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Talking to the Market: Field Evidence on AI Chatbots, Digital Advice Utilization, and Retail Trading Outcomes

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Abstract

Background: Conversational AI chatbots are increasingly embedded in retail brokerage applications, yet empirical evidence on how chatbot-based advice influences investor behaviour in real-world trading contexts remains limited.

Purpose: This study investigates whether perceived chatbot competence and trust predict digital advice utilisation, and whether such utilisation is associated with self-reported trading outcomes, with financial literacy examined as a moderator.

Uniqueness: The study extends prior research by focusing on investor–chatbot interaction and actual utilisation of chatbot guidance among active retail investors, rather than evaluating algorithmic stock-picking performance or purely conceptual advisory models.

Methodology: A cross-sectional survey was conducted with 300 active retail investors who had recently interacted with AI-enabled investment chatbots. Multiple regression models were used to test direct relationships and the moderation effect of financial literacy.

Findings: Perceived competence ($B \approx 0.32$, $p < 0.001$) and trust ($B \approx 0.32$, $p < 0.001$) are independently associated with higher digital advice utilisation ($R^2 = 0.306$). Digital advice utilisation is positively associated with trading outcomes ($B \approx 0.32$, $p \approx 0.02$). Financial literacy also shows a positive association with trading outcomes ($B \approx 0.30$, $p \approx 0.03$), while the utilisation×literacy interaction is not statistically significant.

Implications: The findings suggest that brokerage chatbots may support more disciplined investing behaviour, though causal interpretation is limited by the survey design. Future work should integrate chatbot interaction logs with objective brokerage trading records to evaluate long-run behavioural and performance effects.

Keywords: AI chatbots; Digital advice; Retail investors; Stock trading; Financial literacy; Trading outcomes

JEL Codes: G11; G41; D14; D83; C83

1. Introduction

Artificial intelligence has moved from back-office analytics to the front line of retail investing. Digital brokers now embed conversational agents that answer questions, summarize earnings news, and suggest securities inside mobile trading apps. Recent evidence shows that large language models can screen stocks and construct portfolios with non-trivial predictive power, indicating that generative AI may become a mainstream source of investment guidance for individual investors (Pelster and Val, 2024; Romanko et al., 2023). New things are

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changing the everyday routes of digital retail investment. Yet the spread of AI chatbots in stock trading raises unresolved questions: how retail investors actually interact with conversational advice, which investors follow such guidance, and whether this behaviour is associated with better or worse trading outcomes.

Existing research on automated advice focuses mainly on rule-based robo-advisors and on the performance of algorithms rather than on investor–chatbot interaction. Studies show that investor characteristics and risk attitudes shape adoption of robo-advisors and invested amounts (Oehler et al., 2022; Scherer and Lehner, 2025), while experiments demonstrate that digital nudges and interface design can influence portfolio risk-taking and reduce cognitive biases like the disposition effect (Back et al., 2023; Lisauskienė et al., 2025). Parallel work evaluates whether AI models such as ChatGPT can generate profitable stock recommendations, highlighting both predictive potential and risks of hallucinated or opaque output (Pelster and Val, 2024; Schneider and Yilmaz, 2025). A further stream shows that perceived expertise, benevolence, and institutional reputation, together with technology-specific trust, are central to acceptance of robo-advice and intention to follow recommendations (Lourenço et al., 2020; Oehler et al., 2022). These contributions, however, largely treat advice as static and menu-based, and rarely capture the conversational, iterative nature of chatbot-mediated guidance.

Important gaps follow from this focus. First, there is little field-based evidence on how perceived chatbot competence and trust shape the actual utilization of conversational advice in day-to-day stock trading. Second, prior studies on ChatGPT in investing rely mostly on simulated strategies or backtests rather than on decisions made by retail investors after receiving AI-generated guidance (Pelster and Val, 2024; Schneider and Yilmaz, 2025). Third, the moderating role of investor financial literacy in AI-mediated advice remains underexplored, even though recent work suggests that literacy conditions the ability of robo-advisors and digital nudges to reduce biases and improve portfolio quality (Lisauskienė et al., 2025). The extant literature allows scant insight into questions such as whether an increased application of artificial intelligence chatbot usage is concomitant with enhanced diversification of portfolios, superior performance on a risk-adjusted basis and augmented behavioural discipline or whether an enhanced reliance on conversational artificial intelligence engenders over-trading and unwarranted confidence.

Contribution and positioning. This study advances beyond (i) menu-based robo-advisor adoption studies and (ii) simulated/backtested evaluations of large-language-model stock picks by examining investor–chatbot interaction inside retail trading contexts. Using field survey data from 300 active investors with recent chatbot use, the analysis (a) separates perceived chatbot competence and trust as distinct antecedents of digital advice utilisation, (b) links utilisation to self-reported trading outcomes (diversification discipline, performance relative to expectations, reduced impulsive trading), and (c) tests whether financial literacy conditions these relationships. The evidence therefore complements prior work by focusing on real-user perceptions and behavioural utilisation, rather than algorithm performance alone.

Three questions are intended to be answered by the present inquiry within this setting. First, how does chatbot competence and trust in AI-based financial chatbots affect the extent to which retail investors use information from chatbot-generated stock recommendations to inform trading decisions? Second, to what extent is digital advice utilization associated with self-reported stock trading outcomes, including portfolio diversification, performance relative to expectations, and avoidance of common behavioural errors? Third, does investor financial literacy condition the relationship between digital advice utilization and trading outcomes, such that more financially literate investors benefit more from AI-mediated advice than less literate investors (Lisauskienė et al., 2025)?

In line with these questions, the study has three objectives. The first is to develop and apply survey-based measures of perceived chatbot competence, trust in AI financial chatbots, digital advice utilization, financial literacy, and retail trading outcomes in the context of stock market investing. The second is to test a conceptual model in which perceived competence and trust jointly predict the extent to which investors follow chatbot

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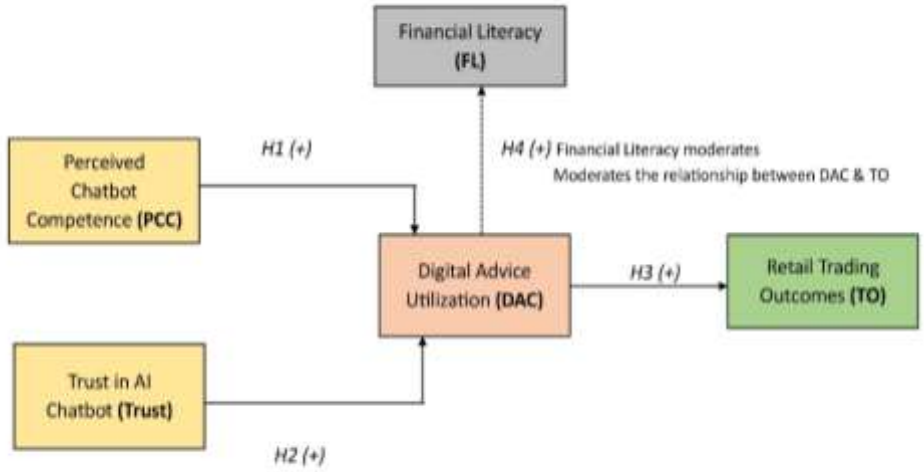
advice, and in which advice utilization in turn relates to reported portfolio quality and performance. The third objective is to look at how financial literacy acts as a moderator, thereby identifying conditions under which conversational AI support is associated with more favourable trading outcomes for retail investors.

Drawing on the preceding arguments, the conceptual model proposes that perceived chatbot competence and trust in the chatbot both enhance digital advice utilization. Higher digital advice utilization is expected to be associated with better self-reported trading outcomes, as consultation of AI-generated guidance can support diversification, more consistent risk-taking, and disciplined execution of trades (Back et al., 2023; Lisauskienė et al., 2025). Concurrently, it is anticipated that financial literacy will enhance the beneficial connection between the use of digital advice and trading results, because more financially knowledgeable investors can interpret chatbot outputs more critically and integrate them with other sources of information. Accordingly, the study tests the following hypotheses:

H1. Perceived chatbot competence is positively associated with digital advice utilization.
H2. Trust in the AI chatbot is positively associated with digital advice utilization.
H3. Digital advice utilization is positively associated with retail trading outcomes.
H4. Financial literacy positively moderates the relationship between digital advice utilization and retail trading outcomes, such that the relationship is stronger at higher levels of financial literacy.

Conceptual and hypothesis model

Figure 1. Conceptual model of AI chatbot perceptions, digital advice utilization, and retail trading outcomes (H1–H4).



Source: Author's conceptualization (2025).

Figure 1 depicts the proposed relationships between perceived chatbot competence, trust in the AI chatbot, digital advice utilization and retail trading outcomes. Perceived competence and trust are specified as antecedents of digital advice utilization (H1–H2), which in turn is posited to enhance retail trading outcomes (H3). Financial literacy is modeled as a moderator strengthening the positive link between digital advice utilization and trading outcomes (H4).

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2. Literature Review

2.1 AI chatbots as conversational financial intermediaries

Research on AI-powered chatbots has expanded, emphasizing their dual role as service technologies and quasi-social actors. Users evaluate chatbots through classic information-systems dimensions information quality, service quality and perceived usefulness—which shape satisfaction and continuance intention (Ashfaq et al., 2020). Conversational design, perceived enjoyment and ease of use translate into strong intentions to keep interacting with chatbots across service domains (Orden-Mejía et al., 2023). Within customer service, AI chatbots enhance perceived efficiency and experience when they deliver timely and contextually appropriate responses (Misischia et al., 2022). Service - quality models also suppose that responsiveness, empathy, and personalization are key factors in customer loyalty through perceived value and the fulfillment of customer needs (Chen et al., 2023). These findings imply that in financial contexts, chatbot-based market interfaces are likely to be judged not as neutral information conduits, but as relationship partners whose competence and responsiveness condition acceptance as sources of trading-related advice.

At the same time, work on chatbots in digital markets warns that anthropomorphic cues and conversational "human-likeness" can strategically influence compliance with recommendations, even when users know the counterpart is non-human (Chen et al., 2023). This raises the possibility that AI trading assistants embedded in brokerage apps might shift order submission behaviour not only through analytics, but also through levers such as sociability and the impression of compassion. Yet the literature is dominated by consumer-service and tourism settings; empirical studies that connect chatbot interaction patterns to concrete financial behaviours such as order volume, portfolio risk or realized returns remain scarce.

2.2 Trust, risk and digital advice utilization

A parallel stream of studies foregrounds trust as the central mechanism linking AI interaction to user behaviour. Review evidence shows that trust in AI chatbots is built on user traits, the qualities of the machine, and the effectiveness of the interactions, that trust predicts engagement, self-disclosure and compliance (Ng and Zhang, 2025). Empirical work demonstrates that trust in AI-based customer-service chatbots drives satisfaction, word-of-mouth and continued usage, while distrust magnifies perceived risk and avoidance (Prakash et al., 2023). Drawing on expectation-confirmation models, problem-solving performance has been shown to foster confirmation, satisfaction and trust, which then sustain continued usage intention in e-commerce contexts (Gao et al., 2025).

In financial advisory settings, trust dynamics become more consequential. Experimental evidence indicates that initial trust in AI financial advisors can be high, yet a single salient error sharply reduces reliance; explanations and repair strategies partially restore, but do not fully rebuild, previous trust levels (Han and Ko, 2025). Review evidence also points to the importance of institution-based trust and perceived safeguards in legitimizing AI services (Ng and Zhang, 2025). Together, these studies suggest that digital advice utilization in retail trading will depend on both recommendation quality and how chatbots communicate uncertainty and repair errors. However, the literature has not yet linked these trust processes to realized trading outcomes such as turnover, leverage or downside risk, especially in real-world brokerage environments.

2.3 Financial literacy, behavioural biases and retail trading outcomes

Classical work on household finance documents that financial literacy is associated with stock market participation and more diversified portfolios, suggesting that information-processing ability lowers the fixed costs of entering risky asset markets (van Rooij et al., 2011). Subsequent studies show that literacy interacts with behavioural biases—such as overconfidence, heuristics and herding—to shape trading decisions, sometimes amplifying excessive trading and risk-taking when investors miscalibrate their own knowledge

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(Suresh, 2021). More recent evidence points to financial literacy as a key determinant of participation in online stock trading and the use of digital investment platforms (Lakoni et al., 2023).

Despite these advances, most financial-literacy and behavioural-finance studies conceptualize "advice" as professional guidance or ad hoc information from peers and media, rather than structured AI advice delivered via chat interfaces. Scholarship on digitalization highlights how mobile apps, trading platforms and robo-advisory services have lowered entry barriers and reconfigured the balance between self-directed and guided investing, but rarely isolates the contribution of conversational agents within this ecosystem. The intersection between literacy, behavioural biases and AI-mediated advice therefore remains underexplored. In particular, there is limited evidence on whether chatbots complement or substitute for financial literacy in shaping retail trading outcomes; whether they attenuate or amplify biases such as overtrading and loss-chasing; and whether their effects differ across investor segments. Addressing these questions by linking field data on AI chatbot interactions, digital advice utilization and trading records would extend both the chatbot and retail-investor literatures and clarify how "talking to the market" through AI-mediated channels reshapes risk-taking and performance. These unresolved issues provide the central motivation for the present empirical field study.

Hypothesis linkage. Prior service-quality and chatbot research implies that stronger perceptions of chatbot capability should increase reliance on conversational guidance, motivating H1. Trust research consistently shows that higher trust increases compliance and continued use of AI recommendations, motivating H2. If chatbot advice functions as a behavioural support tool in trading, greater advice utilisation should be associated with improved trading outcomes, motivating H3. Finally, financial literacy may shape how investors interpret and implement AI outputs, motivating the potential moderating role proposed in H4.

Literature synthesis.

Table 1. Synthesis of key literature

Author(s) & Year	Domain / Focus	Method / Data	Key Findings	How this study builds on it
Ashfaq et al. (2020)	Chatbot satisfaction, continuance	Online survey of chatbot users	Information quality and usefulness drive satisfaction, reuse	Extends satisfaction logic to AI trading chatbots and advice intensity
Chen et al. (2023)	AI service quality, loyalty	Customer survey in AI services	AI service quality increases loyalty via value, satisfaction	Applies service-quality dimensions to financial chatbot evaluation
Ng and Zhang (2025)	Trust in AI chatbots	Systematic literature review	Trust shaped by user, machine and interaction factors	Uses multi-source trust view to specify chatbot trust and its role
Prakash et al. (2023)	Trust in AI service bots	Survey of retail customers	Trust boosts use and word-of-mouth; distrust raises risk	Treats digital advice utilisation as behavioural outcome of chatbot trust
Gao et al. (2025)	Chatbot problem solving, continuance	E-commerce users, ECM survey	Problem solving builds confirmation, satisfaction and trust	Positions advice quality as key driver of digital advice utilisation
van Rooij et al. (2011)	Financial literacy, stock participation	Household survey, econometric tests	Higher literacy linked to participation and diversification	Models' literacy as moderator between advice utilisation and outcomes

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Suresh (2021)	Literacy, biases and investing	Survey of individual investors	Literacy and behavioural biases jointly shape decisions	Connects literacy–bias insights to AI-mediated retail stock trading

Source: Author's synthesis of prior literature.

3. Material and Methods

3.1 Research Design & Sampling

The study adopts a cross-sectional field-survey design focusing on individual retail investors who actively trade listed equities or derivatives and who have interacted with AI-enabled investment chatbots offered by brokerages or fintech platforms during the previous six months. A structured online questionnaire is administered using brokerage mailing lists, online trading forums, and social-media investor communities. This approach aligns with current practice in web-based, non-probability surveys, which emphasise cost-effective access to specialised populations but also highlight issues of coverage and self-selection bias that must be managed transparently (Couper, 2000; Bethlehem, 2010; Lehdonvirta et al., 2020).

Identification considerations. The non-probability online recruitment approach may introduce self-selection, as investors who use chatbots more frequently or hold stronger views may be more likely to participate. In addition, observed relationships may be subject to endogeneity: unobserved traits (e.g., risk preferences, overconfidence, technology affinity) may jointly influence chatbot perceptions, advice utilisation, and outcomes. Reverse causality is also possible if favourable outcomes increase trust and subsequent chatbot use. The regression models therefore estimate associations, and interpretations are framed as correlational patterns rather than causal effects.

To enhance heterogeneity, invitations are disseminated across discount and full-service brokers and across multiple language communities. Screening questions ensure that respondents are at least 18 years old, place trades through recognised exchanges, and have used an AI chatbot for information, alerts, or trade execution support at least once. A target of 300 usable responses is set, consistent with recommendations and empirical evidence on typical response rates and effective sample sizes in online surveys (Wu et al., 2022). The sample size supports exploratory factor analysis and multiple regression with this sample size and the number of indicators and variables in the model.

3.2 Variable definition and data collection tools

All latent constructs are operationalised as multi-item scales measured on five-point Likert response formats ranging from strong disagreement to strong agreement. Perceived chatbot advice quality reflects investors' assessments of the accuracy, clarity, and practical usefulness of AI-generated recommendations. Perceived transparency captures the extent to which chatbot interfaces communicate data sources, modelling assumptions, and risk warnings in an intelligible manner. Algorithmic trust refers toa belief about the competency, reliability, and investor interests-oriented nature of the AI system in normal market conditions. Digital advice utilisation is a measure of the frequency and detail of the consultation between investors and chatbot response before taking a trade or adjusting a portfolio. Retail trading achievements are measured by self-reported measures of risk adjusted performance against benchmark indices, diversification discipline, and avoidance of impulse trading. There are established guidelines for scale development that conduct a scale from items generation, expert review and refinement for adequacy of content clarity (Hinkin, 1995). The draft instrument is pre tested alongside an exclusive group of individuals (active traders) to verify for wording, completion time, and test item variance after which slight modifications are made. Items intended for reflective constructs are designed to be internally consistent and suitable for subsequent exploratory factor analysis (Fabrigar et al., 1999).

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3.3 Statistical methods

Data preparation includes systematic checks for straight-lining, logically inconsistent responses, extreme completion times, and excessive missingness; cases failing these criteria are removed prior to analysis. Remaining missing values on scale items, where limited and apparently random, are handled using expectation–maximisation or mean substitution at the item level, depending on the pattern and proportion involved. Descriptive statistics summarise socio-demographic characteristics, trading experience, chatbot usage patterns, and central tendencies for all construct scores. Exploratory factor analysis (EFA) with principal axis factoring and oblique rotation is applied to the item pool to confirm the dimensionality of the constructs and to eliminate poorly performing indicators, following best-practice recommendations on EFA design and interpretation (Fabrigar et al., 1999). Factor scores or composite indices based on averaged items are then computed. A first look at the bivariate connections among important variables may be obtained using Pearson correlations. Several regression models are estimated several linear regression models to evaluate our hypothesis in which retail trading outcomes are regressed on digital advice utilisation, algorithmic trust, perceived advice quality, and perceived transparency, while controlling for age, gender, education, trading experience, self-assessed risk tolerance, and financial literacy. Model diagnostics examine assumptions of normality, homoscedasticity, and multicollinearity, and robust standard errors are applied if residual patterns indicate heteroscedasticity.

3.4 Validity & Reliability

Using Cronbach's alpha and adjusted item-total correlations, we evaluate the reliability of the multi-item scales. Thresholds for acceptable alpha values are interpreted in line with discussions of how coefficient alpha behaves under varying item numbers and levels of dimensionality, rather than as rigid cut-offs (Cortina, 1993). Exploratory factor analysis (EFA) results are evaluated for significant primary factor loadings and relatively low cross-loadings and conceptually coherent factor structures and are used to provide evidence of internal consistency and convergent validity (Fabrigar et al., 1999). Discriminant validity is measured with examination of factor correlation matrices in order to ensure that constructs are empirically distinct and that these constructs do not merge into a complex that represents one dominant construct. To overcome possible common method bias of self-report measures, procedural safeguards to ensure data accuracy, including ensuring respondent anonymity, separating predictor and outcome sections of the questionnaire, and using varied stems for items, are included. Ex-post diagnostics include Harman's single - factor test and comparison of the power of the first unrotated factor with established benchmarks (Podsakoff et.al., 2003). Collectively, these procedures are designed to provide a strong evaluation of psychometric strength of the tools used to measure AI chatbot perceptions, digital advice utilisation and trading outcomes.

3.5 Ethics & Approvals

The empirical protocol follows institutional and national guidelines for research involving human participants, with particular attention to the digital nature of recruitment and data collection. Prior to launch, the full study design, questionnaire, recruitment messages, and data-management plan are submitted to the host institution’s ethics committee for independent review and approval. Participation is entirely voluntary and based on informed consent presented on the survey landing page, which explains the purpose of the study, the minimal risks involved, approximate completion time, and the right to discontinue at any point without adverse consequences. No personally identifying trading account details are requested; instead, responses are de-identified and stored on secure servers with access restricted to the research team. Findings are only reported in aggregate and no individual or brokerage can be identified. These safeguards are in line with emerging best practices in online behavioural surveys that deal with sensitive financial information (Couper, 2000; Wu et al., 2022).

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4. Results

4.1 Descriptive statistics

The final dataset included 300 retail investors that actively traded listed securities and reported recent interaction with investment chatbots that were enabled by artificial intelligence, as summarized in Table 2.

Table 2. Descriptive profile of respondents and trading activity

Characteristic	Statistic	Value
Age (years)	Mean (SD)	33.15 (7.58)
Trades per month	Mean (SD)	6.85 (2.48)
Gender: Female	n (%)	121 (40.3%)
Gender: Male	n (%)	161 (53.7%)
Gender: Non-binary	n (%)	12 (4.0%)
Gender: Prefer not to say	n (%)	6 (2.0%)
Education: Other	n (%)	10 (3.3%)
Education: Postgraduate	n (%)	79 (26.3%)
Education: School	n (%)	34 (11.3%)
Education: Undergraduate	n (%)	177 (59.0%)
Experience: 1–3 years	n (%)	114 (38.0%)
Experience: 3–5 years	n (%)	56 (18.7%)
Experience: <1 years	n (%)	74 (24.7%)
Experience: >5 years	n (%)	56 (18.7%)

Source: Author's calculations based on survey data, 2025

The sample was relatively young as the mean age was 33.15 years with SD = 7.58. Trading activity was significant in which the average frequency of trade per month was 6.85 (SD = 2.48) indicating that respondents were frequent participants in the market and not occasional investors. The sample consisted of males 53.7%, females 40.3%, non-binary respondents 4.0% and those declining to report on gender 2.0%. Educational attainment skewed towards higher degrees with 59.0% of respondents reporting bachelor's degree and 26.3% reporting postgraduate qualifications. 11.3% of respondents indicated secondary education and 3.3% indicating other.

Trading experience was spread out over <1-year (24.7%), 1-3 years (38.0%), 3-5 years (18.7%) and >5 years (18.7%) years, as there was variation in sophistication and familiarity with the workings of financial markets. Descriptive statistics for the core constructs appear in Table 3 Mean scores for perceived chatbot competence (PCC), trust in the chatbot (TRUST), digital advice utilisation (DAU), financial literacy (FL) and trading outcomes (TO) all centred around the midpoint of the five-point scale (M = 3.00), with standard deviations of approximately 1.30.

Table 3. Descriptive statistics and scale reliability of key constructs

Construct	Mean	SD	Min	Max	Cronbach alpha
PCC	3	1.30	1	5	0.93
TRUST	3	1.29	1	5	0.93
DAU	3	1.32	1	5	0.94
FL	3	1.30	1	5	0.94
TO	3	1.31	1	5	0.94

Source: Author's calculations based on survey data, 2025

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This pattern indicates substantial dispersion, with respondents spanning the full range from strong disagreement (1.00) to strong agreement (5.00) on all constructs. Cronbach's alpha values were very high for all scales ($\alpha \approx 0.94$–0.95), signalling excellent internal consistency and supporting the reliability of the multi-item measures used to represent chatbot perceptions, advice utilisation, literacy, and self-reported trading outcomes.

4.2 Inferential statistics

Table 4 presents the results of the bivariate correlations among the five latent factors. A moderate positive link with digital advice utilization (r = 0.487) and trading results (r = 0.347) was seen for perceived chatbot competency, and there was a high positive relationship with confidence in the chatbot (r = 0.549). Trust in the chatbot was similarly associated with digital advice utilisation (r = 0.486) and, to a lesser extent, trading outcomes (r = 0.284).

Table 4. Correlations among latent constructs

Construct	PCC	TRUST	DAU	FL	TO
PCC	1	0.549	0.487	0.217	0.347
TRUST	0.549	1	0.486	0.209	0.284
DAU	0.487	0.486	1	0.282	0.363
FL	0.217	0.209	0.282	1	0.346
TO	0.347	0.284	0.363	0.346	1

Source: Author's calculations based on survey data, 2025

Digital advice utilisation correlated positively with financial literacy (r = 0.282) and trading outcomes (r = 0.363), while financial literacy itself was moderately associated with trading outcomes (r = 0.346). These coefficients suggest a coherent pattern in which more favourable chatbot perceptions and higher literacy co-occur with more intensive advice use and better reported outcomes.

Multiple regression analysis was used to obtain more precise estimates of these relationships. Table 5 presents the regression of digital advice utilisation on perceived chatbot competence and trust.

Table 5. Regression of digital advice utilisation on chatbot perceptions

Predictor	B	SE	t	p_value	CI_lower_95	CI_upper_95
const	1.088	0.179	6.083	0	0.736	1.44
PCC	0.32	0.059	5.454	0	0.204	0.435
TRUST	0.318	0.059	5.404	0	0.202	0.433

Statistic	Value
N	300
R_squared	0.306
Adj_R_squared	0.301
F	65.405
Model_p	2.90779E-24
f_squared	0.44

Source: Author's calculations based on survey data, 2025

The model explains 30.58% of the variance in DAU ($R^2 = 0.306$; F = 65.41), indicating a substantial overall effect. Table 6 summarises the regression of trading outcomes on digital advice utilisation, financial literacy and their interaction term.

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Table 6. Regression of trading outcomes on digital advice utilisation and financial literacy

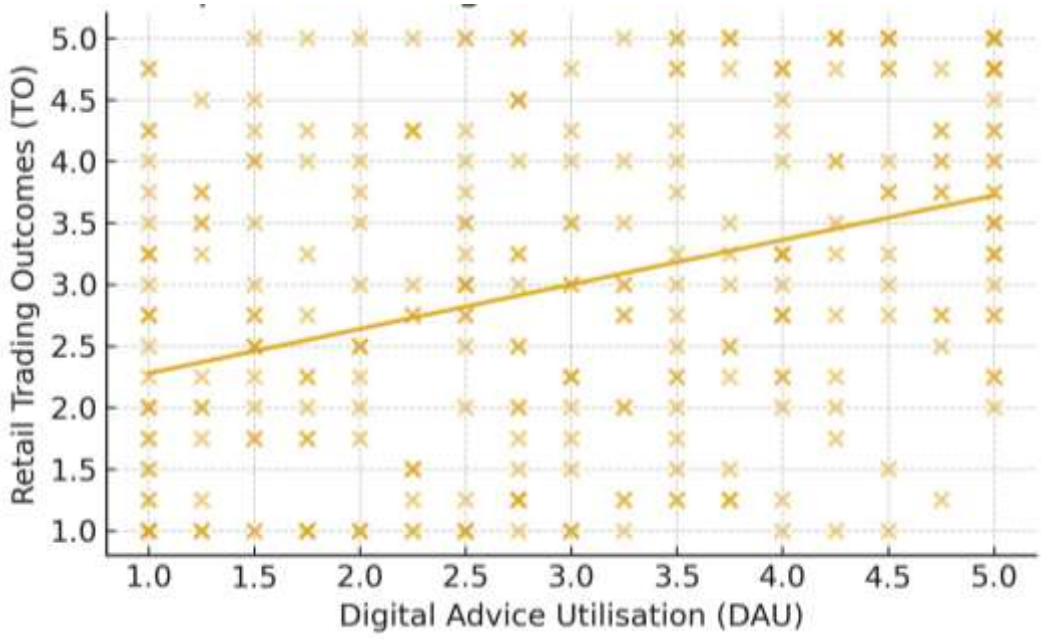
Predictor	B	SE	t	p_value	CI_lower_95	CI_upper_95
const	1.255	0.417	3.012	0.003	0.435	2.074
DAU	0.317	0.136	2.328	0.021	0.049	0.585
FL	0.295	0.134	2.202	0.028	0.031	0.559
DAU_FL_interaction	-0.01	0.04	-0.241	0.81	-0.089	0.069
Statistic	**Value**					
N	300					
R_squared	0.196					
Adj_R_squared	0.188					
F	24.126					
Model_p	5.38E-14					
f_squared	0.245					

Source: Author's calculations based on survey data, 2025

This model accounts for 19.65% of the variance in trading outcomes ($R^2 = 0.196$; $F = 24.13$), consistent with a moderate overall influence.

Figure 2 provides a visual illustration of the positive relationship between digital advice utilisation and trading outcomes based on the same data used for the regression models.

Figure 2 Relationship between digital advice utilisation and trading outcomes



Source: Author's calculations based on survey data, 2025

The upward-sloping regression line in the scatter plot reflects the tendency for higher advice utilisation to be associated with more favourable self-reported trading performance.

4.3 Hypothesis testing

Hypothesis H1 proposed that perceived chatbot competence would be positively associated with digital advice utilisation. As shown in Table 5, competence has a positive unstandardised coefficient (B = 0.3195, SE = 0.0586, t = 5.45, $p < 0.001$), with a 95% confidence interval from 0.2047 to 0.4344. As a result, with trust held

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constant, there is a correlation between a one-unit rise in perceived competence and an increase of around 0.32 points in advice usage, lending support to H1.

Hypothesis H2 stated that trust in the AI chatbot would be positively associated with digital advice utilisation. Trust displays a significant positive coefficient (B = 0.3177, SE = 0.0588, t = 5.40, $p < 0.001$), with a 95% confidence interval between 0.2025 and 0.4330 (Table 4). The similarity of these coefficients indicates that competence and trust contribute almost equally to explaining variation in advice utilisation, underscoring the importance of technical and relational perceptions of AI chatbots.

Hypothesis H3 proposed that digital advice utilisation would be positively related to retail trading outcomes. There is a positive and statistically significant coefficient for DAU (B = 0.3171, SE = 0.1362, t = 2.33, p = 0.0206) with a 95% confidence range spanning from 0.0501 to 0.5840. Higher chatbot-based advice use is associated with diversified portfolios, better perceived performance and reduced impulsive trading, supporting H3.

An individual's level of financial literacy was hypothesized to attenuate the association between the use of digital assistance and trading results (H4 hypothesis). There is a positive correlation between financial literacy and trading results (B = 0.2954, SE = 0.1341, t = 2.20, p = 0.0285, 95% CI [0.0324, 0.5583]). Nonetheless, without a significant interaction term (B = −0.0097, SE = 0.0402, t = −0.24, p = 0.8098, 95% CI [−0.0884, 0.0691]), H4 cannot be sustained.

4.4 Statistical significance and effect sizes

Taken together, the results demonstrate statistically reliable and practically meaningful relationships between chatbot perceptions, advice utilisation and trading outcomes. For the first regression model, the overall R^2 of 0.306 translates into an f^2 effect size of 0.44 (Table 4 meta-information), conventionally considered large in behavioural research (Cohen, 1992). For the trading-outcomes model, an R^2 of 0.196 implies an f^2 of 0.24 Table 5, corresponding to a moderate effect according to widely used benchmarks (Cohen, 1992; Fritz et al., 2012). These values indicate that the combined influence of digital advice utilisation and financial literacy accounts for a non-trivial share of the variability in self-reported trading outcomes.

Practical significance. On the five-point scales used, a one-unit increase in perceived competence (or trust) is associated with approximately a 0.32-point increase in digital advice utilisation Table 5. Given the observed dispersion of DAU (SD≈1.32), this corresponds to roughly 0.24 SD, indicating a meaningful behavioural shift rather than a negligible change. Similarly, a one-unit increase in advice utilisation is associated with about a 0.32-point increase in trading outcomes Table 6, also around 0.24 SD of the outcomes scale (SD≈1.31). While the outcomes are self-reported, these magnitudes suggest noticeable differences in perceived diversification discipline and reduced impulsive trading.

Confidence intervals around key coefficients are relatively narrow, especially in the first model, suggesting reasonably precise estimation in line with recommendations to complement p-values with interval estimates (Cumming, 2014). For example, the 95% intervals for the competence and trust effects on digital advice utilisation do not approach zero, reinforcing the robustness of these associations. In the second model, the intervals for the DAU and literacy coefficients are wider but still entirely above zero, whereas the interaction term's interval straddles zero comfortably, underscoring the absence of moderating effects. The pattern of p-values, confidence intervals and effect sizes is therefore consistent: chatbot competence and trust strongly predict advice utilisation, which in turn, alongside financial literacy, is moderately associated with improved trading outcomes, but the incremental benefit of advice utilisation does not appear to depend on investors' literacy levels.

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5. Discussion

5.1 Interpreting results

The results show that the conversational artificial intelligence within brokerage channels is part of a relational advisory interface as opposed to a neutral source of information. Perceived competence of the chatbot and trust are significantly related to digital advice utilisation, and account for a meaningful share of its variance. This is consistent with evidence that perceived expertise and reliability are considered fundamental antecedents of relying on algorithmic forecast DAS (Dietvorst et al., 2015; Mahmud et al., 2022). Rather than being algorithm averse, the investors seem to be conditionally willing to rely on the chatbot's assistance when it is judged to be technically able and good-intentioned. The positive link between digital advice utilisation and self-reported trading outcomes rises of the idea that conversational AI is linked to a more disciplined investing - rather than speculative overuse. More intensive consultation of chat bot guidance is associated with greater perception of increased diversification, higher levels of satisfaction with performance and lower levels of impulse trading, the respondents suggest. This pattern is consistent with previous works characterizing AI enabled advisory services as digital choice architectures that could help with more consistent financial behaviour (Zhu et al., 2024; Mele et al., 2021). The moderate effect size indicates that chatbot use supplements, rather than disarms, other determinants of performance such as market conditions, risk tolerance and experience. There are two implications of the non-significant interaction between digital advice utilisation and financial literacy. First, the benefits associated with chatbot use seem broadly distributed by literacy, to indicate a possibility of reducing information-processing barriers for less sophisticated investors with digitally-mediated advice. Second, the lack of moderation may indicate that the current generation of chatbots do not yet individually tailor guidance fine-grained to different knowledge profiles and generate relatively standardised outputs. Such patterns have broad appeals to developing human-AI collaboration frameworks for financial decision support contexts relating to retail investor behaviour.

5.2 Limitations

The cross sectional, self-reported design has a significant limitation that it reduces causal inferences and there is possibly bias, overestimating associations, due to common method variance. Endogeneity concerns (omitted variables and potential reverse causality between outcomes, trust, and advice utilisation) further limit causal interpretation. Longitudinal designs with objective trading records would strengthen identification. Objective brokerage records would be a better basis for validating diversification, performance and trading discipline. The non-probability nature of the sample for the online work means that there can also be a limit on the generalisability of the results to the broader population of investors - clients with limited access to the internet or whose more restrictive trading habit and/or pronounced scepticism toward artificial intelligence means that they may be under-represented, raising similar concerns as those discussed in problems created by real world (not lab) reliance on algorithms deviating from survey or laboratory behaviour (Dietvorst et al., 2015; Mahmud et al., 2022). The study also aggregates together the use of chatbots among providers and interfaces for design. Studies of AI-supported financial advisory services note that transparency, explanation capabilities and regulatory mechanisms widely differ among various platforms and drive trust as well as reliance (Zhu et al., 2024). Without platform-level identifiers, it is Concerns with the impact of design on the characteristics of investors. The outcome construct is also a measure of perceived, rather than realised performance; consequently, the evaluation by investors may not be a complete measure of risk-adjusted returns. Finally, the model does not take into account potential mediators such as perceived risk, overconfidence and specific behavioural biases, which may mediate the translation of AI advice to concrete trading behaviours.

5.3 Future research directions

Future studies should combine longitudinal chatbot-interaction logs with objective brokerage trading records to test whether reliance on AI guidance influences diversification, turnover, and risk-adjusted performance

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over time. Field experiments that vary disclosure, explanation depth, and risk warnings can identify which design features improve decision quality and reduce behavioural biases. Comparative analyses of human-only, AI-only, and hybrid advisory settings can clarify when human–AI collaboration yields superior outcomes. Field experiments to manipulate chatbot disclosure, explanation depth, or words of warning may help to examine the influence of different digital nudging strategies (e.g., dependence rates, outcomes) or if market/July experience volatile markets (probability of market intervention), Hettler et al., 2025; Mele et al., 2021. Comparative studies of human- only, AI- only and hybrid advisory configurations would also help us better understand when human-AI collaboration yields better portfolio outcomes. Another avenue is segmenting the investors by attitudinal and cultural orientation towards algorithms. Research on algorithm aversion and appreciation reveal that prior experience with errors, tolerance of ambiguity and perceived responsibility play a role when it comes to willingness to delegate to algorithms (Dietvorst et al., 2015; Mahmud et al., 2022). Extending such frameworks to trading on conventional retailing exchanges may help to expose which parts of the market are most supportive of conversational AI, and what parts still have a reluctance to depend on such a system, even when performance is good. Finally, future studies must more directly address regulatory and ethical questions of AI mediated trading support including transparency obligations, protection mechanisms from exploitation of engagement practices, and design of AI systems to promote increased investor autonomy and financial wellbeing.

6. Conclusion

6.1 Empirical findings

The study offers evidence on how conversational AI advice is woven into retail stock trading. Perceived chatbot competence and trust are strong, independent predictors of digital advice utilisation, explaining variation in how often investors consult and follow chatbot guidance. This aligns with research showing that perceived expertise, reliability and benevolence drive reliance on algorithmic advisors and robo-advice platforms (Lourenço et al., 2020; Mahmud et al., 2022). Instead of broad algorithm aversion, the results indicate reliance once the system is experienced as technically capable and aligned with investor interests (Dietvorst et al., 2015).

Digital advice utilisation shows a positive association with self-reported trading outcomes after accounting for financial literacy. Respondents who consult chatbot recommendations more intensively report better diversification, greater achievement of expected returns and fewer impulsive trades. The effect is moderate, indicating that conversational AI functions as one element alongside literacy, experience and market conditions, in line with work that conceptualises robo-advisors and AI-enabled interfaces as digital choice architectures that help stabilise financial behaviour (Back et al., 2023; Mele et al., 2021; Zhu et al., 2024).

Financial literacy displays a positive direct relationship with trading outcomes but does not significantly moderate the effect of digital advice utilisation. The incremental benefit of chatbot use appears similar across literacy strata, suggesting that conversational AI may partially compensate for lower knowledge while also supporting more sophisticated investors. The absence of a strong interaction effect implies that current chatbots provide largely standardised guidance rather than adapting advice to different profiles. This pattern is important for understanding AI–investor interaction dynamics today.

6.2 Theoretical Implications

The results extend work on algorithm aversion and algorithm appreciation by showing that, in retail trading, reliance on AI advice is shaped jointly by competence beliefs and relational trust rather than by performance feedback alone (Dietvorst et al., 2015; Mahmud et al., 2022). Chatbots appear as hybrid entities, both technical calculators and quasi-social advisors, enriching technology acceptance perspectives with conversational quality and perceived benevolence as mechanisms that convert availability of AI into actual advice use (Lourenço et al., 2020).

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The positive but modest link between digital advice utilisation and trading outcomes supports a balanced view of AI-enabled financial decision support. Conversational AI appears neither a panacea nor a purely hazardous tool. Outcomes depend on how AI inputs are integrated with human judgement, domain knowledge and market context, consistent with emerging human–AI collaboration frameworks in financial services (Zhu et al., 2024). The non-significant moderation by financial literacy challenges substitution narratives in which AI fully replaces domain knowledge; literacy and AI advice instead operate as complementary resources that jointly shape retail trading performance (van Rooij et al., 2011).

Conflict of interest statement

Authors declare no conflicts of interest regarding design, execution, analysis, or reporting of this study, and have no financial or personal relationships influencing interpretation whatsoever.

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Informed consent statement

Participation was entirely optional, participants remained anonymous, and they were free to stop the survey at any moment without penalty; after obtaining research information, all participants electronically gave their informed consent.

Data availability statement

In accordance with data protection rules and the criteria of institutional ethics approval, the corresponding author is willing to provide de-identified survey data and analytic code upon reasonable request.

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