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A Study on Customer Trust in AI-Generated Financial Advice Among Groww Users in Hyderabad, Telangana

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ABSTRACT

Digital investment platforms make financial information and transaction services accessible through mobile applications. Alongside conventional sources, retail investors may encounter AI-generated explanations, summaries, comparisons or investment guidance. This research study proposal examines customer trust in AI-generated financial advice among Groww users who reside in Hyderabad, Telangana. It brings together the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and trust research to examine performance expectancy, effort expectancy, social influence, transparency and perceived risk as factors associated with trust. It also examines the relationship between trust and intention to consider AI-generated financial guidance. A descriptive, cross-sectional survey is proposed for adult Groww users in Hyderabad who can identify an encounter with AI-generated financial guidance. A structured questionnaire will use screening items and five-point Likert statements. Descriptive statistics, scale-reliability assessment, correlation and multiple regression are proposed, subject to sample adequacy and diagnostic checks. The study has not yet supplied respondent-level data; accordingly, this proposal reports no sample profile, statistical results or hypothesis decisions. It offers a framework for conducting the study transparently and for distinguishing trust in an AI system from trust in the platform through which advice is encountered.

Keywords: customer trust, AI-generated financial advice, Groww, TAM, UTAUT, transparency, perceived risk, behavioural intention, Hyderabad.

1 • INTRODUCTION

Digital investment platforms have changed how individuals access financial information and participate in markets. Mobile applications can bring account access, product information, transactions and educational content together in one interface. Users may also consult AI tools for explanations, comparisons or suggestions about investment questions. Because the term “AI-generated financial advice” can describe different activities, this study will record what the respondent encountered, where it appeared and whether it was general information or personalized guidance. The study will not assume that every AI response seen by a Groww user was generated or endorsed by Groww.

Financial choices can expose users to monetary loss. A recommendation may appear clear and useful while its data, assumptions and limitations remain difficult to assess. Users may therefore weigh expected usefulness and ease of use against trust, privacy concerns, perceived risk and confidence in the provider. Trust is particularly important when people consider relying on an automated system under uncertainty. It should be calibrated to the system’s actual role and limits rather than treated as a simple willingness to use technology (Lee & See, 2004).

The present study focuses on Groww users in Hyderabad, Telangana. It aims to understand which perceptions are associated with trust in AI-generated financial guidance and whether trust is associated with intention to consider that guidance. The study concerns user perceptions and stated intentions; it does not test the accuracy of a particular AI system or assess investment performance.

Research Problem Statement

People who use digital investment platforms may encounter AI-generated financial guidance through platform features or other digital tools. They may perceive such guidance as useful and easy to understand, but also question its accuracy, transparency, privacy safeguards or suitability for their circumstances. Without evidence about these beliefs in the selected local group, platforms and educators have limited information about how users evaluate AI-generated financial guidance. The research problem is to examine the level and dimensions of trust in AI-generated financial advice among Groww users in Hyderabad and the factors associated with trust and stated intention to consider that advice.

Research Gap

The theoretical foundations for this study come from established research on technology acceptance, trust and automated advice. TAM and UTAUT explain technology-use beliefs, while trust research addresses vulnerability and expectations about another party or system. Research on robo-advising examines automated financial decision support. The study applies these perspectives together to a focused group of Groww users in Hyderabad and separates trust in the advice-generating AI from trust in the platform. This is a contextual research gap identified for the present project, not a claim that no related Indian study exists; a formal literature search should be completed before final academic submission.

Objectives of the Study

To describe the demographic profile, investment experience and AI-guidance exposure of eligible respondents.

To assess customer trust in AI-generated financial advice among eligible Groww users in Hyderabad.

To examine the association of performance expectancy, effort expectancy, social influence, transparency and perceived risk with trust.

To examine the association between trust and behavioural intention to consider AI-generated financial guidance.

To develop evidence-based suggestions for clearer communication and responsible use of AI-generated financial guidance.

Research Questions

How do eligible Groww users in Hyderabad assess the trustworthiness of AI-generated financial guidance they have encountered?

How are performance expectancy, effort expectancy, social influence, transparency and perceived risk associated with trust?

Is trust associated with intention to consider AI-generated financial guidance?

Do trust perceptions vary with selected user characteristics and prior investment or AI experience?

Research Hypotheses

H1: Performance expectancy has a significant positive association with trust in AI-generated financial advice.

H2: Effort expectancy has a significant positive association with trust. H3: Social influence has a significant positive association with trust.

H4: Transparency has a significant positive association with trust. H5: Perceived risk has a significant negative association with trust.

H6: Trust has a significant positive association with behavioural intention to consider AI-generated financial advice.

For each hypothesis, the null hypothesis states that the specified association is not statistically significant. The proposed cross-sectional analysis tests association and does not establish causation.

Scope of the Study

The geographic scope is Hyderabad, Telangana. The target respondents are adults who currently use Groww and have encountered AI-generated financial guidance relevant to an investment or personal-finance question. The study covers perceived usefulness, ease of use, social influence, transparency, perceived risk, trust and intention to consider the guidance. It does not evaluate the quality of individual investment products, financial returns or the regulatory status of a particular AI feature.

2 • LITERATURE REVIEW

Introduction

This chapter reviews technology acceptance, trust, automated decision-making and robo-advice research that informs the proposed model. It connects the selected constructs to the study questions and identifies the need to measure the AI source and platform separately.

Technology Acceptance Model

Davis (1989) developed the Technology Acceptance Model to explain acceptance of information technology through perceived usefulness and perceived ease of use. Perceived usefulness refers to the belief that a system can help achieve a task; perceived ease of use concerns the effort required to use it. For AI-generated financial guidance, these concepts correspond to whether users believe the guidance helps them understand or compare financial choices and whether they can interact with it without undue effort. The present study labels these related beliefs performance expectancy and effort expectancy where appropriate, while retaining clearly defined survey measures.

Unified Theory of Acceptance and Use of Technology

Venkatesh, Morris, Davis and Davis (2003) integrated factors from earlier acceptance models into UTAUT. Performance expectancy and effort expectancy describe expected benefits and ease, while social influence captures perceptions that important others think a technology should be used.

Facilitating conditions concern resources and support for use. This study focuses on the first three constructs because they are included in the research questions and measures trust-related beliefs in the advice context. Facilitating conditions may be recorded descriptively if included in the final instrument.

Trust and Technology Use

Mayer, Davis and Schoorman (1995) describe trust as willingness to accept vulnerability based on beliefs about another party's ability, benevolence and integrity. Although their model was developed in organizational settings, it provides a useful way to think about reliance when a person cannot fully control or verify an outcome. Gefen, Karahanna and Straub (2003) integrated trust with TAM in online shopping and showed that trust can be considered alongside usefulness and ease of use when explaining intended behaviour in a digital environment. In financial contexts, trust should be linked to a specific source and task rather than treated as general confidence in technology.

Trust in Artificial Intelligence and Algorithm Aversion

Glikson and Woolley (2020) review empirical studies of trust in AI and describe how trust is shaped by features of the system and the interaction context. Their review supports examining trust as more than a single reaction to the label "AI." Transparency, perceived competence and the ability to understand a system's role can affect how users judge its output. Dietvorst, Simmons and Massey (2015) document algorithm aversion: people may reduce their reliance on an algorithm after seeing it make errors. This is relevant to financial guidance because users may weigh the consequences of a mistaken suggestion heavily, even when they perceive the tool as efficient.

Automated Financial Advice

D'Acunto, Prabhala and Rossi (2019) examine the promises and pitfalls of robo-advising, showing that automated portfolio tools can influence investor behaviour and that effects can differ across investors. Lourenço, Dellaert and Donkers (2020) find that perceived trust and expertise of the advice provider, together with the user's experience with the tool, matter for acceptance of automated financial advice. These studies indicate that trust may relate both to system characteristics and to the organization or channel associated with the advice. They also support measuring trust and intention separately.

Literature Synthesis

Author and year	**Focus**	**Relevance to this study**
Davis (1989)	Perceived usefulness and ease of use in	Supports expected usefulness and effort
Venkatesh et al. (2003)	UTAUT and technology acceptance	Supports performance expectancy,
Mayer et al. (1995)	Trust based on beliefs about ability,	Frames trust as willingness to accept
Gefen et al. (2003)	Trust integrated with TAM in online	Supports studying trust alongside
Dietvorst et al. (2015)	Algorithm aversion after users observe	Highlights the role of perceived risk
Glikson & Woolley (2020)	Review of empirical research on trust	Supports context-specific measurement
D'Acunto et al. (2019); Lourenço et al.	Robo-advice, investor behaviour and	Connects trust and adoption to

Research Gap and Chapter Summary

The literature provides established constructs for technology acceptance, trust and robo-advice, but this proposed study brings them together for a defined population of Groww users in Hyderabad. It distinguishes a user's trust in AI-generated guidance from trust in the platform and records the source of the guidance. The next chapter explains how the research questions can be examined through a structured survey without assuming in advance that the guidance originated from Groww.

Conceptual Framework

The proposed framework treats trust as the central outcome of performance expectancy, effort expectancy, social influence, transparency and perceived risk. Trust is then examined in relation to behavioural intention to consider the advice. Prior AI experience, investment experience, financial literacy and demographic characteristics may be included as control variables if the final sample supports the planned model.

PERFORMANCE EXPECTANCY • EFFORT EXPECTANCY • SOCIAL INFLUENCE • TRANSPARENCY • PERCEIVED RISK

↓

CUSTOMER TRUST IN AI-GENERATED FINANCIAL GUIDANCE

↓

BEHAVIOURAL INTENTION TO CONSIDER THE GUIDANCE

3 • RESEARCH METHODOLOGY

Introduction

This chapter outlines a proposed research design for studying customer trust in AI-generated financial guidance among Groww users in Hyderabad. It describes the population, sampling plan, questionnaire, data collection safeguards and statistical analysis. The design will be finalized with the research guide before recruitment begins.

Research Design

A quantitative, descriptive and analytical cross-sectional survey is proposed. It will describe respondents and examine associations among perceived characteristics of AI-generated financial guidance, trust and behavioural intention. Because the survey measures responses at one point in time, its results will not support causal conclusions.

Population and Eligibility

The target population is adults aged 18 years or older who currently use Groww and reside in Hyderabad, Telangana. To answer trust items, respondents should be able to identify at least one recent encounter with AI-generated financial guidance related to an investment or personal-finance question. The survey will record the source, type and approximate timing of the encounter.

Respondents who have not encountered such guidance may answer the exposure and profile items but will not be included in the construct-level analysis.

Sample Size and Sampling Method

A purposive convenience approach, with optional referral-based recruitment, is proposed because a complete sampling frame of local Groww users is not available. An initial target of approximately 200 eligible completed responses is proposed for descriptive analysis and a modest regression model. The target should be checked through an a priori power analysis and confirmed with the guide before data collection. The eventual sample will be described transparently and will not be presented as statistically representative of all Groww users.

Sources of Data

Primary Data

Primary data will be collected through a structured questionnaire distributed electronically or in person after institutional approval. The questionnaire will ask about current Groww use, investment experience and the respondent's encounter with AI-generated financial guidance. It will not request account credentials, account numbers, portfolio screenshots or transaction-level details.

Secondary Data

Secondary information will be drawn from peer-reviewed research on technology acceptance, trust, algorithm use and robo-advising, along with official SEBI materials relevant to investment-adviser responsibilities. Secondary sources provide conceptual and regulatory context; they do not substitute for the proposed primary data.

Research Instrument and Measures

The proposed instrument will include eligibility and exposure questions, demographic and investment-profile items, followed by multi-item measures for performance expectancy, effort expectancy, social influence, transparency, perceived risk, trust and behavioural intention.

Agreement items will use a five-point scale from 1 (Strongly Disagree) to 5 (Strongly Agree), with "Not sure/Not applicable" where needed. Item wording will be reviewed for clarity and pilot-tested before full distribution. The final number of items and any adopted scale sources should be documented after the instrument is finalized.

Construct	Proposed measurement focus	Expected direction
Performance expectancy	Perceived usefulness and decision	Positive with trust
Effort expectancy	Clarity and ease of interacting with	Positive with trust
Social influence	Perceived views of people important	Positive with trust
Transparency	Disclosure of AI source, rationale and	Positive with trust
Perceived risk	Concern about error, loss, privacy or	Negative with trust
Trust	Confidence in the identified AI	Positive with intention
Behavioural intention	Likelihood of considering or	Outcome variable

Data Collection Procedure

Before recruitment, the researcher will obtain required institutional approval and confirm the questionnaire with the research guide. Participants will receive a short description of the study and a consent statement. The survey will use screening questions to confirm age, residence, current Groww use and relevant AI exposure. The researcher will record the recruitment period, channels, eligibility rules and number of valid responses. Responses will be stored in a password-protected file and reported in aggregate.

Ethical Considerations

Participation will be voluntary. The study will avoid collecting direct identifiers and sensitive financial account details. Participants may stop before submitting their responses. Only the researcher and authorized academic supervisor will have access to the study data, which will be retained and disposed of according to institutional requirements. The survey will clarify that it is an academic study and does not provide investment advice.

Data Analysis Techniques

Frequencies and percentages will summarize respondent characteristics, platform use and AI-guidance exposure.

Means and standard deviations will describe scale responses after items are checked and scored as planned.

Cronbach's alpha or another suitable reliability estimate will assess internal consistency for multi-item constructs; reliability will be reported rather than assumed.

Correlation analysis will summarize bivariate relationships among the constructs.

Multiple regression will estimate associations between the five proposed predictors and trust, and a separate model will examine trust in relation to behavioural intention.

Model assumptions, missing data, effect sizes, confidence intervals and p-values will be reviewed. Hypotheses will be assessed at a two-sided 5% significance level, with interpretation focused on effect size and uncertainty.

Limitations of the Proposed Method

Convenience and referral recruitment may create self-selection and limit generalizability. Self-reported trust and intention may not predict actual investment behaviour.

Respondents may use "AI-generated advice" to describe different information sources and levels of personalization.

A cross-sectional survey can identify associations but cannot establish cause and effect.

The survey cannot verify the accuracy, suitability or regulatory status of any specific advice output.

4 • PROPOSED DATA ANALYSIS PLAN

Introduction

This chapter sets out how the collected survey data will be organized and tested. It does not present response frequencies, descriptive scores, regression coefficients or hypothesis decisions because no respondent-level dataset accompanies the draft. Once fieldwork is complete, the researcher can populate the analysis tables using the steps below.

Analysis stage	Purpose	Planned output
Sample description	Describe eligible respondents,	Counts and percentages; report final
Scale review	Check item completeness, coding and	Construct means, standard deviations
Association review	Summarize relationships among	Correlation coefficients with
Predictor model	Examine associations of PE, EE, SI,	Regression estimates, uncertainty
Intention model	Examine trust in relation to behavioural	Regression estimate, model fit and

Interpretation Rules

The analysis will distinguish statistical association from causation. A statistically significant coefficient will not by itself show that a factor causes trust or that a trusted recommendation is accurate. Results will be interpreted alongside effect sizes, confidence intervals, sample characteristics, source of advice and study limitations. Hypothesis decisions will be made only after the dataset is cleaned and the specified tests are run.

5 • EXPECTED CONTRIBUTION AND CONCLUSION

Expected Contribution

The proposed study can contribute local evidence about how Groww users in Hyderabad evaluate AI-generated financial guidance. By combining TAM and UTAUT beliefs with trust, transparency and perceived risk, it can help distinguish perceived convenience from confidence in the advice source. Recording the AI source and platform separately can also help avoid attributing external AI outputs to Groww. Recommendations should be developed only after examining the collected responses.

Conclusion

This research study proposal presents a framework for examining trust in AI-generated financial advice among Groww users in Hyderabad, Telangana. It identifies the research problem, objectives, questions, six hypotheses, proposed survey design, measurement constructs and analysis plan. The study is prospective: empirical conclusions about trust or user behaviour can be drawn only after eligible participants are recruited and their responses are analyzed. The final report should present observed results, explain their limits, and avoid implying that trust alone establishes the accuracy or suitability of financial guidance.

Recommendations for Future Research

Use a larger and more diverse sample, with recruitment across multiple Hyderabad localities and user groups.

Compare different investment platforms and clearly distinguish platform features from independent AI tools.

Examine how financial literacy, investment experience and prior exposure to AI relate to trust.

Use longitudinal or experimental designs to study how trust changes after users encounter correct or incorrect guidance.

Where ethically and institutionally approved, compare stated intentions with observed, privacy-protected behaviour.

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APPENDIX A • PROPOSED QUESTIONNAIRE

The following items are a draft instrument for review and pilot testing. They are not represented as the exact questionnaire already administered. Respondents should be instructed to think about the specific AI-generated financial guidance they identified in the screening section. Agreement scale: 1

= Strongly Disagree; 2 = Disagree; 3 = Neither Agree nor Disagree; 4 = Agree; 5 = Strongly Agree. “Not sure/Not applicable” may be selected where appropriate.

Section A • Eligibility and Profile

1. Are you 18 years of age or older?
2. Do you currently use a Groww account?
3. Do you currently reside in Hyderabad, Telangana?
4. Have you encountered AI-generated financial information or guidance related to investing or personal finance? If yes, identify the source and type of guidance.
5. How long have you used Groww, and how would you describe your investment experience?
6. How often do you use AI tools for financial questions?

Section B • Agreement Statements

1. Performance expectancy: The AI-generated financial guidance I encountered was useful for understanding an investment question.
2. Performance expectancy: The guidance helped me compare financial choices.
3. Performance expectancy: The guidance gave me information relevant to the question I asked.
4. Effort expectancy: It was easy to understand how to interact with the AI tool.
5. Effort expectancy: The financial guidance was presented in language I could understand.
6. Effort expectancy: I could find the information I needed without much effort.
7. Social influence: People whose opinions matter to me think AI tools can be useful for financial information.
8. Social influence: People I trust encourage me to check more than one source before making financial decisions.

9. Social influence: Recommendations from people I respect affect whether I consider AI-generated guidance.
10. Transparency: The source made it clear that the financial guidance was generated by AI.
11. Transparency: The source explained the main reasons or information behind the guidance.
12. Transparency: The source made the limitations of the guidance clear.
13. Perceived risk: Following AI-generated financial guidance without checking it could expose me to financial loss.
14. Perceived risk: I am concerned that AI-generated financial guidance may not fit my personal circumstances.
15. Perceived risk: I am concerned about how personal or financial information may be used by the AI service.
16. Trust: I believe the identified AI source can provide dependable financial information for the purpose it claims.
17. Trust: I feel comfortable considering the identified AI-generated guidance as one input in a decision.
18. Trust: I would trust the guidance more when its source, basis and limitations are clearly disclosed.
19. Behavioural intention: I intend to consider AI-generated guidance as one source of financial information.
20. Behavioural intention: Before acting on AI-generated guidance, I intend to verify it using another credible source.
21. Behavioural intention: I would seek qualified human advice when a financial decision is complex or high-stakes.

APPENDIX B • SIMULATED SURVEY RESULTS DEMONSTRATION

IMPORTANT: The responses and statistics in this appendix are computer-generated examples. No Groww users took part in a survey for these results. The figures do not describe real customers or the study population. Do not cite, submit, publish, or present them as findings from actual research.

Purpose and generation

This appendix shows one way survey results might be summarized after data collection. For practice, I generated 200 fictional records using a fixed random-number seed (2400560057), so the example can be reproduced. The records were not collected from Groww users or from any real group in Hyderabad. Each fictional record includes responses to three Likert-scale items for each construct. The dataset is included only to demonstrate scoring and reporting.

The example questionnaire covers performance expectancy (PE), effort expectancy (EE), social influence (SI), transparency (TR), perceived risk (PR), trust (TRUST) and behavioural intention (INTENT). I built modest relationships into the generated data: the first four perceptions tend to move with trust, perceived risk tends to move against it, and trust tends to move with intention. Because these patterns were part of the simulation design, they say nothing about what real respondents might think and cannot be used to support the study hypotheses.

Synthetic profile (illustrative only)

Synthetic variable	Category	Count	Percent
Age group	18-24	55	27.5%
Age group	25-34	85	42.5%
Age group	35-44	41	20.5%
Age group	45+	19	9.5%
Groww use experience	Less than 1 year	52	26.0%
Groww use experience	1-3 years	89	44.5%
Groww use experience	More than 3 years	59	29.5%
AI guidance source	External generative AI tool	91	45.5%
AI guidance source	Financial website or app	63	31.5%
AI guidance source	Other/unsure	46	23.0%

Synthetic construct summaries

Construct	Mean	SD	Possible range

PE	2.98	0.93	1–5
EE	3.00	0.92	1–5
SI	3.00	0.92	1–5
TR	2.99	0.84	1–5
PR	3.00	0.90	1–5
TRUST	2.99	0.85	1–5
INTENT	2.96	0.91	1–5

These averages and standard deviations describe only the fictional practice records. They should not be read as estimates of how Groww users or Hyderabad residents would respond.

Synthetic regression demonstration

The table below gives standardized coefficients calculated from the generated records. The first example model relates the five perception scores to the generated trust score. The second relates generated trust to generated intention. I have left out p-values and hypothesis decisions: these are teaching examples, not results from the proposed study.

Model 1: outcome = synthetic trust	**Standardized coefficient**
Performance expectancy	0.305
Effort expectancy	0.189
Social influence	0.079
Transparency	0.236
Perceived risk	-0.228
Model RZ	0.244
Model 2: outcome = synthetic intention	**Standardized coefficient**
Synthetic trust	0.520
Model RZ	0.270

Interpretation boundary

The coefficients simply reflect the choices made when generating the example data. They do not tell us how real respondents would answer or how the study variables relate in practice. To complete the empirical paper, this section must be replaced with analysis of eligible participants' actual responses. The final paper should also report when and how recruitment took place, how many responses were excluded, the final sample size and the analysis reviewed with the research guide.

Practice data file

The companion CSV is available for practicing the analysis. Its filename and each row are marked as simulated. It includes fictional profile categories, 21 five-point item responses and calculated construct averages; it contains no real personal or financial details.