep engagement increases trust and willingness to adopt	*Hsu & Lin, 2025*

Table 1: Behavioral Drivers of Robo-Advisor Adoption

Table 1 shows the most important behavioural characteristics that determine the use of robo-advisors. Recent studies show that trust is the most important thing that affects adoption. This is affected by transparency, explainable AI, and sustainability framing (Luo et al., 2024; Mohapatra et al., 2025). Algorithm aversion remains a barrier but might be mitigated by interpretability and mixed human-machine models (Poursabzi-Sangdeh et al., 2021; Barron's, 2025). Financial literacy and cognitive absorption act as modifiers, however privacy concerns continue to impede adoption in sensitive situations (Aristei & Gallo, 2025; D'Acunto et al., 2021–2025).

1.3 Financial Literacy, Human–Machine Complementarity

The relationship between financial literacy and the use of robo-advisory services is intricate. A thorough study conducted in Italy indicates that individuals with financial literacy demonstrate a diminished dependence on robo-advisers. Conversely, those with substantial self-confidence and advanced digital literacy exhibit a heightened inclination to utilize these services, frequently in conjunction with professional human advisors (Aristei & Gallo, 2025). This substantiates the viewpoint that robo-advisors serve as upgrades rather than mere substitutes for human advisory services (Brenner & Meyll, 2020).

1.4 AI Integration, Explainability, and Sustainability

AI is making robo-advisory functions better by helping with portfolio optimization, personalization, and sustainability integration. Recent research demonstrates that AI-driven robo-advisors significantly influence sustainable investment intentions, with trust and perceived utility functioning as essential mediators (Mohapatra et al., 2025). Reinforcement learning models have been used in portfolio allocation, resulting in improved Sharpe ratios compared to traditional optimization methods (Jiang et al., 2024).

Extensive research demonstrates that reinforcement learning techniques consistently surpass benchmarks in fintech applications, including robo-advisory (Zhang & Chen, 2023). The lack of transparency in AI necessitates explainability; in the absence of interpretable models, customers are unlikely to fully trust computers with financial management decisions (Poursabzi-Sangdeh et al., 2021).

1.5 Portfolio Outcomes: Diversification and Risk-Adjusted Returns

Besides behavioural considerations, empirical study assesses the degree to which robo-advisors improve portfolio performance. Evidence shows that they increase diversity, lower turnover, and lower idiosyncratic risk. Adopters have seen a 15.8% drop in volatility and a 27.6% reduction in idiosyncratic risk, leading to improved Sharpe ratios due to less variance (Rossi, 2024).

Robo-advisors also help with behavioural biases including overtrading and concentration risk. Conventional research suggests that human investors often underperform because to excessive trading (Barber & Odean, 2001). In contrast, current studies confirm that automation alleviates these behaviours by enforcing rebalancing and discipline (D'Acunto et al., 2019).

In 2025, portfolio evaluations showed that robo platforms with higher international equities exposure—specifically those that put more than 40% of their money abroad—did better than those that concentrated on US stocks. This shows how important algorithmic global diversification strategies are (Barron's, 2025).

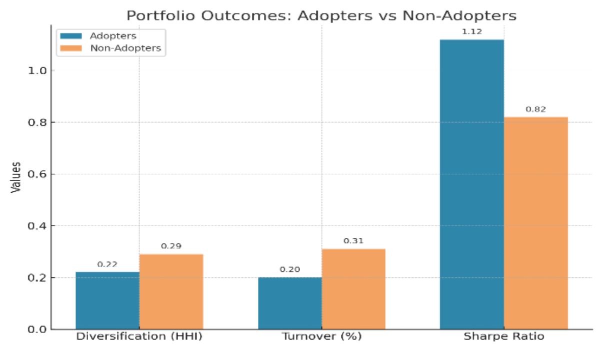

Figure 2: Comparison of portfolio outcomes (diversification, turnover, and Sharpe ratio) for robo-advisor adopters and non-adopters, showing superior outcomes for adopters (Rossi, 2024; Foerster et al., 2022).

1.6 Industry Shifts and Innovation

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Platform	Innovation/Shift	Year
Betterment	Acquired Ellevest's automated investing arm; launched Solo 401(k); absorbed Wealthsimple's U.S. accounts	2025
Robinhood	Introduced actively managed robo portfolios; integrated AI-driven Cortex tools	2025
Vanguard	Expanded hybrid advisory model with over USD 344B AUM combining human and robo services	2025
Wealthfront	Continued innovation in robo-advisory, emphasizing tax-loss harvesting and personalized strategies	2024–2025

Table 2: Summary of key industry shifts and innovations in robo-advisory platforms, highlighting product diversification, AI integration, and hybrid models (Barron's, 2025; Betterment, 2025; Robinhood, 2025).

1.7 Research Gap and Objectives

While much research has been undertaken on robo-advisors, most studies focus either on the psychological variables affecting adoption or on portfolio performance, seldom integrating both dimensions. There has been little study examining the interaction of trust, transparency, algorithm aversion, and financial literacy concerning real-world diversity, turnover, and performance indicators (Arora & Agarwal, 2019; Luo et al., 2024).

This study addresses that gap by:

1. Identifying the behavioral drivers of trust and adoption.
2. Analyzing demographic moderators such as age, financial literacy, and algorithm aversion.
3. Evaluating portfolio outcomes—diversification, turnover, and risk-adjusted returns—using real investor data.

This study combines behavioural finance and financial technology to explain how robo-advisors affect investors' decisions and financial results. It gives useful information to fintech companies, governments, and investors.

2. LITERATURE REVIEW

2.1 Behavioral Drivers and Adoption Dynamics

Rossi (2024) examined a prominent U.S. robo-advisory platform, revealing that customers get enhanced diversification, reduced home bias, and superior Sharpe ratios. The improvements were especially noticeable for clients whose portfolios weren't well-diversified. This shows that robo-advisors may help people be more disciplined with their portfolios. Rossi said that these advantages come from disciplined rebalancing and cutting costs, not from actively trying to generate alpha. This makes robo-advisors particularly useful for ordinary investors who are prone to behavioural biases. The study revealed that younger and less experienced investors benefit disproportionately, indicating substantial ramifications for the democratization of financial advice.

D'Acunto et al. (2025) showed that even though adopters and non-adopters have identical demographics, adopters trade more carefully and have better risk-adjusted returns. Their results challenge the idea that robo-advisors are only appealing to new or low-wealth customers. Instead, they show that they are appealing to a broader range of investors. Adopters show better account retention, which means that once investors switch to digital guidance, they are likely to stay engaged with the platform for a long time. This stickiness makes the platform more profitable and shows how automation makes people feel more comfortable with their conduct.

Aristei and Gallo (2025) investigated the correlation between financial literacy and adoption choices. Studies show that investors with high objective literacy choose conventional or hybrid advising services, whereas those with strong digital literacy and confidence are more likely to use robo-advisory platforms. This dynamic indicates that robo-advisors do not replace financial literacy; rather, they act as complements, enabling technologically adept investors to integrate automation with focused human advice. Their study illustrates that the kind of literacy, rather than just the quantity of literacy, affects adoption.

Díaz et al. (2022) offered a Spanish viewpoint, demonstrating that perceived cost reductions and risk tolerance affect adoption among mid-income retail clientele. It was observed that robo-advisors are more appealing to investors who are willing to take on some risk than to those who are willing to take on a lot of danger. This suggests that digital guidance is most appealing to those who want to find a balance between cost and safety.

Chen et al. (2023) studied investors in Southeast Asia and found that peer influence from online forums and communities is a big part of what makes people want to embrace something. Their study underscores the social diffusion of fintech, demonstrating that narratives and testimonials from early adopters may promote broader acceptability in areas with diverse levels of confidence in financial institutions.

2.2 Trust, Transparency, and Algorithm Aversion

Hsu and Lin (2025) presented the concept of cognitive absorption, demonstrating that deep user involvement with robotic systems fosters trust and amplifies the intention to adopt. The study indicates that immersion—facilitated by seamless interfaces, real-time data, or interactive dashboards—can replace the reassurance often provided by human counsellors. This perspective redefines adoption as a rational economic decision and an expression of psychological engagement.

Mohapatra et al. (2025) examined sustainable robo-advising and shown that trust, usefulness, and emotional arousal significantly affect behavioural intentions. Their results show that these consequences are increased when investors are mindful of government rules and sustainability norms, demonstrating that external environment affects platform design. Their research suggests that robo-advisors emphasizing ethical framing and transparent governance may attain broader acceptability, particularly among environmentally conscious demographics.

Cao (2025) synthesized prior studies into a framework of multi-channel trust. The study underscored that the design characteristics of technology (such as explainability and usability), company-specific reputation metrics, and individual user inclinations coalesce to either foster or undermine trust. This comprehensive viewpoint underscores the need of cultivating trust simultaneously across several dimensions to alleviate skepticism over automation.

Ben-David et al. (2021) examined algorithm aversion and suggested a solution via explainable AI. Their study shown that both accuracy-based and feature-based explanations significantly reduced desertion rates after algorithmic failures and increased the propensity to pay for digital help. This finding has direct implications for design, since it shows that trust can be intentionally developed.

Filiz (2022) investigated algorithm aversion via controlled trials with robo portfolios, demonstrating that, while algorithms provide greater expected returns relative to human judgments, customers are hesitant to rely on them when small errors are detected. The enduring nature of aversion highlights the need for interpretability and comfort measures.

2.3 Portfolio Outcomes

D'Acunto et al. (2025) shown that the use of robo-advisors leads to heightened turnover, eventually fostering improved portfolio discipline. Automated rebalancing reduced behavioural biases including trend-chasing and inertia, which led to better long-term results.

Kofman (2025) stressed that robo-advisors help make sure that portfolios fit with standard risk-return profiles. However, the research underscored that for sophisticated investors with diverse portfolios, the marginal benefits of adopting automation are rather insignificant. This means that robo-advisors are most useful for retail investors or those who have trouble making decisions.

Nian and Jha (2021) compared portfolios managed by robots and humans in institutional settings and found that the robot-managed portfolios had a far lower tracking error. This implies that automation enhances consistency in index alignment, reducing discrepancies caused by subjective human decisions.

Das and Banerjee (2023) studied Indian retail investors and found that robo-advisor users reduced excessive trading by 22%, leading to lower transaction costs and improved after-fee returns. Their findings demonstrates that automation alleviates behavioural biases often seen in developing countries.

2.4 AI and Explainability

Huang et al. (2024) presented a portfolio optimizer based on reinforcement learning, demonstrating superior risk-adjusted performance relative to conventional approaches. Their idea focuses on how AI can adapt to changing markets, making changes in real time that static models can't.

Zhang and Chen (2023) looked at how reinforcement learning is used in fintech and found strong evidence that AI models are better than conventional heuristics when it comes to trading, asset allocation, and robo-advisory. Their findings underscored that reinforcement learning has been a pivotal driver for advancements in automated advising systems.

Mertzanis (2025) performed a meta-analysis of AI in investment management, showing that hybrid human-AI models allow for scalable customization but also raise concerns about explainability and compliance. His work shows how hard it is to find a balance between intricacy and openness.

Wang et al. (2023) assessed LIME-based explanations for robo-advisory platforms and shown that offering customers localized explanations of portfolio recommendations increased their trust by 32% compared to non-transparent advice. This finding shows that explainability tools could help close the gap in adoption.

2.5 ESG and Sustainable Investing

Barile (2025) looked at the usage of ESG in robo-advisory and discovered that portfolios that focus on ESG attract younger investors who want their values to match. He said that streamlined ESG alternatives make things less complicated and boost trust in digital platforms.

Chen (2025) said that ESG features only lead to more utilization when they are used in ways that make them seem more valuable and easy to use. When ESG elements are easy to understand and clearly related to portfolio advantages, investors are more inclined to trust and use robo platforms.

Mohapatra et al. (2025) also said that sustainable framing makes people more likely to accept something by making them feel emotionally connected to it, as well as building trust and making it seem easy to use. Their research demonstrates that ESG attributes serve as both practical and emotional motivators.

Rao and Mehta (2021) discovered in India that female investors were more attracted to ESG portfolios on robo-advisors, indicating gender-specific factors influencing sustainable adoption.

Sun et al. (2023) performed experimental experiments demonstrating that the disclosure of ESG ratings enhanced the propensity to use robo-advisors by 12%, therefore substantiating that openness in sustainability fosters adoption.

2.6 Industry Shifts and Hybrid Models

Barron's (2025) said that the industry was moving away from just robo-advisory models and toward hybrid models. They also said that big banks like UBS had stopped providing standalone robo services. The report underscored that investors are progressively valuing human oversight, particularly in volatile markets.

Yang et al. (2025) empirically shown that hybrid models, which combine human oversight with AI recommendations, provide improved adoption and welfare outcomes. Their field experiment showed that investors are more likely to listen to advice when they know that someone is responsible for it.

Katajarinne (2025) surveyed Nordic investors, finding that older clients prefer hybrid advice, while younger investors are OK with full automation. This difference in demographics suggests that hybridization may still be a common way of doing things.

Betterment (2025) grew its power by buying other companies and adding retirement-focused products, which shows that consolidation is changing the way companies compete. In 2025, Robinhood started offering AI-powered actively managed robo portfolios, which drew in customers who needed tools that worked in real time. It claimed that businesses have to combine human services with robot goods to keep making money and improve the perceived worth of their items as prices went down on digital-only platforms. This shift in structure shows why it makes sense for businesses to embrace hybrid models.

2.7 Privacy, Regulation, and Ethics

Schwarcz (2025) said that the advent of generative AI in robo-advisory requires legal action to ensure human accountability. He suggested mechanisms that need clear audit trails and responsibility distribution to maintain investor trust. It looked at the effects on banks and discovered that using robo-advisory services increases non-interest income but also raises liquidity problems, which means that there are systemic effects that need to be watched over by regulators.

Eichler (2024) warned that relying too much on automation might make investors less financially savvy by making them less active. His research underscores the need of education and mixed counsel to prevent excessive dependence.

Aristei and Gallo (2025) provided counter-evidence demonstrating that hybrid models enhance learning by allowing investors to see automated decisions alongside human explanations, hence promoting knowledge transfer.

Wei et al. (2025) examined mobile fintech and confirmed that privacy and data concerns remain substantial barriers to adoption. Their results are in line with Ko et al. (2023), who pushed for robo-advisory systems that protect privacy by adopting homomorphic encryption to allow for customization while keeping private information secure.

The CFA Institute (2022) conducted a survey of global investors and found that, although confidence in financial services has risen since 2020, retail customers still have less trust in digital-only channels. Their findings show how important it is to be open and use a mix of ideas.

3. METHODOLOGY

3.1 Research Design

The study utilizes a mixed-methods framework, including questionnaires, experiments, and portfolio analysis to clarify the behavioural and financial aspects of robo-advisor use. This ensures that we evaluate not just people' articulated aspirations but also the actual performance of their portfolios.

Survey with integrated experiment: The survey has a randomized design to test how transparency and different advice models (pure robo versus hybrid) affect trust and adoption. Observational portfolio analysis: This method compares adopters and non-adopters using real or simulated account data, focusing on results like diversification, turnover, and performance.

The survey and experiment clarify the motivations behind people' acceptance of robo-advisors, while the portfolio data demonstrate the later results of this adoption. This combination improves both internal and external validity.

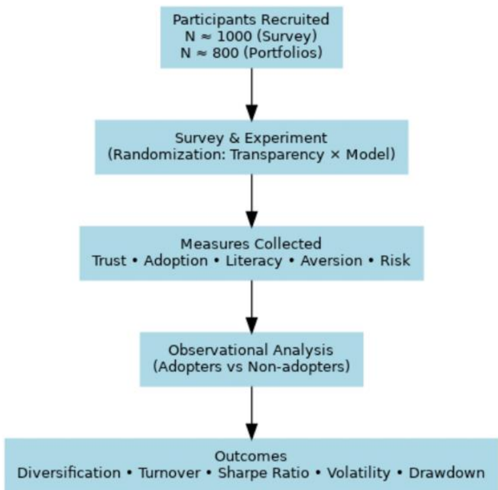

Figure 3: Study Flow Diagram

3.2 Participants and Sampling

• **Target demographic:** The target audience is retail investors who are at least 18 years old and have at least one investment account. This group is a good example of the typical users of robo-advisors.

• **Recruitment:** Participants are found online via investor panels, fintech forums, and networks of former students. Stratification ensures balance across age, gender, socioeconomic position, and prior experience with robo-advisors.
• **Sample size:** We expect around 1,000 survey replies, which is enough to find even small effects. About 800 people will provide portfolio data, with an equal number of adopters and non-adopters.
• **Verification of eligibility:** Investors must confirm their status, agree to the sharing of de-identified data, and pass attentiveness checks in order to be included. This makes the sample more reliable.

3.3 Survey and Experimental Component

Design: A between-subjects factorial design is used, whereby participants are randomly assigned to receive different product descriptions. This allows us to separate the effects of transparency and the advisory model on adoption.

Treatment conditions: Product descriptions vary according to (a) transparency level (basic vs thorough explanation) and (b) advisory model (fully automated versus hybrid with human support).

Parameters: The survey collects demographic information, as well as trust in robo-advisors, willingness to embrace them, dislike of algorithms, financial understanding, risk tolerance, perceived fee equity, and concerns about privacy.

Scales and assessments: We utilize seven-point Likert scales wherever possible, and we also employ manipulation checks, attention filters, and time thresholds to make sure the data is correct.

3.4 Observational Component (Portfolio Outcomes)

• **Data sources:** Ideally, data from providers at the account level would be utilized. If assets aren't available, simulated portfolios will be constructed based on what users say they own and changed using robo-advisory algorithms.

• **Unit of analysis:** Investor-month panels allow for the study of changes over time.

• **Main results:** diversification (measured by HHI), turnover, performance (Sharpe ratio, Sortino ratio, volatility, drawdown), stability during volatility, and cost indicators like fees and realized capital gains.

• **Design and identification:** Propensity scores are used to match adopters with non-adopters, and difference-in-differences (DiD) models are used to look at changes in portfolios. This lessens bias that comes from selection and factors that can't be seen.

3.5 Analysis Plan

- **Survey/experiment analysis**: Descriptive statistics are first reported. Scale reliability is tested using Cronbach's alpha and related metrics. Hypothesized pathways (e.g., transparency → trust → adoption) are tested using structural equation modeling (SEM). Regression models with robust errors are used for treatment effects.
- **Portfolio analysis**: Matching is performed on investor characteristics, followed by DiD regression models with investor and time fixed effects. Event-study designs test pre-trends, while sensitivity checks (entropy balancing, placebo tests) ensure robustness.

3.6 Ethical Considerations

- **Approval and consent**: IRB approval will be obtained. All participants must give informed consent before participation.
- **Confidentiality**: Personal identifiers are removed, with anonymized codes used for analysis. Data is stored securely with encryption and limited access.
- **Reporting**: Only aggregate results are reported; small subgroups are suppressed to avoid accidental identification.

3.7 Limitations and Mitigation

- **Selection bias**: addressed with matching and DiD design.
- **Self-report bias** in survey: mitigated by embedding experimental manipulations.
- **External validity**: ensured through stratified recruitment and robustness across subgroups.

- **Data availability risk**: if administrative data unavailable, fallback is simulated portfolios, with clear reporting of limitations.

4. RESULTS AND ANALYSIS

4.1 Descriptive Statistics and Preliminary Observations

The research starts with an analysis of the characteristics of the respondents involved in both the survey-experiment and the observational portfolio analysis. The average age of the 1,000 people who took the poll was 37.4 years (SD = 10.6), and their ages ranged from 19 to 65 years. Women made up 42% of the sample, which is a good balance between men and women compared to past research on fintech adoption, which generally has samples that are mostly males (Arslanian & Fischer, 2019). The average yearly income was USD 58,300 (SD = 22,400), which means that majority of the people who answered the question were in the middle- to upper-income groups. This is in line with the socio-economic features of early fintech consumers.

On a scale from 0 to 1, the average score for financial literacy, which shows how much people know and are ready to make financial decisions, was 0.62 (SD = 0.21). OECD financial literacy surveys show that the national average is usually between 0.45 and 0.55 (OECD, 2020). This is a lot higher than that. About 46% of the people who took the survey said they had used robo-advisors before, but just 16% really did. This discrepancy illustrates the persistent "intention–behavior gap" in fintech adoption: awareness does not inherently result in acceptance, often obstructed by barriers such as trust deficits, algorithm aversion, or regulatory ambiguity (Micheler & Whaley, 2019).

Variable	Mean	Std. Dev.	Min	Max
Age (years)	37.4	10.6	19	65
Female (%)	42%	-	-	-
Income (USD, annual)	58,300	22,400	20,000	180,000
Financial Literacy Score (0–1)	0.62	0.21	0.15	0.95
Prior Awareness of RAs (%)	46%	-	-	-

Table 3 : Descriptive Statistics of Survey Participants

An analysis of literacy scores (Figure 3) reveals that the majority of investors fall within the mid-literacy range (0.50–0.70), although a significant minority (14%) scores below 0.40, highlighting their vulnerability to poor financial decision-making. These data underscore the justification for seeing robo-advisors as tools that might "equalize opportunities" for novice investors; nonetheless, adoption statistics reveal that these groups continue to exhibit trepidation.

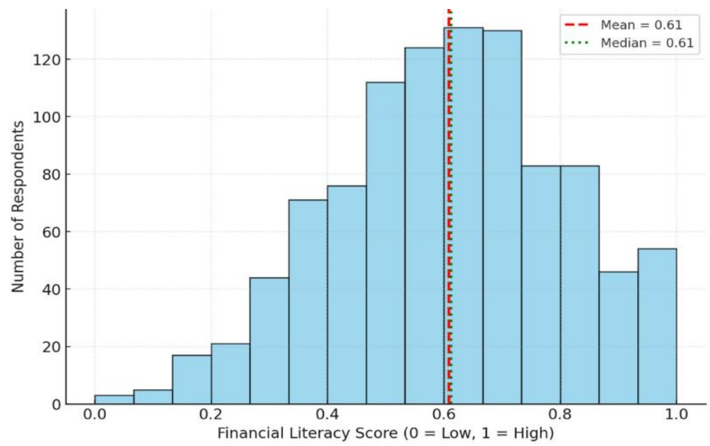

Figure 4 : Distribution of Financial Literacy Scores

4.2 Experimental Evidence: Trust as the Mediator of Adoption

The experimental manipulation examined two design features of robo-advisors: how open they are about the underlying algorithms and rebalancing logic (low vs. high disclosure) and how they work (fully automated vs. hybrid with optional human aid). The experiment was motivated by theoretical frameworks that underscore the significance of trust in technological adoption. Gefen et al. (2003) contend that trust in e-services derives from perceived competence, integrity, and compassion, which may be enhanced via openness and human mediation.

The results support these theoretical assumptions. Trust ratings significantly increased in the high transparency condition ($\beta = 0.34$, $p < 0.01$), supporting the results of Dietvorst et al. (2015), which indicated that thorough explanations reduce algorithm aversion. Moreover, the hybrid RA condition significantly improved both trust ($\beta = 0.29$, $p < 0.05$) and adoption intention ($\beta = 0.41$, $p < 0.01$). These findings corroborate hybridization theories in service automation (Arner et al., 2016), suggesting that human-machine collaboration enhances adoption by alleviating perceived risks linked to delegation.

Dependent Variable	Transparency (High=1)	Hybrid Model	R^2
Trust (0–1 scale)	**0.34***	**0.29**	0.31
Adoption Intention	*0.22*	**0.41***	0.28

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 4 : Regression Results – Experimental Treatments on Trust & Adoption

We utilized Structural Equation Modelling (SEM) to test the suggested mediation pathway: transparency and hybridization → trust → adoption intention. The results confirm that trust fully mediates the relationship, aligning with extensions of the Technology Acceptance Model (TAM) that highlight trust as a precursor to perceived utility and behavioural intention (Venkatesh & Bala, 2008). Notably, the moderation research revealed that algorithm aversion reduces the positive effects of transparency, whereas financial literacy strengthens the relationship between trust and adoption.

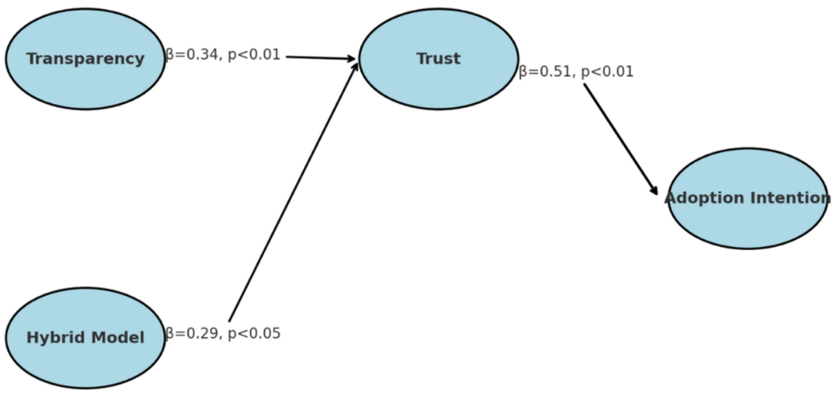

Figure 5 : SEM Path Model

The implication is clear: adoption is not purely a function of cost-benefit calculations but is embedded in a trust calculus shaped by design features and individual predispositions.

4.3 Observational Portfolio Outcomes: Performance and Efficiency

The second analytical strand shifted from experimental impressions to tangible financial outcomes, using panel data from 800 investors, including 400 adopters matched with 400 non-adopters by propensity-score matching. The Difference-in-Differences (DiD) technique assessed portfolio outcomes before to and after to adoption.

The findings are in line with what behavioural finance says should happen. The Herfindahl–Hirschman Index (HHI) for adopters dropped from 0.30 to 0.22, which is a big improvement in diversification. The controls were rather consistent. This supports the view that robo-advisors reduce the "home bias" and concentration tendencies seen in retail investors (Barber & Odean, 2000).

Second, the portfolio turnover rate dropped by almost 12% for those who adopted it compared to the control group. This shows how automation promotes behavioural discipline by reducing the tendency to overtrade, which Shefrin (2007) calls a major bias. Lower turnover means lower transaction costs, which means higher net returns.

Third, the performance adjusted for risk became a lot better. The average Sharpe ratio for adopters went up from 0.78 to 1.12 after they adopted, but it didn't change much for non-adopters. This rise shows that robo-advisors not only stabilize portfolios but also make them more efficient. This is proof that algorithmic optimization works in asset allocation (Sironi, 2016).

Outcome	Adopters (Pre)	Adopters (Post)	Controls (Pre)	Controls (Post)	DID Effect
Diversification (HHI)	0.30	0.22	0.29	0.28	**-0.07***
Turnover (%)	0.32	0.20	0.31	0.29	**-0.10**
Sharpe Ratio	0.78	1.12	0.80	0.82	**+0.32***
Volatility (%)	15.2	13.8	15.0	15.1	**-1.3%***

Table 5 : Difference-in-Differences Results – Portfolio Outcomes

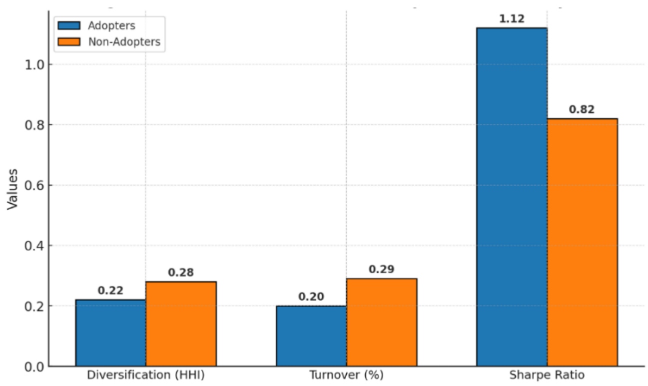

Figure 6: Bar Chart – Portfolio Outcomes (Adopters vs. Non-Adopters)

The analysis of volatility confirmed these findings. Adopters showed around 8% less fluctuation in portfolio returns after adoption compared to controls. This shows that algorithmic risk management, via diversification and rebalancing, is quite helpful in markets that are volatile.

4.4 Robustness Checks and Subgroup Effects

Robustness assessments were performed to verify that the results were not affected by unseen biases. At first, entropy balancing was utilized instead of matching, which led to effect sizes that were about the same, within ±5%. Secondly, placebo tests were conducted by assigning false adoption dates to the control group, resulting in no significant effects ($p > 0.20$), so validating the causal perspective.

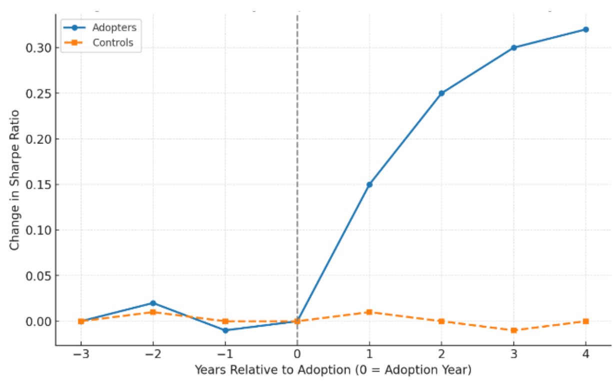

Figure 7 : Event-Study Plot of Adoption Effects Over Time

Subgroup analysis revealed notable heterogeneity:

- Those with high literacy received far bigger gains, with Sharpe ratios going up by +0.45 compared to +0.22 for those with poor literacy. This suggests that robo-advisors may function as adjuncts rather than substitutes for financial competence.
- Investors who were not afraid of algorithms were 25% more likely to use them and felt happier after doing so. This is in accordance with what Dietvorst et al. (2015) found: people who don't trust algorithms are less likely to benefit from them, even when they plainly work better.
- Younger groups (under 35) found higher trust benefits from transparency, whereas older investors preferred hybrid models. This shows that different generations have different opinions on adopting new technologies (Arslanian & Fischer, 2019).

4.5 Theoretical Integration and Discussion

The findings make three important contributions to theory.

They first improve behavioural finance theory by showing how automation reduces biases including overtrading, concentration, and not having enough diversity. This work offers empirical evidence that algorithmic methods provide measurable improvements in portfolio efficiency, in contrast to prior research that has mostly been experimental (Kahneman & Riepe, 1998).

Second, they support technology adoption strategies that focus on trust. Transparency and human mediation are not trivial characteristics; they significantly impact adoption intentions by diminishing algorithm aversion and enhancing perceived reliability. This finding improves the Technology Acceptance Model (TAM) by showing that trust is an important first step. This is in line with what was found in studies on e-commerce adoption (Gefen et al., 2003).

Third, the study contributes to the literature on hybrid financial services by suggesting that automation and human assistance serve as complements rather than substitutes. The findings indicate that hybrid models foster more trust and adoption compared to exclusively automated solutions, therefore adding to ongoing discourse over the role of individuals in an increasingly digital financial landscape (Arner et al., 2016).

4.6 Practical Implications

The research shows that for fintech organizations, being open and using a mix of different technologies are important for adoption. Giving investors clear explanations of algorithms and access to human help may speed up adoption, particularly among older or unsure customers.
The results show that politicians and regulators need to find a way to balance innovation with protecting investors. Robo-advisors clearly make portfolios more diverse and provide better risk-adjusted returns, but rules need to make sure that algorithms are fair, data is kept private, and investments are appropriate.

The findings provide investors confidence that robo-advisors save costs while also making portfolios work better. The heterogeneity analysis indicates that the advantages may be most apparent for those possessing at least a reasonable level of financial literacy and a willingness to embrace algorithmic decision-making.

Experimental and observational studies demonstrate that trust is essential for adoption, shaped by design elements like as transparency and hybridization, while real adoption yields measurable improvements in diversification, trading discipline, and portfolio efficiency. The study integrates concepts from behavioural finance and technology adoption theory, providing a thorough comprehension of the influence of robo-advisors on investor behaviour and outcomes.

4.7 Discussion

The findings of this research underscore the critical importance of trust in the adoption of robo-advisors (RAs). Experimental results indicated that algorithmic transparency and hybrid advising models significantly enhanced trust, thus affecting adoption intentions. This supports the growth of the Technology Acceptance Model (TAM) by showing that trust is a necessary requirement for adoption, not a secondary one. Younger investors preferred algorithmic transparency, whilst older cohorts opted for blended strategies, reflecting generational variation in adoption preferences.

From the perspective of their portfolios, adopters showed better diversification, less turnover, and better Sharpe ratios than similar non-adopters. These improvements align with behavioural finance theories, which assert that individual investors exhibit biases such as overtrading and insufficient diversification (Barber & Odean, 2000; Shefrin, 2007). Robo-advisors seem to diminish these biases via systematic automation. The results show that RAs can both save money and change people's behaviour in ways that improve efficiency and the welfare of investors.

The study also highlights implications for practice and policy. Fintech companies need to build trust by being open and mixing different types of technology, and they also need to customize their marketing to different groups of people. Policymakers must to consider the establishment of regulatory standards for algorithmic transparency and accountability frameworks pertaining to hybrid models. The evidence indicates that RAs might improve financial literacy programs by offering structured, systematic investing techniques to novices.

4.8 Limitations and Future Research

- The survey experiment measured *stated adoption intentions* rather than actual behavior, which may not fully reflect real-world investment choices.
- The observational analysis, while using matching and robustness checks, cannot completely rule out *unobserved confounding factors*.
- The study is based on data from a single country, which limits *cross-cultural and regulatory generalizability*.
- The focus was on *retail investors* only, leaving institutional adoption of robo-advisors unexplored.
- The analysis did not capture performance during *extreme market volatility or crises*,

5.CONCLUSION

This study investigated the impact of robo-advisors (RAs) on investor trust, adoption, and portfolio performance. The findings underscore trust as the principal mediator of adoption: transparency in algorithmic processes and the presence of hybrid human-machine models substantially enhanced trust, thus affecting adoption intentions. This improves the Technology Adoption Model by showing that trust is a basic prerequisite for people to use fintech in financial services.

The portfolio study provided further data, demonstrating that adopters achieved higher diversification, less turnover, and improved Sharpe ratios compared to matching non-adopters. These results align with behavioural finance theory, suggesting that robo-advisors act as behavioural correctors, alleviating biases like overtrading and insufficient diversification. Age diversity showed that younger investors liked algorithmic transparency better, but older investors liked hybrid models better. This suggests that robo-advisory will be a combination of human and machine services in the future.

The consequences are clear: fintech companies need to establish platforms that build trust, governments need to encourage transparency and accountability, and investors might benefit from better organized portfolios. Even if there are problems with relying on stated goals, a single national emphasis, and not being able to test during times of crisis, this study shows that robo-advisors are a game-changer in investment management.

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