

WHEN ALGORITHMS ADVISE: THE ROLE OF ALGORITHMIC TRUST AND PERCEIVED TRANSPARENCY IN SHAPING INVESTORS' RELIANCE ON AI-GENERATED FINANCIAL ADVICE

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Abstract

While artificial intelligence is increasingly creating financial advice via robo-advisors, algorithmic tools and generative AI assistants, investors are not always taking the advice. This study investigates the influence of perceived AI transparency on investors' trust in AI-driven financial advice, as well as the role of algorithmic trust in this relationship. The cross-sectional survey was given to 310 eligible active retail investors who were introduced to AI-based financial advice tools online in investment communities and at investment-club events, based on trust-formation theory in HAI. Confirmatory factor analysis, reliability and validity tests, and bootstrapped mediation regression (5,000 resamples) were used to analyse data. Perceived AI transparency was found to have a modest but significant relationship with algorithmic trust ($\beta = .165, p = .004$), which in turn had a significant relationship with reliance on AI-generated financial advice ($\beta = .376, p < .001$). The effect of transparency on reliance was also direct, and was similar in magnitude to the effect mediated by trust ($\beta = .133, p = .012$). The transparency–reliance relationship was partially mediated by algorithmic trust (indirect $\beta = .062$, 95% CI [.021, .114]), which accounted for about 32% of the total effect of transparency, and the direct effect of transparency on trust and reliance was comparable in strength. The results indicate that transparency influences reliance in two parallel ways, which has implications for explainable AI design, financial institutions' AI deployment, and the regulation of transparency in FinTech.

1. INTRODUCTION

Artificial intelligence (AI) is now a key component of the financial decision-making infrastructure, transforming the way investors access, process, and respond to financial data. Algorithmic recommendations have been made available to investors at almost all points in the investment journey, with the recent emergence of generative AI chatbots, AI-driven investment tools, and robo-advisory platforms (Cardillo & Chiappini, 2024; Oehler & Horn, 2024; D'Acunto et al., 2019).

This increase is also reflected in the empirical interest in the adoption, assessment, and actions that people take with AI-based financial advice (Amnas et al., 2023; Belanche et al., 2019). Engagement with AI tools for financial decisions also appears to differ significantly across retail investor segments; a small proportion of investors incorporate AI recommendations into their investment decisions on a regular basis, while a larger proportion use AI tools sporadically or for limited purposes like information gathering

(Vijayananth & Saravanabhavan, 2026). This diversity implies that simply offering investors AI-driven advice is not enough to ensure they take it seriously, with significant implications for the financial technology industry, regulators, and researchers assessing the utility of AI-driven advisory tools (Northey et al., 2022; Hildebrand & Bergner, 2021).

Central to this heterogeneity is trust. Algorithmic financial advice is fundamentally different from advice provided by a human advisor, as it is a computational process that is often opaque to the end user, and investors' trust in the algorithmic process depends on their perception of the process' competence, reliability, and trustworthiness (Glikson & Woolley, 2020; Hoff & Bashir, 2015). Research on algorithmic decision aids consistently demonstrates that people do not react to algorithms as they do to other people: reactions from aversion to appreciation depend on the way in which the algorithm's advice is framed, how errors are dealt with and how well people understand how the algorithm works (Dietvorst et al., 2018; Logg et al., 2019; Dietvorst et al., 2015). In financial applications, this is further emphasised by the stakes at hand: the decisions made by an AI have real financial consequences, and the perceived reliability of an AI system is a key precondition for its actual use (Lourenço et al., 2020; Niszczoła & Kaszás, 2020).

The increasing prevalence of advice provided by AI thus leaves a problem in the way of not only access, but also uptake of AI-generated advice (Northey et al., 2022; Zhang et al., 2021). These recommendations involve AI tools like robo-advisors, algorithmic assistants, and generative AI chatbots, which investors regularly interact with, but to what extent they consider them in their investment decisions, or whether they opt out based on their own analysis, is a complex psychological process that is not fully understood (Oehler & Horn, 2024; Greiner et al., 2025; Prahll & Van Swol, 2017). The degree of transparency, that is, how easily investors can understand how an algorithm's recommendation is derived, has been a recurring theme in the algorithmic-advice literature as a potential explanation for this variation (Kleanthous et al., 2022; Hadji Misheva

& Papenbrock, 2022). This leads to the main question that this study aims to answer: What gives investors trust, and ultimately, dependence in AI-generated financial advice? Perceived transparency is a critical antecedent, but it is not just an informational effect (as direct as possible); it is a factor that builds trust in the system (Hildebrand & Bergner, 2021; De Brito Duarte et al., 2023).

Transparency and explainability are widely researched design properties that are expected to positively influence attitudes towards algorithmic decisions (Starke et al., 2022; Jacovi et al., 2021; Kleanthous et al., 2022). There has been a significant focus on trust in AI in general (McGrath et al., 2025; Glikson & Woolley, 2020) and in the context of FinTech and robo-advisory (Devlin et al., 2025; Zarifis & Cheng, 2022; Hildebrand & Bergner, 2021). Another stream focuses on the adoption of algorithmic financial advice from the perspective of technology-acceptance and trust-based models (Amnas et al., 2023; Nourallah et al., 2022; Belanche et al., 2019).

What remains less established is the specific mechanism by which perceived transparency becomes relied upon by means of trust, tested in one integrated model in an investor population engaged in real financial decisions. The concept of mediation-type reasoning is implicit in previous research on trusting beliefs and robo-advisor trust formation (Jacovi et al., 2021; Zhang et al., 2021; Hildebrand & Bergner, 2021), but relatively little research has been conducted that explicitly tests the statistical mediation of reliance on transparency by relying on a separate measure of reliance from general adoption intention. We are not the first to examine the three constructs of transparency, trust, or advice adoption separately, nor do we intend to advance the examination of these constructs. What we do aim to do is to incorporate all three constructs into a single, empirically tested mediation model within the investor decision-making context (Silber et al., 2025; Greiner et al., 2025).

1.1. Research Objectives

The study aims at four goals, which are based on this gap:

RO1: To explore the impact of perceived transparency of AI on algorithmic trust by investors.

RO2: To explore how algorithmic trust influences investors' trust in AI-driven financial advice.

RO3: To investigate how perceived transparency of AI impacts investors' dependence on AI-facilitated financial guidance.

RO4: Does algorithmic trust play a mediating role between perceived AI transparency and investors' reliance on AI advice?

1.2. Research Questions

Corresponding to these objectives:

RQ1: Is there a significant relationship between perceived AI transparency and investors' algorithmic trust?

RQ2: Does algorithmic trust play a significant role in investors' trust of AI-based financial advice?

RQ3: Does perceived AI transparency have a direct impact on investors' dependence on AI-generated financial advice?

RQ4: Does the mediating role of algorithmic trust exist between perceived AI transparency and investors' reliance on AI-generated financial advice?

Theoretically, the study builds on the algorithmic trust and human-AI interaction literatures (Glikson & Woolley, 2020; McGrath et al., 2025) by incorporating transparency and trust into a testable mediation framework specific to financial advisory contexts, thus complementing the call for more mechanism-focused, rather than purely descriptive, accounts of algorithmic decision-making (Jacovi et al., 2021; Starke et al., 2022). The results have several practical implications. The findings help AI/FinTech developers understand if transparent and explainable system design leads to user trust and, ultimately, to users relying on the AI-generated recommendations (Hadji Misheva & Papenbrock, 2022; Silber et al., 2025). This pathway is relevant to financial institutions when they are designing their AI advisory tools to be used in client-facing services, as it helps them

understand how to present and explain the advice to their clients (Devlin et al., 2025; Northey et al., 2022). The study provides valuable insights for investors on how their cognitive processes influence their reliance decisions with AI-powered tools. The results provide empirical evidence to support a debate on the transparency and disclosure demands of automated financial advice, which is currently underway for regulators and policymakers (Helberger et al., 2020; Ingrams et al., 2022).

This study contributes to the literature in three ways. First, it builds and empirically tests an integrated mediation model between perceived AI transparency, algorithmic trust, and reliance on AI-generated financial advice in one investor sample, instead of separately. Second, it distinguishes reliance from behavioural intention or adoption intention, which is in line with literature that calls for a more precise measurement of the extent to which investors rely on and act on algorithmic recommendations (Greiner et al., 2025; Zhang et al., 2021). Third, it offers empirical evidence, derived from bootstrapped mediation analysis on a sample of 310 eligible investors with previous experience of using AI-based financial tools, which can be used for both theory refinement and transparency design decisions in the context of FinTech.

2. Literature Review

From data aggregation and pattern recognition to the creation of personalised investment recommendations through robo-advisors, algorithmic trading platforms, and now, more than ever, generative AI assistants (Roy et al., 2025; Cardillo & Chiappini, 2024), AI has infiltrated every aspect of the investment decision-making process. Initial studies in the field of robo-advisories have mainly focused on using these systems as low-cost alternatives to human portfolio management (Phoon & Koh, 2018; D'Acunto et al., 2019); more recent research has demonstrated AI's potential in generating personalised advice and engaging with clients in real-time (Capponi et al., 2022; Helms et al., 2022). In more recent studies, conversational and generative AI's abilities have also been found to be competitive with, and

in some assessments equal to, traditional robo-advisors in providing financial guidance (Oehler & Horn, 2024). This shift has led the research question from can AI produce good financial advice to will investors do what is suggested by AI, a question that relies not just on the accuracy of the algorithm but also on how investors psychologically process and evaluate the output of AI (Belanche et al., 2019; Devlin et al., 2025).

There is a recurring theme of differentiation between exposure to advice generated by AI and dependence on it in this literature. The AI tools can be used by investors to obtain financial data on a regular basis but not use the recommendations to make any meaningful investment decisions (Northey et al., 2022; Zhang et al., 2021). In this context, reliance means more than being aware of and exposed to an algorithmic recommendation; it is the extent to which a person pays attention to and takes action on a recommendation made by an algorithm (Greiner et al., 2025; Silber et al., 2025). Theoretically, this is important because the learning factors that lead to exposure (for example, accessibility, convenience, low cost) differ from factors that lead to reliance (for example, competence and trustworthiness of the system; Hildebrand & Bergner, 2021; Nourallah et al., 2022). This separation is supported by survey evidence in recent times, which indicates that few respondents report using these tools to get deep insights from AI-generated financial recommendations, while most report using them as additional sources of information but not as decision drivers (Vijayananth & Saravanabhavan, 2026; Nourallah, 2023). This more action-oriented definition and measure of reliance on financial advice generated by AI is consistent with the present study's dependent variable.

The perceived transparency of AI is the degree to which users feel they understand how the AI recommendation was created; this includes the visibility of the data or factors used, the clarity of the rationale behind the recommendations, and the information provided explaining how advice was generated (Hadji Misheva & Papenbrock, 2022; Starke et al., 2022). Perceived transparency is a subjective user judgement that is different

from technical explainability, which is an objective property of how the system is designed (Kleanthous et al., 2022; Jacovi et al., 2021). Previous studies on algorithmic fairness and users' perceptions of the understandability of an algorithmic system demonstrate that users' evaluative reactions to an automated system are independent of the actual accuracy of the system, and that their evaluation of the understandability of the system influences their evaluation of the system (Helberger et al., 2020; Ingrams et al., 2022). In the context of financial advice specifically, transparency has been defined as the extent to which investors believe they can understand the reasons behind a specific recommendation and the information that it was based on (as in this study) (De Brito Duarte et al., 2023).

Algorithmic trust refers to an investor's trust in the competence, reliability, and accuracy of AI tools in finance in particular, which is different from three related but conceptually distinct concepts. It is also distinct from generalized trust in technology, as when people have a general attitude toward computers, independent of their specific purpose (Hoff & Bashir 2015; Glikson & Woolley 2020); from institutional trust, as when they have trust in an organization or firm using the technology and not necessarily the technology itself (Zarifis & Cheng 2022); and from trust in human financial advisors, which relies on interpersonal and professional-relationship dynamics that do not directly transfer to an algorithmic advisor (Lourenço et al. 2020). In the financial space, by contrast, algorithmic trust is object-specific, meaning that it is trust in a specific financial AI tool that will deliver reliable and user-beneficial financial recommendations (McGrath et al., 2025). This specificity doesn't matter in a world where the same level of trust that has been established with one algorithm cannot be assumed to transfer to another one, which means that it is necessary to measure one's trust in an AI-based financial tool and not as a general disposition (Hildebrand & Bergner, 2021).

Familiarity and predictability are important in the formation of trust with an unfamiliar agent, whether human or algorithmic (Glikson &

Woolley, 2020). For algorithmic systems, this form of evidence is more difficult to obtain because the reasoning process is not naturally observable as would be the case in a human advisor's explanations (Jacovi et al., 2021). Perceived transparency fills this void: if investors can understand how and why a system came to a particular recommendation, it may be easier for them to predict how the system works and to verify its outputs, both of which are important factors in the formation of trust (Kleanthous et al., 2022; Starke et al., 2022). Conversational and interactive AI-advisory formats that bring the process of recommending to the foreground for the user are found to be "surrogates of trust", which lower the uncertainty that would otherwise be present when recommending with an opaque algorithmic recommendation system (Hildebrand & Bergner, 2021). In this context, transparency-oriented design has been theorised as a direct tool to create warranted trust in AI systems, which is based on the assumption that trust should be proportional to the actual, evidenced trustworthiness of a system, rather than simply being a matter of faith (De Brito Duarte et al., 2023). By applying the same logic to the financial advisory industry, we suggest that a financial advisory tool that is perceived as transparent would be in a stronger position to evaluate its competence and trustworthiness, resulting in greater trust in the tool by the investors. This results in the first hypothesis:

H1: Perceived AI transparency positively influences algorithmic trust.

Trust serves as an alternative to verification: If a decision-maker trusts an information source, he or she will act on the information without verifying each of the decisions' premises. (Logg et al., 2019) This logic is reflected in the literature on algorithm appreciation, which suggests that when users become confident that an algorithm can perform well, they tend to trust its recommendations as much as – or even more than – similar human recommendations (Logg et al., 2019; Dietvorst et al., 2018). However, when the level of trust is low or impaired, for example, as a result of an algorithmic error, people's reliance will decline significantly, even if the algorithm's

average performance is better than possible alternatives (Dietvorst et al., 2015; Prah & Van Swol, 2017). In the context of FinTech, trust is also a prerequisite for the uptake of robo-advisors and algorithmic advice, as several studies have identified it as the key driver for behavioural intention to use AI financial services, other than perceived usefulness (Belanche et al., 2019; Nourallah et al., 2022; Amnas et al., 2023). Since trust in the competence and reliability of the AI system is supposed to directly lead to higher trust in the recommendations, it is theorised that this trust will directly lead to a greater willingness to give weight to, and act on, the recommendations made by the AI system:

H2: Algorithmic trust positively influences investors' reliance on AI-generated financial advice.

In addition to fostering trust, transparency could also directly affect reliance, in an informational fashion. Investors can assess the suitability of a recommendation for themselves, which means that even if they didn't trust the system as a whole, they might trust the recommendation. Investors can evaluate the relevance of a recommendation to their own situation if they can understand the factors and data underlying the recommendation, which can increase their willingness to act on the recommendation even if they aren't confident in the system overall (Silber et al., 2025; Greiner et al., 2025). This direct pathway is supported by evidence that the framing and presentation of algorithmic advice influences reliance regardless of one's broader attitude toward the algorithm (Greiner et al., 2025), and evidence that opacity hurts reliance on algorithmic recommendations, even when trust in the algorithm itself is high (Bigman & Gray, 2018; Castelo et al., 2019). It is therefore hypothesised that perceived transparency will affect reliance beyond its impact on trust:

H3: Perceived AI transparency positively influences investors' reliance on AI-generated financial advice.

The above arguments suggest two different pathways through which transparency can influence reliance. The first is the direct one: transparency allows investors to have access to

information which they can assess without being influenced by their opinion of the overall trustworthiness of the system. The second is indirect, through trust: transparency makes the operation of the system more understandable and verifiable, which increases confidence in its competence and reliability, and it is this confidence, not the information that transparency provides, per se – that most directly enables an investor to act on a recommendation without independent verification (Hildebrand & Bergner, 2021; Jacovi et al., 2021). This reflects the general literature on trust formation, which sees transparency-related cues as inputs to a trust evaluation process that then dictates reliance behaviour on those cues, not as drivers of reliance behaviour themselves (Glikson & Woolley, 2020; Lourenço et al., 2020). That is, an investor could be aware of the process behind a recommendation and be reluctant to follow it if they think the process is not reliable; but if the process behind the recommendation can be made transparent and show that it is reliable, the investor will be more inclined to trust the process and follow the recommendation. Therefore, we suggest that algorithmic trust is a mediating factor that bridges a significant part of the link between transparency and reliance:

H4: Algorithmic trust mediates the relationship between perceived AI transparency and investors' reliance on AI-generated financial advice.

2.1. Theoretical Framework

As a whole, this theoretical perspective frames perceived transparency of AI as a precursor that influences investor use of AI-driven financial advice in two ways. The dominant channel in this case is algorithmic trust (which is consistent with the development of human trust-AI interaction as described by trust-formation theory; Glikson & Woolley, 2020; Hoff & Bashir, 2015), which takes place through the evidential basis provided by transparency, and that evidence will in turn inform trust in the system's competence and

reliability, which will then inform the investor's willingness to rely on the system's output. A secondary, indirect channel can affect reliance when there is transparency of the information it provides in addition to trust. In this framing, trust is not a rival predictor of reliance, but rather the primary psychological mechanism that brings transparency of the system down to individual reliance behavior, as tested through the mediation model stated below.

2.2. Hypotheses Development

The following hypotheses are suggested based on the theoretical arguments presented above:

H1: Perceived AI transparency positively influences algorithmic trust.

H2: Algorithmic trust positively influences investors' reliance on AI-generated financial advice.

H3: Perceived AI transparency positively influences investors' reliance on AI-generated financial advice.

H4: Algorithmic trust mediates the relationship between perceived AI transparency and investors' reliance on AI-generated financial advice.

The conceptual model tested in this study is shown in Figure 1. Perceived AI transparency (X) is the independent variable, whereas algorithmic trust (M) is the mediating variable, and reliance on AI-generated financial advice (Y) is the dependent variable. The model includes two pathways through which transparency influences reliance: an indirect pathway via algorithmic trust ($X \rightarrow M \rightarrow Y$, with the indirect pathway tested as H4) and a direct pathway from transparency to reliance that is independent of trust ($X \rightarrow Y$, tested as H3). This structure enables the model to assess not only if transparency and trust are related to reliance, but also how much the overall effect of transparency on reliance is mediated by the trust that is created by transparency, and how much is not mediated by trust.

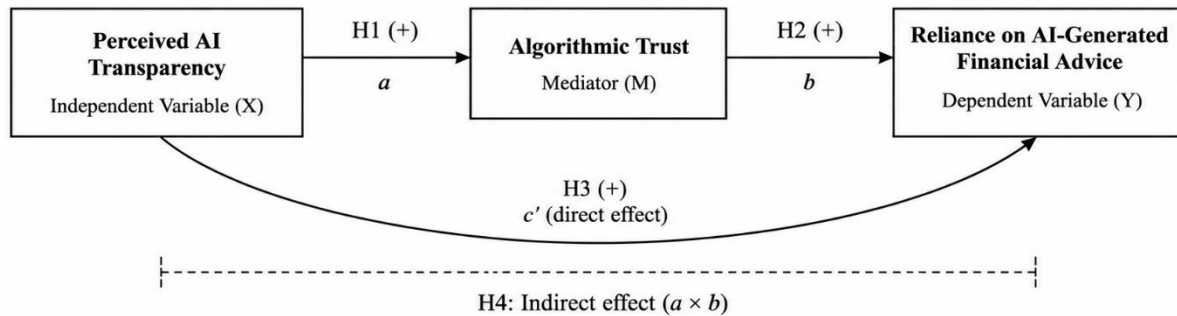


Figure 1. Conceptual framework of the study.

3. Methodology

3.1. Research Approach

The quantitative research approach was selected to examine the proposed relationships between perceived AI transparency, algorithmic trust, and reliance on AI-financial advice. A deductive approach was used, where hypotheses were tested statistically against primary survey data from previous theory and empirical literature (Amnas et al., 2023; Greiner et al., 2025).

3.2. Research Design

A cross-sectional, questionnaire-based survey design was used, and data for all three constructs were obtained. The choice of this design is due to the objective of this study, which is to examine the strength and direction of hypothesised statistical relationships between perceived transparency, trust, and reliance, rather than the changes that occur in these constructs over time. Cross-sectional designs have been used in the literature of FinTech and algorithmic advice to test structural relationships between perception-, trust-, and behaviour-related constructs (Zhang et al., 2021; Northey et al., 2022).

3.3. Study Population

The target population consisted of active retail investors who: (a) had used AI-based financial advisory tools like generative AI assistants, AI-powered investment platforms or robo-advisors before, and (b) were currently engaged in or actively looking for information on investment decisions. This definition is based on previous

research on robo-advisors and FinTech adoption, which limits analysis to people who actually have a real contact with the systems they are studying (Nourallah et al., 2022; Isaia & Oggero, 2022). There were a variety of ways to assess eligibility, including a screening item to determine whether respondents had used an AI-based tool to get financial or investment information or advice.

3.4. Sampling Technique

A non-probability purposive sampling technique was used, with online and offline sampling of active retail investors in organised investment communities. Recruitment was done online via investment communities on Reddit (r/investing), LinkedIn, and social media investment groups on Facebook and Instagram. Offline recruitment happened with the help of investment club meetups held in Karachi and investor networking events in investor co-working areas in Lahore. The choice of this mixed online/offline method was due to the lack of a formal sampling frame for investors using AI-based financial tools, which is also the case with similar studies in this field (Nourallah, 2023; Niszczoła & Kaszás, 2020).

3.5. Sample Size

A minimum sample size for the study was calculated with the formula for a minimum sample size for frequency in a population from the OpenEpi website:

$$n = [DEFF \times N \times p(1-p)] / [(d^2/Z^2)(N-1) + p(1-p)]$$

The anticipated population frequency (p) was calculated based on a published prevalence estimate for reliance on AI-generated financial advice that was closest available, which was 21.8% of retail investors surveyed who reported engaging in “Advanced” financial advice using AI tools, as reported by Vijayananth and Saravanabhavan (2026). With a population size $N = 1,000,000$, an assumed design effect of 1 (simple random sampling) and an absolute precision of $\pm 4\%$, the minimum sample size was determined to be $n = 410$ with a 95% confidence level ($Z = 1.96$). This target was supported by power considerations specific to mediation: Fritz and MacKinnon (2007) found a sample size of 200-400 would typically be sufficient for the bootstrapped tests of mediation with small-to-medium path effect sizes. This threshold was comfortably met by the collected sample of 410 and remained adequate after screening, with 310 eligible responses retained for the final analysis.

3.6 Data Collection Procedure

Data collection was carried out online and offline for two months (from May to July 2026). Eligible respondents who met the inclusion criteria of being active retail investors with some prior exposure to AI-based financial advice tools were asked to fill out a structured questionnaire, both online (Google Forms) and in person. The respondents answered the eligibility screening item, informed consent, items about using AI tools and experience with investing, the 15 substantive Likert-type items, and demographic items. After data cleaning, completed responses were exported for analysis. Of the 410 responses, 100 were deemed ineligible due to not having used an AI-based tool for financial or investment information or advice, leaving 310 responses for all subsequent analyses.

3.7 Data Analysis Strategy

Data were analysed in stages: data screening, reliability, confirmatory factor analysis and bootstrapped mediation testing were conducted using Python. Eligible responses ($n = 310$) were initially examined for missing responses and inconsistent response patterns. The descriptive

summary of the respondents' characteristics was then given. Internal consistency reliability (Cronbach's alpha), confirmatory factor analysis (standardised loadings, average variance extracted, and composite reliability for convergent validity) and the heterotrait-monotrait ratio of correlations (HTMT) for discriminant validity (Henseler et al., 2015) were used to assess the measurement properties of the three constructs, supported by a nested model comparison (Anderson & Gerbing, 1988) between a freely estimated measurement model and constrained models with merged construct pairs. The single-instrument self-report design was addressed procedurally during design (anonymous responses, neutral wording of items, separation of constructs within the instrument), and tested statistically after the procedures outlined by Podsakoff et al. (2003). First, descriptive statistics and bivariate correlations between the three constructs were examined, and then the hypothesised structural relationships (H1-H3) were tested using a structural path model, which also included the indirect effect of transparency on reliance, tested using a bootstrapped confidence interval (5,000 resamples) as recommended by contemporary recommendations for mediation testing (MacKinnon et al., 2007; Fritz & MacKinnon, 2007).

3.8 Measurement of Variables

All substantive items were measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The 15 items were independently developed based on the conceptual definitions and dimensions of the three constructs established previously, informed by the relevant published literature (Hadji Misheva & Papenbrock, 2022; McGrath et al., 2025; Greiner et al., 2025), rather than adopted directly from a single named published instrument.

- **Perceived AI Transparency.** Based on 5 items that measure respondents' perception of the clarity of AI-generated recommendations, the factors that influence the AI's recommendations, and the information that the AI system uses to generate advice.

- **Algorithmic Trust.** On a scale of 5, rating respondents' confidence in the competence, reliability, and accuracy of AI-powered financial tools.

- **4.9.3 Reliance on AI-Generated Financial Advice.** Measured with 5 items assessing the extent to which respondents gauge the

importance they place on and their willingness to follow AI-driven financial advice.

- **4.9.4 Demographic and Background Variables.** To characterise the sample, age, gender, level of education, employment status, income, experience of investing and characteristics of using AI were recorded.

Table 1. Measurement of Study Constructs

Construct	Operational Definition	Items	Scale
Perceived AI Transparency (PAT)	Perceived clarity and understandability of how AI-generated financial recommendations are produced.	5	5-point Likert
Algorithmic Trust (AT)	Confidence in the competence, reliability, and accuracy of AI-based financial tools.	5	5-point Likert
Reliance on AI-Generated Financial Advice (RA)	Extent to which investors give weight to and are willing to act on AI-generated financial recommendations.	5	5-point Likert

4. Results

4.1. Data Screening

The initial number of responses received to the structured questionnaire (both online and physically) was 410. After the eligibility screening question, 100 respondents who had indicated that they never used an AI-based tool for financial or investment information or advice were removed from the study due to not being within the scope

of the study. There were no duplicate responses that were found. The final analytic sample consisted of $N = 310$ eligible responses, which exceeded the minimum of $n = 410$ collected responses needed for the prevalence-based power calculation and comfortably surpassed the range of 200–400 collected responses that Fritz and MacKinnon (2007) determined to be sufficient for detecting mediated effects through bootstrapping.

4.2. Respondent Characteristics

Table 2. Respondent Demographic and Investment/AI-Use Characteristics (N = 310)

Characteristic	Category	n	%
Gender	Male	224	72.3
	Female	86	27.7
Age	18–24	17	5.5
	25–34	100	32.3
	35–44	93	30.0
	45–54	42	13.5
	55 or above	58	18.7
Education	Intermediate / Higher Secondary	54	17.4
	Bachelor's degree	121	39.0
	Master's degree	50	16.1
	MPhil / MS	44	14.2

Characteristic	Category	n	%
	PhD	6	1.9
	Other	35	11.3
Employment	Employed	103	33.2
	Self-employed / Business	101	32.6
	Entrepreneur	59	19.0
	Multiple roles	47	15.2
Monthly Income	Below PKR 50,000	44	14.2
	PKR 50,000–99,999	38	12.3
	PKR 100,000–199,999	47	15.2
	PKR 200,000–299,999	74	23.9
	PKR 300,000–499,999	56	18.1
	PKR 500,000 or above	51	16.5
Investing Experience	Not yet invested, seeks information	51	16.5
	Less than 1 year	51	16.5
	1–3 years	57	18.4
	4–6 years	54	17.4
	7–10 years	45	14.5
	More than 10 years	52	16.8
AI-Tool Use Frequency	Less than once a month	88	28.4
	1–3 times a month	61	19.7
	Once a week	64	20.6
	Several times a week	58	18.7
	Daily or almost daily	39	12.6

The sample consisted primarily of males (72.3%), ages 25-44 (62.3% combined), and highly educated (82.5% with at least a bachelor's degree). The distribution of employment was fairly even, with 33.2% working on salary and 51.6% self-employed or working as entrepreneurs, which indicates that the sample had a high level of financial independence and decision-making power in relation to the study's focus on investment behavior. Investing experience was

widely distributed across categories, with 16.5% of respondents having never invested in their own name, but actively looking for information on investing, and 16.8% having been investing for over 10 years, suggesting that the sample was not skewed towards either novices or more highly experienced investors. The frequency of using AI tools was also fairly even, with 31.3% of respondents using AI financial tools several times per week or more, and a further 40.3% using AI

financial tools at least once per week or a few times a month, suggesting that the majority of respondents had regular, meaningful interactions with AI-generated financial advice, not incidental or one-off interactions.

4.3. Reliability and Measurement Model

All three constructs showed good to excellent internal consistency reliability, with Cronbach's alpha values above .70: Perceived AI Transparency ($\alpha = .846$), Algorithmic Trust ($\alpha = .820$), and Reliance on AI-Generated Advice ($\alpha = .858$). The results of a three-factor confirmatory factor analysis (CFA) ($\chi^2(87) = 103.22$, $p = .113$, CFI = .991, TLI = .989, RMSEA = .025) were excellent, comfortably exceeding the conventional model acceptability thresholds (CFI/TLI $\geq .90$; RMSEA $\leq .08$), and the non-significant chi-square ($p = .113$) indicates that the model is not statistically distinguishable from the observed covariance structure. All standardized factor loadings were statistically significant ($p < .001$) and strong in all fifteen items, ranging from .680 to .795 for the Transparency items, .646 to .720 for the Trust items, and .725 to .753 for the Reliance items, with no comparatively weak items that would warrant special attention this time, consistent with the measurement approach described.

4.4. Convergent and Discriminant Validity

The standardized CFA loadings were used to calculate composite reliability (CR) which was .847 (Transparency), .821 (Trust), and .858

(Reliability) and all exceeded the .70 threshold and supported the Cronbach's alpha results reported above. Average variance extracted (AVE) was .526 (Transparency), .479 (Trust), and .548 (Reliance); all three constructs had good convergent validity at the item level (AVE $> .50$), with Transparency and Reliance being above the .50 threshold, and Trust being just below the .50 threshold.

All three pairs of constructs (Transparency–Trust, HTMT = .201; Transparency–Reliance, HTMT = .230; and Trust–Reliance, HTMT = .474) met the criterion for discriminant validity (HTMT $< .90$; Henseler et al., 2015). This result was supported by the nested model comparison procedure as described by Anderson and Gerbing (1988) that compared the freely estimated three-factor model with a constrained two-factor model with Trust and Reliance items combined on a single factor, the free three-factor model fit significantly better ($\chi^2_{\text{free}}(87) = 103.22$ vs. $\chi^2_{\text{constrained}}(89) = 418.96$; $\Delta\chi^2(2) = 315.74$, $p < .001$), thus supporting the empirical separation of the three constructs in this sample. Common method bias was assessed using Harman's single factor test and correlation-matrix inspection, with the first factor accounting for 31.3% of the total variance across all 15 items (which is below the 50% concern threshold) and the maximum bivariate item correlation being .593 (which is below the .90 threshold), indicating that common method bias is unlikely to be a major concern (Podsakoff et al., 2003).

Table 3. Descriptive Statistics, Reliability, and Correlations Among Composite Construct Scores (N = 310)

Variable	M	SD	α	CR	AVE	1	2	3
1. Perceived AI Transparency	3.45	0.72	.846	.847	.526	—		
2. Algorithmic Trust	3.45	0.68	.820	.821	.479	.165**	—	
3. Reliance on AI-Gen. Advice	3.51	0.74	.858	.858	.548	.195**	.398**	—

Note. ** $p < .001$. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

Table 4. Measurement Model: Loadings, Fit Indices, and Discriminant Validity (HTMT)

Construct	Standardised Loadings (range)	CFA Fit	HTMT (vs. other constructs)
Perceived AI Transparency	.680 - .795	$\chi^2(87)=103.22$, $p=.113$ CFI=.991, TLI=.989 RMSEA=.025	vs. Trust: .201 vs. Reliance: .230
Algorithmic Trust	.646 - .720		vs. Transparency: .201 vs. Reliance: .474
Reliance on AI-Gen. Advice	.725 - .753		vs. Transparency: .230 vs. Trust: .474

Note. HTMT values below .90 indicate adequate discriminant validity; all three construct pairs meet this criterion.

4.5. Hypothesis Testing (H1-H3)

The analysis plan outlined above was followed, with composite (mean) construct scores being used in a series of ordinary least squares (OLS) regressions to test structural relationships. Perceived AI transparency significantly and positively predicted algorithmic trust (path a: $b = 0.156$, $SE = 0.053$, $t = 2.94$, $p = .004$, $\beta = .165$, 95% CI [.052, .261]), explaining 2.7% of variance in trust ($R^2 = .027$), supporting H1. While statistically significant, this effect size is small in comparison to conventional standards in social science research (Cohen, 1988), suggesting that perceived transparency is a limited rather than overpowering factor in trust in AI financial tools. The model predicting reliance from both trust and transparency simultaneously showed that algorithmic trust significantly and positively

predicted reliance, controlling for transparency (path b: $b = 0.407$, $SE = 0.057$, $t = 7.16$, $p < .001$, $\beta = .376$, 95% CI [.295, .519]), supporting H2. Trust also had a significant direct effect on reliance, with perceived AI transparency having a similar direct effect (path c': $b = 0.136$, $SE = 0.054$, $t = 2.52$, $p = .012$, $\beta = .133$, 95% CI [.030, .242]). This direct effect was also positive and significant, supporting H3, and was comparable in magnitude to trust's effect on reliance, rather than smaller. The two-construct model of transparency and trust accounted for a medium-to-large effect size (Cohen, 1988) in explaining investors' reliance on AI-generated financial advice, with a total R^2 of .176, meaning that the two constructs together accounted for a meaningful, albeit less substantial, proportion of the variance in reliance.

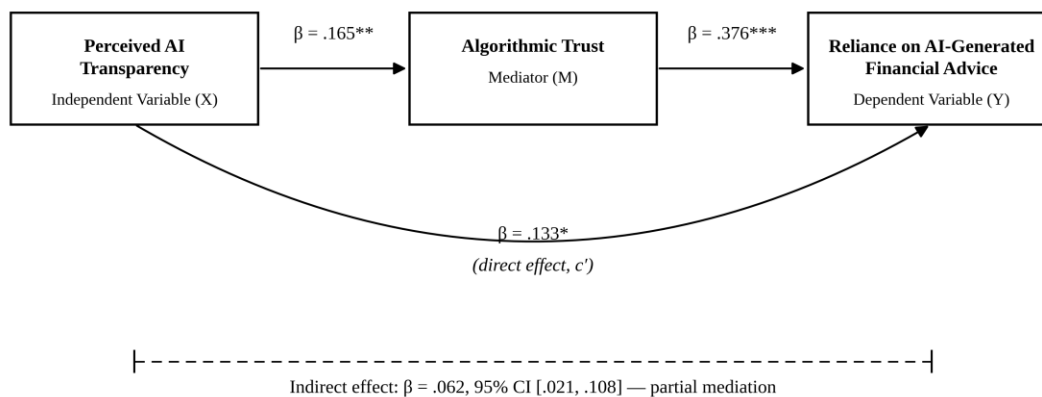


Fig. 2. Structural model with standardised path coefficients (N = 310). *** $p < .001$, ** $p < .01$, * $p < .05$.

5.6 Mediation Analysis (H4)

We estimated the indirect effect of perceived AI transparency on reliance through algorithmic trust (ab) as 0.064 (standardized $\beta = .062$) with a bootstrapped confidence interval of 5,000 resamples (Figure 3). The 95% bootstrap CI [0.021, 0.114] excluded zero, suggesting that there was a statistically significant mediation effect and thus supporting H4. Since the direct effect ($c' = 0.136$, $p = .012$) was significant in addition to the significant indirect effect, and both effects had a positive sign as the total effect ($c = 0.199$, $\beta = .195$), the mediation pattern was consistent with partial (complementary) mediation. The indirect effect, however, does not dominate the total effect as it

does in a pattern in which the mediator dominates the total effect, but rather accounts for about 31.9% of the total effect of transparency on reliance. This suggests that in this sample, algorithmic trust is a secondary pathway to reliance, and a significant amount of the effect of transparency on reliance is direct, without the mediation of trust. In practical terms, this means that investors in this sample were willing to follow AI-generated recommendations to some extent, even when they were not fully motivated by trust in the AI system, but rather by the information they derive from the transparency of the recommendations.

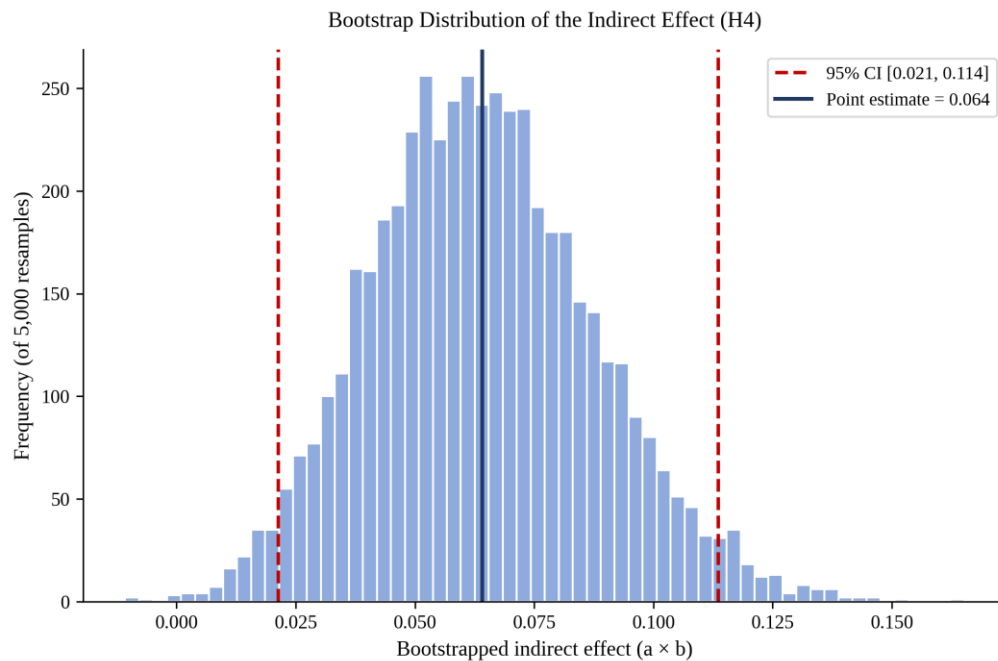


Fig. 3. Bootstrap Distribution of the Indirect Effect (H4), 5,000 Resamples

5.7 Summary of Hypothesis Results

Table 5. Hypothesis Testing and Mediation Results

H	Relationship	b / β	SE	p	95% CI	Decision
H1	Transparency $\rightarrow$ Trust	.156 / .165	.053	.004	[.052, .261]	Supported
H2	Trust $\rightarrow$ Reliance	.407 / .376	.057	< .001	[.295, .519]	Supported
H3	Transparency $\rightarrow$ Reliance (direct)	.136 / .133	.054	.012	[.030, .242]	Supported
H4	Transparency $\rightarrow$ Trust $\rightarrow$ Reliance (indirect)	.064 / .062	—	boot CI excl. 0	[.021, .114]	Supported (partial mediation)

Note. Unstandardized b / standardised β effects reported. The 95% CI reported for H4 is the percentile bootstrap CI for the indirect effect, not a t -test-based CI. All four hypotheses were supported.

In summary, all four hypothesised relationships were empirically supported. The perceived transparency of AI had a significant, yet small, impact on algorithmic trust (H1), which then had a significant impact on reliance on AI-generated financial advice (H2). In addition, transparency had a direct effect on reliance, beyond the indirect effect (H3), and of similar magnitude. The effect of transparency on reliance was significantly mediated by algorithmic trust, but only a small portion (31.9%) of the effect of transparency was

indirect through algorithmic trust. This pattern suggests that, while establishing investor trust in AI-powered financial tools is a significant factor in driving reliance, it is not the primary one in this sample, as transparency appears to have a direct impact on investors' reliance decisions as well, which has important implications for the design and communication of AI-generated financial advice by FinTech providers, financial institutions, and regulators.

6. Discussion

The aim of this study was to explore not only the relationship between perceived transparency and trust in AI but also the interaction between these two factors and their impact on AI dependence in financial advice. All four hypotheses were confirmed, but the pattern found is not simply "transparency creates trust, and trust leads to everything." All four hypotheses were supported, but the pattern was not a simple one of "transparency creates trust, and trust leads to everything." Trust was found to have a moderate positive relationship with reliance, and, significantly, a direct effect on reliance was found to be similar in size to the indirect effect of transparency through trust. Algorithmic trust accounted for approximately one-third of the overall impact of transparency, with most of the impact occurring directly. The overall picture is one in which trust is a real, statistically validated mechanism, but not the most important reason why transparency affects reliance in this sample; transparency seems to have an independent effect in investors' reliance decisions.

6.1. Transparency and Algorithmic Trust

The relationship between H1 and trust was modest ($\beta = .165$, explaining 2.7% of variance in trust), but was supported. This means that the extent to which people feel that the information is transparent is a genuine factor in the trust-building process for AI-powered financial tools in this sample, but it is not enough. While this is consistent with the notion that transparency provides evidence to assess a system's competence (Kleanthous et al., 2022; Jacovi et al., 2021), the small effect size indicates that transparency alone does not explain the majority of the variance in trust – it is likely that additional factors were not accounted for in this model and are important for trust in AI-based financial tools, including prior experience with the specific tool, general disposition to trust automated systems, and perceived institutional support (Hoff & Bashir, 2015; Zarifis & Cheng, 2022). The current finding indicates that transparency's role in trust could be real but relatively small, as the trust-building effect of transparency is more likely to be mediated by a

broader range of experiential and dispositional factors than by transparency perceptions per se, for a more diverse and heterogeneous group of retail investors (as compared to a particular platform).

6.2. Algorithmic Trust and Reliance

Algorithmic trust had the highest correlation with reliance of any path in the model ($\beta = .376$), followed by H2. This aligns with the broader idea that trust replaces independent verification: An investor who trusts an AI-based tool to be competent is more likely to follow its advice without verifying each of its individual judgments (Logg et al., 2019; Dietvorst et al., 2018). This discovery is consistent with the research on FinTech adoption, which indicates that trust-based pathways are more likely to result in behavioral engagement with robo-advisory and AI-generated financial services than simply perceived usefulness (Belanche et al., 2019; Nourallah et al., 2022). Concurrently, the variance in reliance was less explained by trust in this more heterogeneous sample of investors than in some previous single-platform studies, indicating that reliance in this more diverse investor sample is influenced by trust as well as other factors of similar importance.

6.3. Transparency and Reliance

H3 was supported, and importantly, the direct effect of transparency on reliance ($\beta = .133$) was not a small residual after the control of trust was taken into account, but was of a similar magnitude. This means that transparency has some informational value in and of itself: If investors can see what information or reasoning is being used to make a recommendation, this seems to affect their willingness to follow the recommendation somewhat independently of their overall trust in the system. This aligns with previous research showing that the presentation and framing of algorithmic advice can impact reliance, beyond just general trust attitudes (Greiner et al., 2025; Silber et al., 2025), which indicates that investors in this sample may rely on the rationale provided to assess the relevance of the advice to their own situation, rather than the overall trustworthiness of the system (Castelo et al., 2019).

6.4. Mediating Role of Algorithmic Trust

The main question this study posed was: What is the reason for reliance (directly or via trust) on transparency? The answer here is both, but with trust being a less important factor than dominant-mediation accounts of transparency would suggest. When it came to the influence on reliance, about 32% was through algorithmic trust, meaning about two-thirds of transparency's influence was direct on reliance. This pattern indicates a more complex process than a simple "transparency → trust → reliance" sequence: some investors seem to need to establish the trust-building step before they can rely on a recommendation, but a significant proportion seem to be able to rely on the information they have been made transparent without first drawing a comprehensive trust judgment about the system as a whole, for example, using the rationale provided to assess the relevance of the recommendation to their own investment situation.

The reasonable explanation is the small transparency-trust link itself: if transparency is only weakly associated with trust in this population, then trust has little remaining to carry downstream the influence of transparency, as there is relatively little transparency-trust influence to carry downstream. This is a reorientation of the mediating role of trust: it is not the only channel through which transparency can work, but one of at least two parallel channels, the other being the direct informational channel, which carries a similar weight. This is a theoretical distinction, since it suggests that the more transparent an AI system is, the more it will be relied upon, but not necessarily by an amount that correlates with the increase in transparency. A significant amount of reliance would increase even if trust did not increase at all.

6.5. Comparison with Previous Research

This is consistent with, and contrasts with, previous studies. It is consistent with research highlighting that transparency and explainability cues are directly relevant to the decision-making process, regardless of the overall trust judgment (Greiner et al., 2025; Bigman & Gray, 2018), and

with studies showing that framing and presentation aspects of algorithmic advice reliance are somewhat orthogonal to general trust attitudes (Silber et al., 2025).

It differs significantly from studies in which trust was the primary or almost sole mechanism that connects transparency-related features to downstream engagement, such as research on conversational robo-advisors where interactive, transparency-enhancing features acted as strong trust surrogates that led to positive outcomes (Hildebrand & Bergner, 2021), and studies on perceptions of human-versus-robo-advisors where trust was established as the central differentiator of engagement (Zhang et al., 2021). This is also noteworthy as a contrast to research findings that the use of AI in financial services can sometimes lead to a decrease in consumer trust in, the financial advice given (Northey et al., 2022) which this study's positive (albeit small) link between transparency and trust does not replicate.

Several factors could explain these differences. First, the sample and context: the sample was large and diverse, with a cross-section of retail investors in Pakistan, and the study was conducted in the wild, meaning that the experience of using AI tools could be different across platforms and not captured in a single study. Second, measurement: the items used to measure transparency and trust were new, not adapted from a previously validated instrument, and some of the attenuation in the transparency, trust relationship may be due to measurement, not a lack of a stronger underlying relationship. Third, the context of the decision: retail investment decisions may be different from the more mundane or less consequential decisions studied in some previous robo-advisor studies, and therefore more likely to be influenced by the transparent information available rather than a general trust in the investment process. With the current cross-sectional data, it is not possible to differentiate between these explanations, but each suggests a specific path for future research.

7. Theoretical and Practical Implications

7.1. Theoretical Implications

This study contributes to four bodies of literature on AI trust, algorithmic decision-making,

FinTech, and transparency. Only 32% of the impact of transparency on reliance was mediated by trust, indicating that transparency affects reliance both directly and indirectly, via trust (Glikson & Woolley, 2020). The modest transparency-trust relationship ($\beta = .165$) also undermines the notion that transparency leads to more trust (Jacovi et al., 2021). The results also advance the FinTech literature by moving beyond intentions to adopt to reliance on FinTech (Belanche et al., 2019; Nourallah et al., 2022), and imply that transparency and trust should be considered as two partially distinct mechanisms (Hildebrand & Bergner, 2021).

7.2. Implications for AI/FinTech Providers

It is important for providers to not assume that transparency will affect reliance mainly through trust. Clear recommendation rationales can directly reduce reliance by enabling investors to assess the specific recommendations, whereas trust-building elements like performance history and onboarding are also important (Hildebrand & Bergner, 2021). Therefore, providers must integrate the level of recommendations with other trust-building measures.

7.3. Implications for Investors

Transparency and trust are two different things to consider when investing. A good recommendation does not necessarily imply that the overall system is trustworthy. Rather, investors should evaluate the logic of specific recommendations and take into account the overall reliability and history of the system.

7.4. Implications for Financial Institutions and Regulators

Transparency and trust building are separate objectives for financial institutions. The direct effect of transparency implies that disclosure rules can have an impact on investor reliance, beyond the impact on trust (Helberger et al., 2020; Ingrams et al., 2022). Thus, the frameworks for responsible AI and investor protection should focus on disclosure as well as the accuracy of disclosed information.

8. Conclusion

This study asked what makes investors trust, and ultimately rely on, AI-generated financial advice. The findings point to two parallel mechanisms operating at roughly comparable strength rather than one dominant pathway. Perceived transparency modestly increases algorithmic trust, and that trust meaningfully increases reliance, but transparency also exerts a direct effect on reliance nearly as large as its trust-mediated effect, with trust accounting for only about a third of transparency's total influence. Transparency shapes investor reliance through two distinct channels: one operating through trust in the underlying system, and a comparably weighted direct channel in which investors act on well-explained recommendations without that action being fully routed through trust. For research and practice focused on explainable AI, the clearest message is that transparency carries meaningful behavioural weight in its own right, not only insofar as it builds trust.

8.1. Limitations

Several limitations should be acknowledged. Because of its cross-sectional design, it is not possible to make inferences about temporal or causal relationships between transparency, trust, and reliance. The use of self-reported measures may not fully reflect actual investment behaviour. Furthermore, the recently developed transparency and trust measures need to be validated. Limited generalizability is also due to the use of non-probability convenience/purposive sampling, where the sample was mainly from Pakistan, male and highly educated. Lastly, reverse and reciprocal relationships are not ruled out in the correlational design.

8.2. Future Research

Longitudinal designs should be used in future studies to investigate the development of trust and reliance and transparency over time. Further experimental studies on the effects of transparency manipulation might further separate direct and trust-mediated effects. Findings would be tested for generalizability if replicated with different investor groups and cultural contexts. Future

research should also include actual investment behaviour and not just self-reported investment dependence.

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