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Antecedents and Boundary Conditions of Trust in Algorithmic Financial Advisory Systems: A Structural Examination within Nepal's Retail Investment Ecosystem

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Abstracts

This study explores how retail investors in Nepal build trust in Financial Robo-Advisory (FRA) services and how that trust affects their willingness to use such platforms. Using data collected from 520 retail investors and analyzed through PLS-SEM, the study found that trust is strongly shaped by factors such as personal trust tendency, perceived reliability and competence of robo-advisors, social influence, enjoyment in using digital platforms, supporting infrastructure, price value, and ease of access. However, effort expectancy showed a negative effect, suggesting that many investors in Nepal still perceive FinTech systems as difficult to understand due to limited digital literacy and low exposure to advanced financial technologies. The findings further reveal that younger investors are more confident and willing to adopt robo-advisory services than older investors, who generally prefer traditional financial consultation methods. By extending the UTAUT framework with trust-related dimensions, the study offers useful insight into digital financial adoption in emerging economies. The results highlight the need for financial institutions and policymakers to improve digital awareness, simplify platform design, strengthen internet accessibility, and ensure transparent and secure financial services to encourage wider adoption of robo-advisory systems.

Keywords: *Algorithmic financial advisory; Robo-advisory systems; Behavioral intention; Technology adoption; AI-driven wealth management*

Introduction

Financial Robo-Advisory (FRA) services are transforming the delivery of investment advice and portfolio management across global financial markets. Through the integration of artificial intelligence, data analytics, and algorithm-based decision systems, these platforms provide automated investment recommendations at lower cost and with limited human involvement. As digital finance continues to expand, robo-advisory platforms are increasingly viewed as an accessible alternative to traditional financial consultation, particularly for retail investors seeking convenient and technology-driven investment solutions. Global assets managed through robo-advisory platforms are expected to exceed USD 2 trillion by 2027 (Statista, 2024), reflecting the rapid expansion of automated financial services worldwide.

Despite this growth, investor trust remains a major challenge in the adoption of robo-advisory systems. Financial decisions involve uncertainty and risk, and many individuals continue to prefer direct interaction with human advisors before making investment commitments (OECD, 2022). The absence of personal communication, concerns regarding data security, limited understanding of algorithm-based recommendations, and uncertainty about system reliability often discourage investors from fully relying on automated advisory services. Consequently, trust has emerged as one of the most important determinants influencing the acceptance of digital financial platforms.

In Nepal, the financial sector is undergoing a gradual digital transformation driven by increasing internet penetration, digital payment adoption, and regulatory encouragement toward financial technology innovation. Nepal Rastra Bank has introduced several initiatives, including the Digital Payment Strategy and FinTech Regulatory Framework, to strengthen digital financial ecosystems and promote financial inclusion (Nepal Rastra Bank, 2019; 2023). By mid-2023, Nepal recorded more than 21 million digital wallet accounts, indicating growing public engagement with digital financial services. Similarly, the number of Demat account holders surpassed 5 million, demonstrating increasing participation in the capital market (SEBON, 2023).

Although these developments indicate a positive shift toward digital finance, trust in automated investment advisory systems remains uncertain. Many retail investors in Nepal still depend on informal investment guidance from peers, family members, and social media platforms due to moderate levels of financial and digital literacy. While online trading and digital brokerage platforms are gaining popularity, empirical evidence regarding the factors that shape trust in robo-advisory services within the Nepalese context remains limited. Existing studies on technology adoption have primarily focused on developed economies and general FinTech acceptance, providing insufficient attention to trust formation in emerging financial markets such as Nepal. Furthermore, previous research has rarely examined how demographic factors such as age influence the relationship between trust propensity and initial trust in automated advisory systems. This creates a significant research gap, particularly in understanding investor behaviour toward AI-driven financial services in developing economies.

The Unified Theory of Acceptance and Use of Technology (UTAUT) explains that factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions influence individuals' willingness to adopt digital technologies (Venkatesh et al., 2003). However, in financial technology environments where investment decisions involve perceived risk and uncertainty, trust-related dimensions require deeper examination. Initial trust is especially important in robo-advisory services because investors must depend on algorithm-generated recommendations without direct human reassurance (Gefen et al., 2003). Therefore, understanding how trust is developed and how it influences behavioural intention has become increasingly important in Nepal's evolving digital investment environment.

Against this background, the present study examines the determinants of trust in robo-advisory platforms among retail investors in Nepal. Specifically, the study aims:

- To examine the influence of trust propensity on initial trust in robo-advisory services;
- To analyse the effect of initial trust on behavioural intention to adopt robo-advisory platforms; and
- To evaluate whether age moderates the relationship between trust propensity and initial trust.

This study holds both theoretical and practical significance. Theoretically, it extends the UTAUT framework by incorporating trust-related constructs within the context of AI-driven financial advisory services in an emerging economy. Methodologically, the study applies Structural Equation Modelling (SEM) to analyse relationships among behavioural and trust-related variables using survey-based quantitative data. Practically, the findings may support fintech companies, brokerage firms, financial institutions, and policymakers in developing strategies that strengthen investor confidence, improve digital financial literacy, simplify platform usability, and encourage broader participation in automated investment services.

Despite its contributions, the study is subject to certain limitations. The analysis is confined to retail investors in Nepal, which may limit the generalizability of the findings to other countries or demographic groups. In addition, the use of self-reported survey responses may introduce response bias, while the cross-sectional nature of the study restricts the ability to establish long-term causal relationships. Nevertheless, the research provides important insight into the evolving dynamics of trust in digital financial services and contributes to the growing discussion on technology-driven investment behaviour in emerging economies.

Theoretical View

Confidence in AI-Driven Automated Services

Financial robo-advisory (FRA) services are still at a formative stage within Nepal's financial ecosystem. While digital payment platforms such as eSewa and Khalti have achieved widespread public acceptance, automated investment advisory systems remain relatively unfamiliar to most retail investors. Nepal Rastra Bank (2023) reports rapid growth in digital financial transactions; however, participation in capital markets through technology-enabled advisory systems is still emerging. In such an environment, initial trust becomes a decisive factor influencing whether retail investors are willing to experiment with FRA services. Existing studies in developing economies indicate that trust plays a critical role in the adoption of digital financial technologies, particularly in contexts where awareness, digital literacy, and confidence in automated systems remain limited (Alalwan et al., 2017; Shin, 2021). However, empirical evidence regarding trust formation in robo-advisory services within the Nepalese context remains scarce. Most Nepalese studies have focused primarily on mobile banking, online banking, and digital payment adoption, while limited attention has been given to AI-driven investment advisory services.

Trust Propensity and Initial Trust in FRA

The term trust propensity refers to an individual's natural tendency to trust others or unfamiliar systems even when complete information is unavailable. According to Mayer, Davis, and Schoorman (1995), trust propensity represents a stable personality trait that influences how individuals evaluate new technologies and service providers. Research in online financial services suggests that individuals with stronger trust orientation are more willing to adopt emerging technologies and digital financial systems (Gefen, 2000). In Nepal, increasing exposure to online banking applications, mobile wallets, and online trading systems may strengthen retail investors' familiarity with digital financial environments. Such familiarity can positively shape initial confidence toward robo-advisory platforms, even when users possess limited technical understanding of algorithm-based systems.

At the same time, robo-advisory services involve higher levels of uncertainty because investment recommendations are generated through automated algorithms rather than direct human interaction. This indicates the need to integrate Trust Theory with technology adoption frameworks. Although the Unified Theory of Acceptance and Use of Technology (UTAUT) explains adoption behaviour through variables such as performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003), scholars argue that traditional technology adoption models alone are insufficient in high-risk financial environments where trust becomes a central concern (Gefen et al., 2003; Shin, 2021). Therefore, extending UTAUT with trust-related constructs provides a more comprehensive explanation of behavioural intention toward FRA services.

Therefore, the following hypothesis is proposed:

- H1: Trust propensity positively influences initial trust in using FRA services.

Retail Investors and Trust in FRA

Retail investors differ in terms of technological adaptability, financial awareness, and willingness to adopt innovative financial solutions. Studies conducted in developing economies indicate that individuals with greater digital exposure are more likely to adopt FinTech services and automated financial platforms (D'Acunto et al., 2019). Similarly, Vanguard (2021) reports that digitally active investors show stronger preference toward hybrid and automated advisory models compared to traditional advisory approaches. In Nepal, the expansion of online share trading after the COVID-19 pandemic reflects growing participation of retail investors in digital investment activities (Nepal Stock Exchange, 2023). However, despite increased participation, trust in automated advisory systems remains uncertain due to concerns related to technological reliability, transparency, and data security.

Previous studies also suggest that demographic factors such as age may influence trust formation in digital financial technologies. Younger individuals are generally more comfortable with digital systems and online financial transactions, whereas older investors often rely more heavily on traditional financial consultation methods. However, evidence from developing countries indicates that digital familiarity and technological exposure may be more important than age alone in determining FinTech adoption (OECD, 2023). Therefore, examining the moderating influence of age remains important within Nepal's emerging digital financial environment.

Accordingly:

- H2A: Age significantly influences initial trust in using FRA services.
- H2B: Age moderates the relationship between trust propensity and initial trust in FRA services.

Behavioural Intention to Use FRA and Initial Trust

Behavioural intention refers to an individual's willingness or plan to use a particular technology or system (Ajzen, 1991). Trust has consistently been identified as one of the strongest predictors of behavioural intention in online financial services and AI-supported technologies (Gefen et al., 2003). McKnight, Choudhury, and Kacmar (2002) further argue that initial trust becomes especially important when users have limited prior experience with a system. In Nepal, where misinformation, financial uncertainty, and concerns regarding digital security occasionally weaken confidence in financial services, trust becomes even more critical. When retail investors perceive FRA platforms as transparent, secure, reliable, and professionally designed, their willingness to adopt such services is likely to increase.

Thus:

- H3: Initial trust positively influences behavioural intention to use FRA services.

Performance Expectancy

Performance expectancy refers to the extent to which individuals believe that using a system will improve their performance or outcomes (Venkatesh et al., 2003). In the context of FRA services, investors are more likely to trust platforms that provide accurate market analysis, efficient portfolio management, and reliable investment recommendations. Prior studies on FinTech adoption consistently report that perceived usefulness positively influences trust and technology acceptance. If Nepalese investors perceive robo-advisory platforms as capable of improving investment decision-making and portfolio performance, their initial trust in such systems is likely to strengthen.

- H4: Performance expectancy positively influences initial trust in FRA services.

Effort Expectancy

Effort expectancy reflects the degree to which a system is perceived as easy to use (Davis, 1989). Conventional technology adoption studies generally suggest that simpler and more user-friendly systems positively influence trust and adoption behaviour. However, research in AI-driven financial services indicates that highly automated systems may also create uncertainty among users with limited technological familiarity or financial literacy (Shin, 2021). In developing economies such as Nepal, some investors may perceive algorithm-based advisory systems as technically complex, difficult to understand, or lacking transparency. Therefore, although effort expectancy is theoretically expected to strengthen trust, the relationship may vary depending on users' digital exposure and understanding of automated financial technologies.

- H5: Effort expectancy influences initial trust in FRA services.

Social Influence

Social influence refers to the extent to which individuals perceive that important others believe they should use a technology (Venkatesh et al., 2003). In collectivist societies such as Nepal, financial decisions are often influenced by family members, peers, social networks, and institutional recommendations. Positive opinions from trusted financial institutions, market participants, or experienced investors can reduce uncertainty and encourage trust in robo-advisory services.

- H6: Social influence positively influences initial trust in FRA services.

Facilitating Conditions

Facilitating conditions refer to the availability of technical infrastructure, institutional support, and resources necessary to use a system effectively (Venkatesh et al., 2003). Reliable internet access, customer support, cybersecurity protection, and regulatory oversight are important determinants of trust in digital financial services. Nepal Rastra Bank's digital finance initiatives and cybersecurity guidelines may contribute to stronger investor confidence in automated advisory systems.

- H7: Facilitating conditions positively influence initial trust in FRA services.

Hedonic Motivation

Hedonic motivation refers to the enjoyment or positive experience derived from using a technology (Venkatesh et al., 2012). Features such as interactive dashboards, visual analytics, personalised investment insights, and user-friendly interfaces may make digital investment activities more engaging and less intimidating for investors. Positive user experiences can reduce anxiety and contribute to stronger trust in automated financial platforms.

- H8: Hedonic motivation positively influences initial trust in FRA services.

Price Value

Price value reflects users' evaluation of the trade-off between the benefits received and the costs incurred while using a technology (Venkatesh et al., 2012). In price-sensitive markets such as Nepal, affordability remains an important consideration in financial decision-making. If FRA platforms provide lower advisory costs than traditional brokerage or financial consultation services while maintaining transparency and reliability, investors may perceive greater value and develop stronger trust toward such systems.

- H9: Price value positively influences initial trust in FRA services.

This study develops a conceptual framework to explain the factors influencing retail investors' trust and behavioural intention toward Financial Robo-Advisory (FRA) services in Nepal. The framework integrates Trust Theory with the UTAUT model by incorporating trust propensity and initial trust alongside technology adoption variables such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and price value. The study proposes that these factors shape investors' initial trust in FRA platforms, which subsequently influences their behavioural intention to adopt such services. Furthermore, age is examined as a moderating factor influencing trust formation within Nepal's emerging FinTech environment. Through this integrated framework, the study seeks to provide context-specific evidence regarding trust development and technology adoption behaviour toward robo-advisory services in a developing economy where digital investment platforms are gradually expanding but investor confidence in automated financial advice remains limited.

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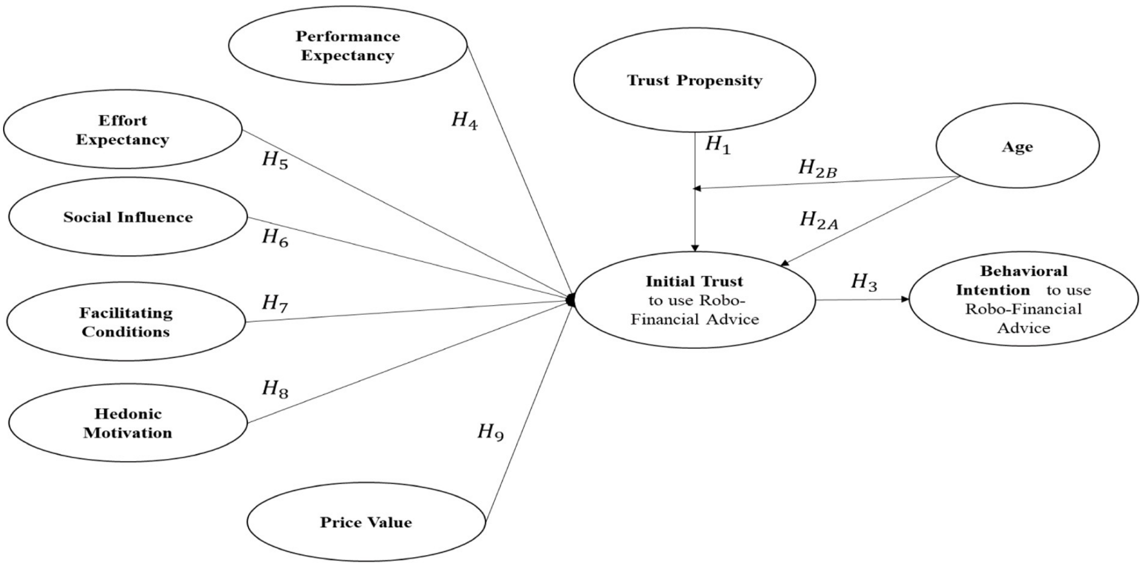

Fig. 1. Conceptual model based on UTAUT.

Research Methodology

Research Design

This study is grounded in a positivist research philosophy as it seeks to examine measurable relationships between clearly defined constructs such as trust propensity, initial trust, and behavioural intention. Positivism is suitable when the objective is to test theoretical relationships using observable data and statistical methods (Creswell & Creswell, 2018). Since the study aims to validate hypotheses derived from established theories such as trust theory and UTAUT, a structured and objective research design was necessary. A deductive approach was employed. The study began with theoretical foundations drawn from prior literature and then developed specific hypotheses to be empirically tested. Saunders, Lewis, and Thornhill (2019) assert that deductive reasoning is suitable when researchers seek to confirm or reject propositions through systematic data analysis. In the present research, constructs were clearly operationalized before data collection, and statistical procedures were applied to examine the proposed relationships.

The study adopted a quantitative methodology. Quantitative research allows researchers to identify patterns, measure relationships, and test causal assumptions using numerical data (Hair et al., 2019). Because the objective was to evaluate structural relationships among multiple constructs simultaneously, quantitative analysis provided a reliable and generalizable framework.

Methodology for Gathering Data

Data for this study were collected through a structured online questionnaire designed to examine retail investors' trust and behavioural intention toward Financial Robo-Advisory (FRA) services in Nepal. The survey link was distributed through widely used digital platforms and investment-related online communities, including Facebook groups focused on stock market discussions, LinkedIn professional networks, NEPSE-related forums, and WhatsApp groups associated with share trading and investment activities. The online distribution approach was considered appropriate due to the increasing use of digital trading platforms and online investment participation following the expansion of electronic trading services introduced by the Nepal Stock Exchange (2023).

A non-probability convenience sampling technique was employed because retail investors actively participating in online financial communities were more accessible through digital platforms. However, the study acknowledges the possibility of sampling bias associated with convenience sampling and online survey methods. Since the questionnaire was circulated primarily through internet-based platforms, respondents with higher digital access, stronger technological familiarity, and greater online engagement may have been overrepresented. Consequently, retail investors with limited internet access or lower digital literacy may not have been adequately captured in the sample. Although this limitation may affect the generalizability of the findings, the selected approach was considered suitable for reaching active retail investors who are more likely to engage with emerging digital financial services such as robo-advisory platforms.

Before participating in the survey, respondents were informed about the purpose of the study and assured that their responses would remain confidential and be used solely for academic purposes. Participation was entirely voluntary, and informed consent was obtained prior to questionnaire completion. To maintain privacy and anonymity, no personally identifiable information was collected during the survey process.

Target Population and Time Frame

The study focused on retail investors in Nepal who actively participate in digital financial and capital market activities. Retail investors were selected as the target population because the increasing adoption of online trading systems, mobile banking applications, and digital financial services has created greater exposure to technology-enabled investment platforms within this group. Reports published by Nepal Rastra Bank (2023) indicate a steady rise in digital financial service usage and online financial participation in Nepal, making retail investors an appropriate population for examining trust and behavioural intention toward Financial Robo-Advisory (FRA) services.

Data for the study were collected over a three-month period from January to March 2025 using a cross-sectional research design. Cross-sectional studies are considered appropriate when the objective is to capture individuals' attitudes, perceptions, and behavioural intentions at a particular point in time (Bryman, 2016). The study employed a structured questionnaire developed from previously validated scales used in earlier studies related to technology adoption, trust, and FinTech services. To ensure contextual relevance, measurement items were carefully adapted to the FRA environment and reviewed to maintain conceptual consistency with the objectives of the study.

Prior to the main survey, a pilot test was conducted with a small group of retail investors to evaluate the clarity, readability, and relevance of the questionnaire items. Feedback obtained during the pilot phase helped refine ambiguous wording, improve question sequencing, and enhance overall comprehensibility. Since respondents in Nepal commonly use both English and Nepali in digital communication, the questionnaire was prepared in simple and easily understandable language. Translation validation procedures were also considered to maintain consistency of meaning between English and Nepali interpretations of key constructs and survey items. These steps helped strengthen the reliability, clarity, and contextual suitability of the research instrument before full-scale data collection was conducted.

Sample Size Determination

The target population of this study consisted of retail investors in Nepal who actively participate in capital market and digital financial activities. According to Securities Board of Nepal (SEBON, 2025), the total number of registered investors in Nepal reached 2,505,031. This population includes individuals involved in online share trading, Demat account operations, mobile banking, and other technology-enabled financial activities associated with investment participation. The growing expansion of online trading systems and digital financial services in Nepal has increased retail investor engagement in technology-based financial platforms, making this population appropriate for examining trust and behavioural intention toward Financial Robo-Advisory (FRA) services.

The required sample size for the study was determined based on commonly accepted recommendations for Structural Equation Modelling (SEM). According to Hair et al. (2021), SEM studies require an adequate sample-to-indicator ratio to ensure stable parameter estimation, model reliability, and statistical validity. Since the study included 31 observed indicators, the minimum recommended sample size exceeded 300 respondents. To improve statistical power and increase the robustness of the findings, the study collected 520 valid responses from retail investors across Nepal. Kline (2016) further explains that larger sample sizes contribute to greater model stability, lower estimation error, and stronger confidence in the generalizability of research findings. Therefore, the final sample of 520 usable responses was considered adequate for conducting SEM analysis and hypothesis testing.

The study adopted a cross-sectional survey design, and data were collected over a three-month period from January to March 2025. Responses were obtained primarily through online investment communities, digital trading groups, and financial discussion platforms where retail investors actively engage in investment-related activities. Although probability sampling techniques were not feasible due to the absence of a complete and accessible sampling frame of FRA users in Nepal, efforts were made to obtain responses from participants with active involvement in digital financial and capital market activities.

Eligibility and Screening Requirements

The questionnaire started with four screening questions to ensure the data's appropriateness and quality. These items were included to make sure that only the intended group participated in the study. First, respondents were required to confirm that they fell within the 18–29 age range. Second, they were asked about their basic exposure to financial markets, such as whether they had experience trading shares or investing in mutual funds. Third, the questions checked their awareness of digital financial platforms. Finally, individuals who were already using sophisticated robo-advisory or automated portfolio management services were excluded, as the study focused on understanding initial trust among potential or early-stage users rather than experienced users. Respondents who lacked basic exposure to financial investment activities were excluded. The focus on individuals with at least minimal market engagement was important because research on initial trust formation requires some degree of contextual awareness (McKnight et al., 2002).

This sampling approach ensured that participants were capable of meaningfully evaluating FRA systems while still representing potential first-time adopters.

Research Instrument and Measurement of Variables

The current study modified validated measurement scales from earlier empirical research to create a structured questionnaire studies on technology adoption, trust, and robo-advisory services. Rather than using the instruments verbatim, the items were carefully revised to reflect the Nepalese financial context, particularly the emerging environment of digital investment platforms and automated advisory services. There were three main sections to the questionnaire. There were three primary sections to the questionnaire. The respondents' gender, age, educational attainment, investment experience, and digital device were among the background data gathered in the first section, they most frequently used for financial transactions, prior exposure to robo-advisory services, and their approximate annual transaction volume. These factors were included as control variables because earlier research has demonstrated that demographic characteristics can shape both technology adoption and the development of trust (Venkatesh et al., 2012; McKnight et al., 2011). In the context of Nepal, age and familiarity with digital tools are particularly meaningful. Younger investors tend to be more active users of mobile banking and digital wallet services such as eSewa and Khalti, reflecting broader digital engagement trends (Nepal Rastra Bank, 2023). Likewise, higher levels of education and prior experience in financial markets may enhance financial literacy, which can influence how individuals perceive and trust automated advisory technologies. The Unified Theory of Acceptance and Use of Technology (UTAUT2) core constructs were measured in the second section of the survey. These included hedonic motivation, price value, habit, social influence, facilitating conditions, performance expectancy, and effort expectancy. A seven-point Likert scale, with 1 denoting strongly disagree and 7 denoting strongly agree, was used to rate each item. Using a seven-point rating system is in line with accepted methods in research on technology adoption, as it allows respondents to express more nuanced opinions and improves variability in responses (Hair et al., 2022). The final section focused specifically on trust-related variables.

Trust propensity was assessed using three statements designed to capture an individual's general inclination to trust technology-driven systems. Initial trust in financial robo-advisors was measured through four items addressing perceptions of reliability, integrity, and competence. Behavioral intention to use robo-advisory services was evaluated using seven items that reflected the likelihood and willingness of respondents to adopt such services in the future. Including demographic control variables in the model made it possible to better isolate individual differences in trust development and usage intention. This is particularly important in Nepal, where digital financial inclusion is growing but remains uneven across different socioeconomic segments (World Bank, 2022).

Typical Method Bias

Measurement error that occurs when data for independent and dependent variables are gathered simultaneously from the same respondents using a single survey instrument is known as common method bias (CMB). Such bias has the potential to skew or inflate correlations between variables, endangering the reliability of results (Podsakoff et al., 2012). Both statistical and procedural remedies were used to address this issue. To determine whether a single latent factor explained the majority of the covariance between the measures, Harman's single-factor test was first performed. It would have suggested possible common method bias if a single dominant factor had accounted for the majority of the variance (Fuller et al., 2016). The lack of a single factor controlling the variance in the results suggested that CMB was not a significant problem. Second, a number of procedural safeguards were put in place when designing the questionnaire: To lessen social desirability bias, respondents were guaranteed anonymity and confidentiality. It was made very clear in the instructions that there was no right or wrong response. To reduce consistency motifs, demographic and construct-related questions were kept apart. Though not overly grouping related constructs together, the items were arranged logically. Together, these actions lessened response bias and increased the reliability of the data gathered.

Methods of Estimation

The study used Partial Least Squares Structural Equation Modelling (PLS-SEM) to analyse the suggested framework. It is commonly acknowledged that structural equation modelling is a suitable method for analysing intricate relationships between multiple latent variables simultaneously (Kline, 2023). PLS-SEM was selected for this study because it aligns well with the study's goal and the characteristics of the data. It works well with small to medium sample sizes and doesn't require strict requirements of multivariate normality, and is particularly useful in exploratory and prediction-oriented studies. Moreover, it emphasizes maximizing the explained variance (R^2) of endogenous constructs, making it suitable for research that seeks to understand and predict behavioral intention (Hair et al., 2022). Given that Nepal is still in the early stages of robo-advisory services and theoretical development in this area is ongoing, a flexible and prediction-focused method such as PLS-SEM was considered appropriate. Descriptive statistics for demographic and socioeconomic characteristics were generated using SPSS 30. The measurement model was evaluated by looking at composite reliability, convergent validity using Average Variance Extracted (AVE), outer loadings, and Variance Inflation Factor (VIF) values. Both the Fornell–Larcker criterion (Fornell & Larcker, 1981) and the Heterotrait–Monotrait (HTMT) ratio of correlations (Henseler, Ringle, & Sarstedt, 2015) were used to assess discriminant validity. Path coefficients, t-values obtained from bootstrapping procedures, significance levels, and the coefficient of determination (R^2) were then examined in order to analyse the structural model. By assessing both the measurement and structural components in a systematic manner, this variance-based SEM approach enhances the robustness, reliability, and predictive strength of the overall research model.

Analysis of Data

Responses' demographic profile

For the final analysis, 520 valid responses were used. A summary of the demographic and background traits of the participants is shown in Table 1. The sample's gender distribution was 37.9% female (n = 197) and 62.1% male (n = 323). The majority of participants were young adults. Specifically, 29.4% (n = 153) were aged 18–23 years, while 41.3% (n = 215) fell within the 24–29 age group. Respondents aged 30–35 accounted for 17.1% (n = 89), and 12.2% (n = 63) were between 36–41 years. This age distribution reflects Nepal's growing youth participation in capital market activities, particularly through digital platforms (Nepal Rastra Bank, 2023). In terms of educational background, 57.5% (n = 299) reported having a master's degree, 32.7% (n = 170) had finished a bachelor's degree, and 9.8% (n = 51) said they had a PhD or another professional credential. The high proportion of postgraduate respondents suggests that financial and investment awareness may be relatively strong within the sampled group. With respect to trading and investment experience, 49.6% (n = 258) reported 1–2 years of experience. 12.3% (n = 64) reported having more than 10 years of experience, 10.8% (n = 56) had 6–10 years, and about 27.3% (n = 142) had 3–5 years. This indicates that a substantial portion of respondents were relatively new investors, which aligns with the expansion of online trading platforms in Nepal following the digitization of the Nepal Stock Exchange (NEPSE). Concerning device usage for financial transactions, 74.0% (n = 385) primarily used smartphones or handheld devices, while 26.0% (n = 135) relied on computers or laptops. This pattern corresponds with the increasing dominance of mobile-based financial transactions in Nepal (Nepal Rastra Bank, 2023).

In terms of familiarity with financial robo-advisory services, 65.4% (n = 340) reported no prior experience. Approximately 23.1% (n = 120) had less than one year of exposure, and 11.5% (n = 60) had between one and two years of experience. These figures suggest that robo-advisory services are still at an early stage of awareness and adoption in the Nepalese financial market.

Finally, regarding the frequency of annual financial transactions, 34.6% (n = 180) conducted 3–5 transactions per year. Around 22.5% (n = 117) performed 1–2 transactions, 14.2% (n = 74) conducted 6–10 transactions, 16.5% (n = 86) reported 11–30 transactions, 4.0% (n = 21) conducted 31–50 transactions, and 8.3% (n = 42) reported more than 50 transactions annually.

Table 1: Demographic Summary (N = 520)

Participant Features	N	%
Gender		
Female	197	37.9
Male	323	62.1
Age		
18–23 Years	153	29.4
24–29 Years	215	41.3

Participant Features	N	%
30–35 Years	89	17.1
36–41 Years	63	12.2
Qualification		
Graduate	170	32.7
Masters	299	57.5
PhD/Professional	51	9.8
Trading/Investment Experience		
1–2 Years	258	49.6
3–5 Years	142	27.3
6–10 Years	56	10.8
>10 Years	64	12.3
Device Used		
Smartphone/Handheld	385	74.0
Computer/Laptop	135	26.0
FRA Experience		
No Experience	340	65.4
<1 Year	120	23.1
1–2 Years	60	11.5
Annual Financial Transactions		
1–2	117	22.5
3–5	180	34.6
6–10	74	14.2
11–30	86	16.5
31–50	21	4.0
>50	42	8.3

Source: Author's calculation using SPSS 30.

Evaluation of Measurement Models

Smart-PLS 4 was used to analyse the measurement model. First, outer loadings were used to assess indicator reliability. Factor loadings of 0.70 or greater denote acceptable indicator reliability, as advised by recent PLS-SEM literature (Sarstedt et al., 2022). This threshold was reached by all constructs, including price value, hedonic motivation, social influence, facilitating conditions, performance expectancy, effort expectancy, trust propensity, initial trust, and behavioural intention. Three observed indicators were used to model trust propensity as a latent construct. Four indicators were used to gauge initial trust, and three indicators were used to gauge behavioural intention to use financial robo-advisory services. Cronbach's alpha and composite reliability were used to assess internal consistency reliability. Reliability was deemed satisfactory when values exceeded 0.70. Average Variance Extracted (AVE) was used to evaluate convergent validity; values greater than 0.50 meant that constructs accounted for over half of the variance of their indicators (Hair et al., 2022). Both inner and outer Variance Inflation Factor (VIF) values were analysed in order to address multicollinearity issues. The absence of collinearity issues in both measurement and structural models was indicated by the fact that all VIF values were below the suggested cut-off value of 5 (Kock, 2020).

Structural Model Evaluation

The results of the structural model show a high degree of explanatory power. With an R^2 value of 0.846 for initial trust, trust propensity and UTAUT-related factors (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and price value) accounted for 84.6% of the variance in initial trust. Likewise, 81.9% of the variation in behavioural intention to use financial robo-advisory services was explained by the model. This implies that there is significant predictive relevance in the suggested framework. With a standardised coefficient of $\beta = 0.887$, path coefficient analysis showed that initial trust had a strong positive effect on behavioural intention. This suggests that higher levels of trust significantly increase the intention to use robo-advisory services. The statistical significance of the proposed relationships was validated by bootstrapping results. All things considered, the model does a good job of explaining adoption intentions in the context of digital investment in Nepal, as evidenced by the high R2 values and significant path coefficients. Utilising variance-based SEM enhances the findings' predictive validity and robustness.

Validity and Reliability of Discriminants

The Heterotrait – Monotrait (HTMT) ratio was used to assess discriminant validity, making sure that each construct in the model measured a unique concept. For variance-based SEM, the HTMT criterion is generally advised; values below the strict threshold of 0.85 or the liberal threshold of 0.90 signify sufficient discriminant validity (Henseler et al., 2015; Hair et al., 2022).

All of the HTMT values, as shown in Table 3, are below 0.90, indicating that the constructs – hedonic motivation, price value, social influence, performance expectancy, effort expectancy, facilitating conditions, trust propensity, initial trust, and behavioural intention – are empirically different in the Nepalese context. The Standardised Root Mean Square Residual (SRMR) and Normed Fit Index (NFI) were used to further evaluate the model fit. Good model fit is indicated by SRMR values for PLS-SEM models that are less than 0.08 (Hu & Bentler, 1999; Hair et al., 2022). Both the estimated and saturated model SRMR values in this investigation fell below the suggested cutoff, indicating a suitable fit. According to Sarstedt et al. (2022), the NFI values also surpassed 0.90, indicating satisfactory model adequacy. These figures collectively show that the measurement model is suitable for structural analysis in the financial technology environment of Nepal and is well-defined**.**.

Table 2: Validity, Reliability, VIF, and CFA (N = 520)

Constructs	Loading	VIF	Cronbach's Alpha	CR	AVE
Performance Expectancy (PE)			0.901	0.927	0.761
PE1	0.918	1.984			
PE2	0.907	1.956			
PE3	0.912	1.938			

Constructs	Loading	VIF	Cronbach's Alpha	CR	AVE
PE4	0.925	2.021			
Effort Expectancy (EE)			0.872	0.884	0.708
EE1	0.889	1.934			
EE2	0.903	2.011			
EE3	0.914	2.088			
EE4	0.896	1.978			
Social Influence (SI)			0.854	0.889	0.693
SI1	0.921	1.978			
SI2	0.883	1.901			
SI3	0.897	1.926			
Hedonic Motivations (HM)			0.893	0.930	0.816
HM1	0.882	1.952			
HM2	0.931	2.014			
HM3	0.953	2.269			
Price Value (PV)			0.871	0.915	0.782
PV1	0.821	1.842			
PV2	0.906	1.973			
PV3	0.952	2.076			
Facilitating Conditions (FC)			0.862	0.952	0.700
FC1	0.829	2.006			
FC2	0.907	2.173			
FC3	0.903	2.114			
FC4	0.815	1.984			
Trust Propensity (TP)			0.866	0.893	0.735
TP1	0.918	2.054			
TP2	0.936	2.117			
TP3	0.901	1.998			
Initial Trust (IT)			0.912	0.934	0.781
IT1	0.903	2.031			
IT2	0.941	2.142			
IT3	0.928	2.088			
IT4	0.914	2.004			
Behavioral Intention (BI)			0.925	0.921	0.796
BI1	0.931	1.967			
BI2	0.944	2.103			
BI3	0.925	1.988			

Source: SmartPLS 4 estimation (Author's computation).

Recommended reliability and validity criteria are met by all factor loadings exceeding 0.70, VIF values staying below 5, Cronbach's alpha and composite reliability exceeding 0.70, and AVE values exceeding 0.50 (Hair et al., 2022).

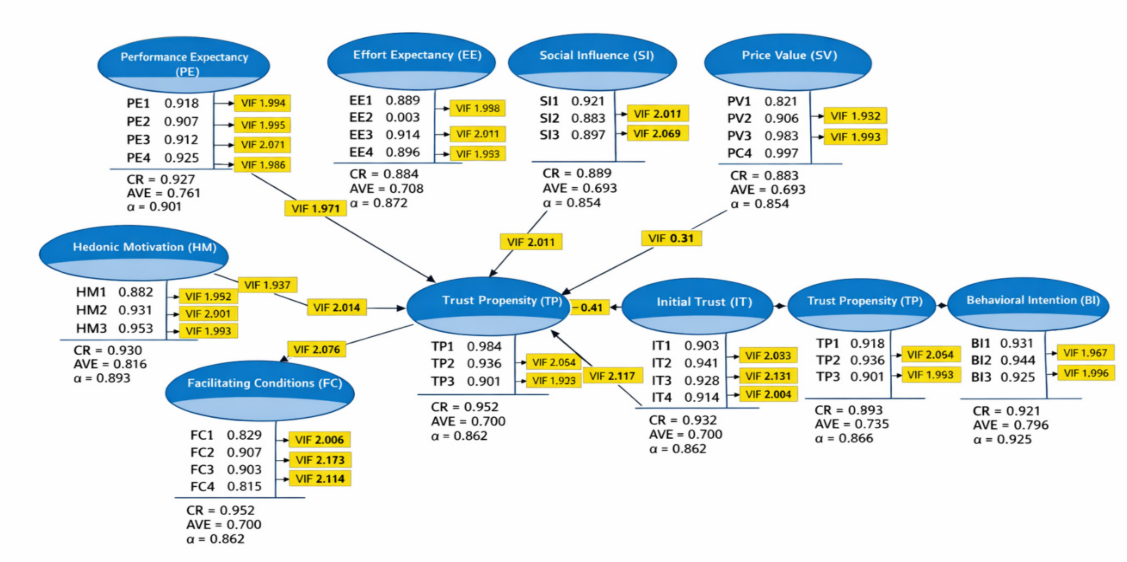

Fig. 2. Measurement model (Source: Smart PLS 4).

Table 3: HTMT Ratio

	BI	EE	FC	HM	IT	PE	PV	SI	TP
BI	—								
EE	0.804								
FC	0.842	0.831							
HM	0.851	0.718	0.879						
IT	0.863	0.736	0.867	0.791					
PE	0.857	0.794	0.876	0.803	0.839				
PV	0.839	0.641	0.829	0.769	0.785	0.672			
SI	0.742	0.842	0.792	0.763	0.776	0.768	0.569		
TP	0.562	0.398	0.615	0.569	0.648	0.352	0.546	0.449	

Since every HTMT value is less than 0.90, discriminant validity is confirmed.

Table 4: Model Fit Indices

	Saturated Model	Estimated Model
SRMR	0.074	0.069
d_ULS	2.745	2.018
d_G	10.421	11.536
Chi-square	2748.532	3012.418
NFI	0.904	0.921

A good model fit is confirmed by both SRMR values being below 0.08 and NFI values being above 0.90.

Table 5: Predictive Relevance (Q^2) and Effect Size (F^2)

IV	DV	F^2	Effect Size	Q^2	Predictive Power
TP	IT	0.24	Medium	0.46	High
PE	IT	0.26	Medium	0.43	High
EE	IT	0.14	Small	0.38	Moderate
SI	IT	0.39	Large	—	High
HM	BI	0.41	Large	0.49	High
IT	BI	0.55	Large	0.47	High

Cohen's (1988) guidelines state that small, medium, and large effects are indicated by F2 values of 0.02, 0.15, and 0.35, respectively. According to the results, trust propensity and performance expectancy have moderate effects on initial trust in the Nepalese context, whereas social influence has a significant impact. Effort expectancy makes a small contribution. Both hedonic motivation and initial trust show significant effect sizes for behavioural intention, underscoring the significance of trust and emotional engagement in promoting the uptake of robo-advisory services in Nepal. The model's sufficient predictive relevance is confirmed by Q^2 values larger than zero (Hair et al., 2022).

Evaluation of Structural Models

To test the structural relationships, 5,000 subsamples were bootstrapped. Trust is a key factor in determining the intention to use financial robo-advisory services in Nepal, as evidenced by the strong and statistically significant relationship between initial trust and behavioural intention ($\beta = 0.901$, $p < 0.001$). Among antecedents of initial trust, social influence showed a substantial positive impact, reflecting the collective and relationship-oriented nature of Nepalese society, where peer opinions and financial networks strongly shape adoption decisions. Trust propensity and performance expectancy also demonstrated meaningful positive effects. Effort expectancy showed a weaker but statistically significant relationship. All things considered, the structural model shows great predictive and explanatory power in comprehending the uptake of robo-advisory services within Nepal's developing digital investment ecosystem.

Table 6
Direct Effects (Bootstrapping Results, N = 520)

Direct Effects	Mean	STDEV	T-value	P-value	Decision
Trust Propensity → Initial Trust	0.224	0.018	12.411	0.000	Supported
Age → Initial Trust	–0.012	0.013	0.923	0.356	Not Supported
Performance Expectancy → Initial Trust	0.338	0.029	11.655	0.000	Supported
Effort Expectancy → Initial Trust	–0.148	0.026	5.692	0.000	Not Supported (Negative Effect)
Social Influence → Initial Trust	0.072	0.018	4.000	0.000	Supported
Facilitating Conditions → Initial Trust	0.347	0.032	10.844	0.000	Supported
Hedonic Motivation → Initial Trust	0.287	0.028	10.250	0.000	Supported
Price Value → Initial Trust	0.041	0.021	1.952	0.051	Weakly Supported
Initial Trust → Behavioral Intention	0.901	0.007	138.574	0.000	Supported

The findings indicate that initial trust in robo-advisory services is increased by trust propensity, performance expectancy, social influence, facilitating conditions, and hedonic motivation. Expecting too much effort has a detrimental impact, meaning that when people think the system is difficult to use, their trust decreases. Initial trust strongly increases the intention to use robo-advisory services. Age alone does not directly affect initial trust.

Table 7: Moderating Effects (N = 520)

Moderating Path	Mean	STDEV	T-value	P-value	Decision
Age × Trust Propensity → Initial Trust	–0.132	0.014	9.428	0.000	Supported
Age × Trust Propensity → Behavioral Intention	–0.119	0.013	9.154	0.000	Supported

As age increases, the positive influence of trust propensity becomes weaker. Younger investors are more influenced by their natural tendency to trust when forming trust in robo-advisory services.

Table 8
Specific Indirect Effects (Mediation Results, N = 520)

Indirect Path	Mean	STDEV	T-value	P-value	Decision
Trust Propensity → Initial Trust → Behavioral Intention	0.202	0.017	11.882	0.000	Supported
Performance Expectancy → Initial Trust → Behavioral Intention	0.305	0.025	12.200	0.000	Supported
Facilitating Conditions → Initial Trust → Behavioral Intention	0.313	0.027	11.593	0.000	Supported
Social Influence → Initial Trust → Behavioral Intention	0.065	0.016	4.062	0.000	Supported
Effort Expectancy → Initial Trust → Behavioral Intention	–0.133	0.023	5.783	0.000	Negative Indirect Effect

Indirect Path	Mean	STDEV	T-value	P-value	Decision
Hedonic Motivation → Initial Trust → Behavioral Intention	0.259	0.024	10.792	0.000	Supported
Price Value → Initial Trust → Behavioral Intention	0.037	0.019	1.921	0.055	Weakly Supported
Age → Initial Trust → Behavioral Intention	–0.011	0.012	0.917	0.359	Not Supported
Age × Trust Propensity → Initial Trust → Behavioral Intention	–0.118	0.013	9.077	0.000	Supported

The results demonstrate that young investors' willingness to use robo-advisory services is significantly influenced by their level of trust. People who have a natural tendency to trust new systems are more likely to do so at first, which increases their intention to use those platforms down the road. In the same way, when investors believe that the service will improve their performance, feel that proper support and resources are available, observe positive opinions from people around them, and find the experience enjoyable, their trust becomes stronger. This strengthened trust, in turn, encourages them to consider using robo-advisory services. However, investors lose confidence if they believe the system is hard to use, which subsequently lessens their desire to use it. Age does not directly determine whether someone intends to use the service through trust alone. However, age influences how strongly trust-related factors operate. As people age, the beneficial effects of trust propensity on initial trust and behavioural intention diminish. In simple terms, trust acts as the connecting link between these influencing factors and the decision to adopt robo-advisory services. Younger investors tend to respond more positively to trust-building elements, while relatively older investors approach such technologies with greater caution.

Discussion

The study found that initial trust strongly influences retail investors' intention to use Financial Robo-Advisory (FRA) services in Nepal. Investors are more likely to adopt FRA platforms when they perceive them as reliable and secure. This finding supports earlier studies by Gefen et al. (2003) and Shin (2021). Trust propensity positively influenced initial trust, showing that investors who naturally trust new technologies are more willing to trust FRA services. This result is consistent with Mayer et al. (1995) and Gefen (2000).

Performance expectancy also had a positive effect on trust. Investors trusted FRA platforms more when they believed the systems could improve investment decisions and financial performance, supporting Venkatesh et al. (2003). Effort expectancy showed a negative effect on trust. This suggests that many investors in Nepal may perceive robo-advisory systems as difficult or complex. Similar concerns regarding AI transparency were highlighted by Shin (2021). Social influence and facilitating conditions positively affected trust. Support from peers, financial communities, technical infrastructure, and institutional support increased investor confidence in FRA services. These findings align with Venkatesh et al. (2003) and Sharma and Sharma (2019). Hedonic motivation also strengthened trust, indicating that enjoyable and interactive digital experiences encourage investors to trust FRA platforms. This result supports Venkatesh et al. (2012). Price value showed a positive but weaker effect, suggesting that affordability matters, although trust and system performance remain more important. The study further found that age did not directly influence trust. However, younger investors responded more positively to trust-related factors than older investors, supporting D'Acunto et al. (2019). Overall, the findings confirm that trust is the key factor influencing the adoption of FRA services in Nepal and extends the UTAUT framework by incorporating trust-related variables in the context of AI-driven financial services.

Conclusion

This study investigated the formation of initial trust among Nepalese retail investors in financial robo-advisory (FRA) services and the influence of that trust on their intention to utilise these platforms. Utilising survey data from 520 participants and employing partial least squares structural equation modelling, the results elucidate the psychological and technological determinants affecting adoption. The findings indicate that trust propensity, performance expectancy, social influence, facilitating conditions, and hedonic motivation substantially enhance the formation of initial trust. Among these factors, performance expectancy and facilitating conditions demonstrate particularly strong effects. This implies that when investors think robo-advisory services can enhance their financial performance, they are more likely to trust them, their investment performance and when proper technical and institutional support is available. Effort expectancy, however, showed a negative relationship with initial trust. Users become less confident when they believe the system is complicated or challenging to use. This emphasises how crucial usability and simplicity are when designing financial technology. The best indicator of behavioural intention was found to be initial trust. In other words, investors' willingness to adopt robo-advisory services largely depends on whether they trust the system. The mediation analysis further confirms that most adoption drivers influence behavioral intention indirectly through trust. Age did not directly influence initial trust or behavioral intention. However, it played a significant moderating role. As people age, the beneficial effects of trust propensity on both trust and intention diminish. This suggests that when assessing new financial technologies, younger investors are more receptive to their innate trust disposition. Overall, the study demonstrates that trust acts as the central mechanism linking technological perceptions to adoption behavior in Nepal's emerging digital investment environment.

Research Implications

- **Practical Implications**

The results provide financial institutions with valuable information, fintech firms, policymakers, and digital investment platforms operating in Nepal. First, building trust should be treated as a strategic priority. Transparent communication about how algorithms work, clear risk disclosures, secure authentication systems, and visible regulatory compliance can strengthen investor confidence. Prior research consistently shows that trust is essential in online financial environments (McKnight et al., 2011). Second, usability must be emphasized. Since perceived difficulty reduces trust, platforms should prioritize intuitive interfaces, simplified dashboards, step-by-step guidance, and local language options. Improving digital literacy through educational campaigns or tutorials may also help reduce psychological barriers (Venkatesh et al., 2012). Third, in the Nepalese context, social influence is significant. Peers, family, and professional networks frequently have an impact on financial decisions. As a result, referral schemes, endorsements, and collaborations with reliable organisations could hasten adoption. Fourth, trust is greatly increased by enabling factors like reliable internet access, prompt customer service, and technical support. Policymakers should continue improving digital financial infrastructure to support fintech innovation (Nepal Rastra Bank, 2023). Fifth, hedonic motivation suggests that user experience matters. Investors are more willing to use platforms that feel engaging and satisfying. This means that design quality, interactivity, and personalization features are not merely aesthetic but strategic.

Finally, marketing tactics may need to be modified because the relationship between trust propensity and adoption is moderated by age. Younger investors may respond more positively to innovation-focused communication, while older investors may require reassurance regarding safety, transparency, and reliability.

- **Theoretical Implications**

The Unified Theory of Acceptance and Use of Technology is theoretically expanded in this study by including moderating effects and trust constructs in an emerging market context. It demonstrates that trust is not only an outcome variable but also a mediating mechanism through which behavioural intention is impacted by technological perceptions. The results also highlight the importance of cultural and generational context in technology adoption research. In collectivist societies, social influence may be more important than in highly individualistic ones. Therefore, future models of technology adoption in emerging economies should specifically take contextual moderators and trust dynamics into account.

Restrictions and Prospects

This study has a number of limitations that provide opportunities for additional research despite its contributions.

First, Nepali retail investors who are active online were the main focus of the study. The results might not accurately reflect investors in rural areas or those with limited access to digital technology, even though the sample size of 520 offers strong statistical power. To increase generalisability, future research should incorporate a wider range of demographic and geographic representation. Second, self-reported survey data were used in the study. Even though statistical techniques were employed to reduce bias, responses from respondents might represent opinions rather than real actions. To improve validity, future studies could include behavioural data like transaction frequency or real usage statistics. Third, perceptions are captured at a single moment in time by the cross-sectional design. As users gain experience, their trust in financial technologies may change. Deeper understanding of how trust grows, stabilises, or deteriorates over time would be possible with longitudinal research. Fourth, while age was a moderator in this study, other moderating factors might also be important. Differences in trust formation may also be explained by factors such as income level, risk tolerance, technological experience, and financial literacy. Investigating these factors would improve our comprehension of adoption behaviour. Lastly, qualitative methods like focus groups or interviews may be used to supplement quantitative results. Researchers would be able to investigate more deeply the cultural attitudes, anxieties, and motivations that affect trust in automated financial advisory systems using such techniques. Future studies can develop a more thorough understanding of how social context, technology perception, and trust interact to influence fintech adoption in Nepal and other emerging markets by addressing these limitations.

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