

Original Research Article

Artificial Intelligence and Mutual Fund Investment Decisions: A Mediation Analysis of the Role of Investment Confidence

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1. Introduction

Artificial intelligence (AI) has rapidly permeated retail financial services, reshaping how investors access information, evaluate alternatives, and execute transactions. From robo-advisory platforms that automate portfolio allocation to chatbots that deliver personalised guidance, AI-driven tools are now embedded throughout the mutual fund distribution channel (D'Acunto, Prabhala, & Rossi, 2019; Philippon, 2016). These technologies promise lower costs, broader access, and faster decision support, yet they also raise questions about how cognitive and affective responses to AI translate into actual investment behaviour. Understanding this translation process is critical for fund houses, regulators, and platform designers seeking to harness AI's potential without distorting investor decision-making.

Three psychological constructs are repeatedly invoked in the technology adoption literature: awareness, adoption, and trust (Davis, 1989; Gefen, Karahanna, & Straub, 2003; Venkatesh, Morris, Davis, & Davis, 2003). Awareness reflects the cognitive recognition that AI exists and is relevant to a task; adoption captures the behavioural integration of AI tools into routine practice; trust denotes the affective willingness to rely on AI-generated outputs. Although these constructs are well established in the technology acceptance literature, their differential and joint effects on mutual fund investment decisions remain underexplored, particularly in markets where retail participation is expanding alongside AI penetration.

A plausible pathway through which AI-related attitudes might influence investment behaviour is investment confidence. Behavioural finance research has long recognised that subjective confidence shapes risk-taking, portfolio allocation, and trading frequency (Statman, 2018; Shiller, 2015). If awareness of AI tools, hands-on adoption, and trust in their outputs each bolster an investor's sense of competence, then investment confidence could serve as a mediating mechanism channelling AI exposure into actual investment decisions. This mediation logic is consistent with broader models in which technology acceptance influences behaviour partly through self-efficacy and perceived control (Venkatesh et al., 2003). Yet the empirical validity of this pathway has not, to our knowledge, been rigorously tested in the mutual fund context.

The present study addresses this gap using a GLM mediation framework with a sample of 300 retail investors. The model specifies investment confidence as a mediator linking three AI-related antecedents to mutual fund investment decisions. Indirect effects are estimated via the delta method, with 95% confidence intervals used to evaluate statistical significance. The central research question is whether investment confidence transmits the influence of AI constructs to investment decisions, or whether AI constructs instead exert direct effects that bypass the hypothesised mediator. The remainder of the paper reviews the literature and develops hypotheses, describes the methodology, reports the results, discusses the implications, acknowledges limitations, and concludes.

2. Literature Review and Hypotheses

2.1 AI Awareness, Adoption, and Trust in Financial Contexts

The technology acceptance literature provides a robust scaffold for understanding how individuals adopt new technologies. Davis's (1989) Technology Acceptance Model (TAM) identifies perceived usefulness and perceived ease of use as the primary determinants of technology adoption, while the Unified Theory of Acceptance and Use of Technology (UTAUT) extends this framework to incorporate social influence, facilitating conditions, and performance expectancies (Venkatesh et al., 2003). These models have been widely applied to consumer and financial technologies, including online banking, mobile payments, and robo-advisory services (Gefen et al., 2003; Goldfarb & Tucker, 2019).

Awareness is the cognitive precursor to adoption: before individuals can adopt a technology, they must recognise its existence, understand its functionality, and perceive its relevance. In AI-in-finance contexts, awareness encompasses knowledge of robo-advisors, AI-driven portfolio analytics, algorithmic trading tools, and machine-learning-based risk assessment systems. Higher awareness is theorised to facilitate more informed investment decisions by broadening the decision set and reducing information asymmetry. Adoption, by contrast, reflects the behavioural integration of AI tools into an investor's routine - the actual use of robo-advisors, reliance on AI-generated recommendations, and incorporation of algorithmic outputs into portfolio decisions. Adoption transforms latent awareness into active engagement and is expected to exert a more proximal influence on investment outcomes.

Trust occupies a distinct affective-cognitive space. Drawing on the online trust literature (Hoffman, Novak, & Peralta, 1999), trust in AI reflects the investor's belief that AI systems are reliable, transparent, and aligned with their interests. Trust is particularly salient in financial contexts where decisions involve risk, uncertainty, and delegation of authority to opaque algorithmic processes. Gefen et al. (2003) demonstrated that trust operates alongside perceived usefulness in shaping online consumer behavior, and subsequent work has extended this insight to algorithmic and AI-mediated services. Together, awareness, adoption, and trust constitute a tripartite framework for understanding how investors engage with AI in financial decision-making.

2.2 Investment Confidence and Behavioural Finance

Investment confidence - the subjective sense of competence an investor feels about making financial decisions - occupies a central role in behavioural finance. Kahneman and Tversky's (1979) prospect theory established that decision-making under risk is shaped by subjective perceptions rather than objective probabilities, while subsequent work on heuristics and biases (Tversky & Kahneman, 1974) demonstrated that overconfidence, anchoring, and availability biases systematically distort investment judgments. Shiller's (2015) account of irrational exuberance further underscores the role of psychological confidence in driving market-level phenomena, and Statman (2018) has articulated a second-generation behavioural finance framework in which confidence, emotions, and cognitive framing interact to shape individual investment behaviour.

Lo's (2017) adaptive markets hypothesis offers a complementary perspective, suggesting that investor confidence is not a fixed trait but an evolving response to environmental feedback, learning, and technological change. Exposure to AI tools - which promise data-driven insights, reduced emotional interference, and disciplined execution - may plausibly bolster investment confidence by enhancing perceived competence. Lusardi and Mitchell (2014) emphasise that financial literacy and competence are foundational to sound investment decisions, raising the question of whether AI-mediated information access functions analogously to literacy in bolstering confidence. If AI awareness, adoption, and trust each enhance an investor's sense of competence, investment confidence becomes a theoretically plausible mediator of the AI-investment decision relationship.

2.3 Hypotheses

Integrating the technology acceptance and behavioural finance literatures, the study proposes a parallel mediation model in which three AI-related constructs influence mutual fund investment decisions both directly and indirectly through investment confidence. The hypotheses are as follows:

H1a. AI awareness has a positive direct effect on mutual fund investment decisions.

H1b. AI adoption has a positive direct effect on mutual fund investment decisions.

H1c. Trust in AI has a positive direct effect on mutual fund investment decisions.

H2. Investment confidence mediates the relationships between AI awareness, AI adoption, trust in AI, and mutual fund investment decisions.

The mediation hypothesis (H2) is the focal test of the study. If supported, it would suggest that AI-related constructs shape investment behaviour partly by enhancing subjective confidence. If rejected, the finding would imply that AI constructs influence investment decisions through direct pathways that bypass investment confidence, raising questions about the construct's theoretical centrality in the AI-finance nexus.

3. Methodology

3.1 Participants and Sampling

The study employed a cross-sectional survey design. A sample of 300 retail investors was recruited through an online panel, with eligibility restricted to individuals aged 21 years and older who reported holding at least one mutual fund investment in the preceding 12 months. Sample size was determined a priori to provide adequate statistical power for detecting small-to-medium indirect effects in a mediation framework, following the recommendations of Hayes (2018). The sample size of 300 exceeds the minimum of 200 commonly recommended

for detecting indirect effects with bootstrap or delta-method confidence intervals and provides sufficient observations for stable parameter estimation across the four-item indicators of each construct. The recruitment platform employed quota sampling on age and income to mitigate demographic skew. While the sample is not nationally representative, it provides a reasonable basis for testing the hypothesised relationships. All participants provided informed consent electronically, and the study protocol was reviewed in accordance with standard ethical guidelines for survey research with human participants.

3.2 Measures

Five constructs were measured using multi-item scales: AI awareness, AI adoption, trust in AI, investment confidence, and mutual fund investment decision. Each construct was operationalised with four items (indexed 1 through 4), reflecting increasing intensity or specificity. AI awareness items captured recognition of AI applications in finance, from general familiarity (item 1) to specific knowledge of AI-driven mutual fund tools (item 4). AI adoption items measured behavioural integration, from occasional use of AI features (item 1) to routine reliance on AI-generated investment recommendations (item 4). Trust in AI items assessed confidence in AI's reliability, transparency, and alignment with investor interests, with item 4 capturing the strongest trust endorsement.

Investment confidence items measured subjective competence in making investment decisions, with item 1 reflecting general confidence and item 4 reflecting confidence under market uncertainty. Mutual fund investment decision items captured behavioural intentions and actual decisions, with item 1 representing basic allocation decisions and item 4 representing more committed investment actions. Items were rated on Likert-type scales, and item-level scores were analysed as indicators of each construct. The four-level structure enabled examination of dose-response patterns across intensity levels.

3.3 Procedure

The survey was administered online and took approximately 15 minutes to complete. Participants first provided demographic information, then responded to the AI awareness, AI adoption, and trust in AI items, followed by the investment confidence items, and finally the mutual fund investment decision items. The order was fixed to minimize order effects, with antecedent constructs preceding the mediator and outcome. Participants received a small monetary incentive upon completion. Data quality checks excluded inattentive respondents via straight-lining detection and minimum response time thresholds.

3.4 Analytical Strategy

The hypothesised relationships were tested using a Jamovi 2.6.26, applying a GLM mediation framework with two linked models. The mediator model (m1) regressed investment confidence on the three antecedents: $\text{Investment_Confidence} \sim \text{AI_Awareness} + \text{AI_Adoption} + \text{Trust_in_AI}$. The full model (m2) regressed mutual fund investment decisions on investment confidence and the three antecedents: $\text{Mutual_Fund_Investment_Decision} \sim \text{Investment_Confidence} + \text{AI_Awareness} + \text{AI_Adoption} + \text{Trust_in_AI}$. Three indirect effects were estimated, one per antecedent, each passing through investment confidence to the investment decision outcome.

Indirect effects were estimated using the delta method to construct 95% confidence intervals, appropriate for large-sample inference on products of regression coefficients (MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002). An indirect effect was deemed significant when its 95% confidence interval excluded zero. Standardized betas (β) were reported for all paths. The analysis was conducted at the item level, with each of the four indicators

of each AI construct serving as a separate predictor, yielding twelve indirect effect estimates (four per antecedent). It should be noted that the dependent variable was treated as a factor in the analysis software, prompting a warning that it should ideally be continuous. This issue is addressed in the limitations section; nevertheless, the directional and inferential patterns remain informative for testing the hypothesised relationships.

4. Results

4.1 Direct Effects on Mutual Fund Investment Decisions

The GLM mediation analysis yielded a clear and consistent pattern of direct effects. AI adoption exhibited the strongest direct influence on mutual fund investment decisions. All four item-level indicators of AI adoption were statistically significant: item 1 (Estimate = 0.252, $\beta = 0.082$, $z = 2.225$, $p = .026$), item 2 (Estimate = 0.695, $\beta = 0.232$, $z = 4.706$, $p < .001$), item 3 (Estimate = 1.108, $\beta = 0.364$, $z = 6.280$, $p < .001$), and item 4 (Estimate = 1.354, $\beta = 0.419$, $z = 6.631$, $p < .001$). The monotonic increase in both raw estimates and standardised betas across the four adoption items indicates a robust dose-response relationship: investors who report deeper behavioural integration of AI tools into their investment routines also report stronger mutual fund investment decisions.

Trust in AI produced a parallel pattern. All four trust items exerted significant direct effects: item 1 (Estimate = 0.303, $\beta = 0.094$, $z = 2.966$, $p = .003$), item 2 (Estimate = 0.634, $\beta = 0.214$, $z = 5.247$, $p < .001$), item 3 (Estimate = 1.016, $\beta = 0.346$, $z = 7.013$, $p < .001$), and item 4 (Estimate = 1.109, $\beta = 0.338$, $z = 6.583$, $p < .001$). The dose-response pattern was again evident, with effect sizes climbing sharply from item 1 to item 3 before plateauing between items 3 and 4, suggesting a saturation effect at the highest trust levels.

AI awareness showed a somewhat different pattern. The first awareness item was not statistically significant (Estimate = 0.182, $\beta = 0.054$, $z = 1.652$, $p = .099$), but the higher-intensity items were all significant: item 2 (Estimate = 0.441, $\beta = 0.157$, $z = 3.384$, $p < .001$), item 3 (Estimate = 0.679, $\beta = 0.229$, $z = 4.238$, $p < .001$), and item 4 (Estimate = 0.877, $\beta = 0.255$, $z = 4.667$, $p < .001$). The non-significance of the lowest-intensity awareness item, combined with significant effects at higher levels, suggests that mere peripheral awareness of AI in finance is insufficient to influence investment decisions; what matters is specific, applied knowledge of AI-driven mutual fund tools.

4.2 Effects on Investment Confidence (Mediator)

A critical and unexpected finding emerged from the mediator model (m1). None of the twelve paths from the AI constructs to investment confidence reached statistical significance. AI awareness items produced betas from -0.006 to -0.104 ($p = .941$ to $.461$); AI adoption items produced betas from -0.046 to 0.126 ($p = .629$ to $.440$); and trust in AI items produced betas from -0.063 to 0.044 ($p = .662$ to $.728$). In every case, the 95% confidence intervals comfortably included zero. Similarly, the path from investment confidence to mutual fund investment decisions in the full model was negligible (Estimate = $3.39\text{e-}5$, $\beta = 3.83\text{e-}5$, $z = 0.0017$, $p = .999$).

4.3 Indirect Effects

Consistent with the null paths in the mediator model, all twelve estimated indirect effects were non-significant. Every indirect effect had $p = .999$, and every 95% confidence interval tightly bracketed zero. For example, the indirect effect of AI_Awareness4 through investment confidence was $-1.37\text{e-}5$ (95% CI [-0.016, 0.016]); AI_Adoption4 was $1.56\text{e-}5$ (95% CI [-0.018, 0.018]); and Trust_in_AI4 was $-7.97\text{e-}6$ (95% CI [-0.009, 0.009]). The standardised betas for all indirect effects were on the order of $1\text{e-}6$, four to five orders of magnitude smaller than

the corresponding direct effects. Hypothesis H2 was therefore decisively rejected: investment confidence does not mediate the relationships between AI constructs and mutual fund investment decisions.

4.4 Total Effects

Because the indirect effects were effectively zero, the total effects closely mirrored the direct effects. For all twelve antecedent-outcome paths, total effect estimates and standardised betas were nearly identical to their direct-effect counterparts, differing only at the fourth decimal place. For instance, the total effect of AI_Adoption4 was 1.354 ($\beta = 0.419$, $p < .001$), compared with a direct effect of 1.354 ($\beta = 0.419$, $p < .001$). This correspondence confirms that the influence of AI constructs on investment decisions operates almost entirely through direct pathways rather than through investment confidence. Table 1 summarises the key effects. The combined pattern of significant direct effects and null indirect effects supports H1a (at higher awareness levels), H1b, and H1c, while rejecting H2.

Table 1. Selected Indirect, Direct, and Total Effects from the GLM Mediation Model (N = 300)

Path	Estimate	Beta	z	p	95% CI
Indirect: AI_Awareness4 -> Conf -> Decision	-1.37e-5	-3.98e-6	-0.0017	0.999	[-0.016, 0.016]
Indirect: AI_Adoption4 -> Conf -> Decision	1.56e-5	4.83e-6	0.0017	0.999	[-0.018, 0.018]
Indirect: Trust_in_AI4 -> Conf -> Decision	-7.97e-6	-2.43e-6	-0.0017	0.999	[-0.009, 0.009]
Investment Confidence -> Decision	3.39e-5	3.83e-5	0.0017	0.999	[-0.039, 0.039]
Direct: AI_Awareness4 -> Decision	0.877	0.255	4.667	<.001	[0.509, 1.245]
Direct: AI_Adoption4 -> Decision	1.354	0.419	6.631	<.001	[0.954, 1.754]
Direct: Trust_in_AI4 -> Decision	1.109	0.338	6.583	<.001	[0.778, 1.439]
Total: AI_Awareness4 -> Decision	0.877	0.255	4.664	<.001	[0.508, 1.245]
Total: AI_Adoption4 -> Decision	1.354	0.419	6.627	<.001	[0.953, 1.754]
Total: Trust_in_AI4 -> Decision	1.109	0.338	6.575	<.001	[0.778, 1.439]

Note. Only the highest-intensity item (item 4) of each construct is shown; patterns for items 1-3 are consistent. β = completely standardised effect size. CI = confidence interval via the delta method.

5. Discussion

5.1 Summary of Key Findings

This study set out to test whether investment confidence mediates the relationships between three AI-related constructs and mutual fund investment decisions. The results provide a clear answer: it does not. All twelve indirect effects through investment confidence were statistically indistinguishable from zero, with p-values of .999 and confidence intervals tightly bracketing zero. The mediator itself was not significantly predicted by any AI construct,

nor did it significantly predict mutual fund investment decisions. The mediation pathway, hypothesized on the basis of technology acceptance and behavioural finance theory, was not supported.

In contrast, the direct effects told a coherent story. AI adoption and trust in AI exerted strong, positive, and significant direct effects across all four item levels, with standardised betas reaching 0.419 and 0.338 at the highest intensity. AI awareness produced significant direct effects at higher intensity levels but not at the lowest, suggesting that peripheral awareness is insufficient to influence behaviour. The dose-response pattern across item intensity levels for all three constructs reinforces the interpretation that deeper engagement with AI - cognitive (awareness), behavioural (adoption), or affective (trust) - translates directly into stronger mutual fund investment decisions without requiring investment confidence as an intermediate mechanism.

5.2 Theoretical Implications

The null mediation finding carries several theoretical implications. First, it challenges the assumption, drawn from self-efficacy and technology acceptance literatures, that AI-related attitudes shape investment behavior by bolstering subjective confidence (Venkatesh et al., 2003). In the present data, the AI constructs and investment confidence operate as largely independent predictors, with only the former exerting meaningful influence on investment decisions. This suggests that the role of confidence in technology-mediated financial decision-making may be more nuanced than prevailing models assume, and that the self-efficacy pathway central to TAM and UTAUT may not generalise cleanly to AI-mediated investment contexts.

Second, the strong direct effects of AI adoption and trust in AI are consistent with the thesis that technology acceptance in finance operates through behavioural engagement and affective reliance rather than cognitive appraisal of competence (Gefen et al., 2003; Goldfarb & Tucker, 2019). Investors who actually use AI tools and who trust the outputs those tools generate make stronger investment decisions regardless of how confident they feel. This resonates with D'Acunto et al.'s (2019) findings on robo-advisory, where behavioural and trust-related dimensions of AI engagement were more predictive of investment outcomes than abstract cognitive appraisals. Third, the dose-response pattern for all three AI constructs suggests that the influence of AI on investment decisions is graded rather than threshold-based, aligning with Brynjolfsson, Rock, and Syverson's (2019) characterisation of AI as a general-purpose technology whose effects accumulate through sustained, intensive use rather than one-time adoption.

5.3 Practical Implications

For financial institutions and robo-advisory platforms, the findings suggest that interventions targeting AI adoption and trust are likely to influence investment decisions directly, without needing to first cultivate investment confidence. Platforms seeking to deepen user engagement should prioritise features that facilitate hands-on adoption of AI tools - such as guided onboarding, interactive analytics, and personalised recommendations - rather than features that merely boost confidence through motivational messaging. Trust-building mechanisms, including transparent algorithm explanations, auditable performance track records, and clear disclosure of limitations, are equally important given the strong direct effect of trust on investment decisions.

For regulators, the direct pathway from AI adoption and trust to investment decisions underscores the importance of ensuring that AI-driven financial tools are reliable, transparent, and aligned with investor interests. The finding that AI awareness alone (at low intensity) does not significantly influence decisions suggests that disclosure-based interventions may be insufficient on their own; behavioural and trust-oriented safeguards are

likely to be more effective. For fund houses, the dose-response pattern implies that customer education and engagement programs should be sequenced to move investors along the awareness-adoption-trust continuum rather than treating each dimension in isolation.

6. Limitations and Future Research

Several limitations should be acknowledged. First, the dependent variable - mutual fund investment decision - was treated as a factor in the analysis software, triggering a warning that it should ideally be continuous. While the directional and inferential patterns remain informative, the magnitude of the estimated coefficients should be interpreted with caution, and future studies should ensure the outcome is measured and modelled continuously. Second, the cross-sectional design precludes causal inference. Although the GLM mediation framework specifies directional paths, the data are correlational, and reverse causation or bidirectional effects cannot be ruled out. Longitudinal and experimental designs are needed to establish causal direction.

Third, the reliance on self-report measures introduces the possibility of common method bias and social desirability effects. Future research could complement self-reports with behavioural trace data from robo-advisory platforms, such as login frequency and recommendation acceptance rates. Fourth, the single-sample design limits generalizability; replication across different cultural, regulatory, and market contexts is needed. Finally, the study examined only one candidate mediator. Future research should explore alternative mediators - such as risk perception, financial literacy, perceived behavioural control, or algorithmic aversion - which may yet transmit the influence of AI constructs to investment decisions, tested in a multiple-mediator framework.

7. Conclusion

This study examined whether investment confidence mediates the relationships between AI awareness, AI adoption, trust in AI, and mutual fund investment decisions among 300 retail investors. The GLM mediation analysis produced a decisive null finding: all twelve indirect effects through investment confidence were non-significant, while direct effects of AI adoption and trust in AI were strong, positive, and monotonically increasing across item intensity levels. AI awareness exhibited a similar direct-effect pattern at higher intensity levels. The findings challenge the widely assumed mediation pathway and suggest that AI-related attitudes influence investment behavior through direct mechanisms that bypass investment confidence. For theory, this calls for refined models of technology acceptance in finance that do not rely uncritically on self-efficacy or confidence mediators. For practice, it implies that interventions targeting AI adoption and trust are likely to shape investment decisions directly. Future research should test alternative mediators, employ longitudinal designs, and ensure continuous measurement of the outcome variable.

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