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Building trust in robo-advisory: technology, firm-specific and system trust

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Abstract

Purpose – This study sits at the intersection of financial planning and FinTech, focusing on robo-advisory, an affordable and accessible digital financial advisory service. Individuals' lack of trust has resulted in low adoption of robo-advice. This study aims to understand the psychological process of how individuals build trust in robo-advice, helping them engage with it more effectively and access affordable financial advice.

Design/methodology/approach – Using a trust transfer theory framework and 15 semi-structured interviews, this study identifies the sources people rely on to build trust in robo-advice.

Findings – The authors highlight four themes – social influence, psychological comfort, safeguarding and compliance and personal capacity – that shape individuals' trust in robo-advice. In addition to direct trust in robo-advice, firm-specific trust and system trust can also transfer to trust in robo-advice. This study finds that

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financial literacy and risk tolerance moderate individuals' trust in robo-advice, while psychological comfort first shapes trust and then drives adoption. The findings suggest that even young, tech-savvy individuals may not fully benefit from robo-advice due to low personal capability. They also prefer a hybrid model, where combining robo-advice with traditional advisory services could offer greater benefits.

Originality/value – This study details the concept of trust in the robo-advice context into three dimensions: technology trust, firm-specific trust and system trust. Existing research on robo-advice lacks quantitative tests on firm-specific and systemic trust; therefore, this qualitative exploratory study offers foundational theoretical insights.

Keywords Robo-advice, Trust, FinTech, Trust transfer theory, Human–AI interaction

Paper type Research paper

1. Introduction

Traditional financial advice is provided by high-quality financial advisors with expertise and experience, making it cost-intensive and expensive (Tiberius *et al.*, 2022). Roughly 6% of Australians can afford traditional financial advice, and only 3% of the population aged 21–34 receive financial advice (ARdata, 2022). Robo-advice is a FinTech service that uses artificial intelligence (AI) to automatically provide digital financial advice (Tao *et al.*, 2021). Algorithms can act as human financial advisors to provide affordable financial advice (Tiberius *et al.*, 2022), and robo-advice is a virtual platform that is easily accessible (Isaia and Oggero, 2022; Lourenço *et al.*, 2022). Accordingly, the Australian government reports that robo-advice could be an alternative approach to traditional financial advisory services, helping individuals access affordable professional financial advice and potentially helping to improve financial well-being (Callaghan *et al.*, 2020). Existing research has found robo-advice is suitable for investors with limited investment experience (Jung *et al.*, 2019) and groups who are not able to afford traditional financial advisory services, such as young people and low-income individuals (Brenner and Meyll, 2020; Bai, 2021; Baulkaran and Jain, 2023).

However, the adoption of robo-advice remains low (Aw *et al.*, 2023; Belanche *et al.*, 2019; Belanche *et al.*, 2023; Flavián *et al.*, 2022; Tiberius *et al.*, 2022), with roughly 1% of Australians adults having used robo-advice (ASIC, 2019). This is primarily due to a lack of trust (Bedué and Fritzsche, 2021; Nourallah, 2023; Zhu *et al.*, 2024). For innovative technologies, trust is a prerequisite for adoption (Belanche *et al.*, 2019), which determines whether an individual is willing to adopt robo-advice (Eren, 2023; Nourallah *et al.*, 2022; Roh *et al.*, 2022). In the context of robo-advice, trust means individuals believe that robo-advice is honest and benevolent and prioritises their best interests (see Grayson *et al.*, 2008). Trust is a shortcut in personal financial decision-making (Smith, 2009), as it determines whether an individual is willing to establish connections with banking, financial advisors or other financial services, such as robo-advice (Bruhn, 2019) and actively seeking financial advice (Calcagno and Monticone, 2015; Kramer, 2016).

The financial services industry is shifting its focus on building trust from traditional in-person interactions to AI-driven advisory engagements (Goldstein *et al.*, 2019). Nonetheless, research towards trust and robo-advice remains limited (Brenner and Meyll, 2020; Bhatia *et al.*, 2021; Gillath *et al.*, 2021; Hendershott *et al.*, 2021; Nourallah *et al.*, 2022). Venkatesh *et al.* (2016) emphasise the necessity of broadening trust within the unified theory of acceptance and use of technology (UTAUT), as trust can positively influence the application of digital technology (D'Acunto *et al.*, 2019; Werth *et al.*, 2023). Nourallah (2023) builds on this by adding trust into the UTAUT, examining the initial trust of young investors in robo-advice, presenting the statistical relationships between trust and influence factors and providing speculative explanations. Most existing research on robo-advice is empirical, failing to provide a deeper understanding of the phenomena of people's lack of trust in robo-advice (Belanche *et al.*, 2023), and robo-advice requires extended new theoretical theories (Barone *et al.*, 2024).

This study aims to understand the process of individuals building trust in robo-advice, driven by the research question: *How do different sources influence individuals' trust in robo-advice?* Namely, we shift from focusing on "*what*" influences individuals' trust in robo-advice to explaining the "*how*", that is, individuals' psychological process of building trust. Using a qualitative approach to gather raw data, this study develops a conceptual model based on trust transfer theory to explain why people trust or do not trust robo-advice. By applying this theory, this study highlights that trust in robo-advice is also process-based (see Zucker, 1986). Existing research involving trust only focuses on technology trust (Eren, 2023; Nourallah *et al.*, 2022; Nourallah, 2023). However, in addition to the direct trust clients have in robo-advice (technology trust), we highlight that individuals' firm-specific trust and system trust can also transfer to their trust in robo-advice. These extended dimensions of trust in robo-advice could inform and support future quantitative research. This study also extends the existing robot implementation framework (see Belanche *et al.*, 2020) to the robo-advice context, supplementing details of how robo-advice design, customer features and service encounter characteristics affect individuals' trust, which in turn, affects their behavioural intentions.

The rest of the study is as follows. Section 2 reviews the related theoretical background. Section 3 outlines the methodology used in this study, followed by Section 4, which details the data analysis. Section 5 presents the findings, and Section 6 introduces the conceptual model with discussions and concludes the study, highlighting its contributions and limitations.

2. Theoretical background

2.1 Definitions of trust

In this study, trust aligns with the concept of trust in the business context, where it is seen as the belief that robo-advice is honest and benevolent, with a certain level of capability, and acts in the best interests of clients (Grayson *et al.*, 2008). Trust, as explained by Johnson-George and Swap (1982), comprises cognition-based trust and affect-based trust. Cognition-based trust is based on personal knowledge or "good reasons", such as records (Lewis and Weigert, 1985, p. 970). On the other hand, affect-based trust is formed through emotional connections between two parties (McAllister, 1995).

For a new technology product or service, individuals might build *ex ante* trust before direct interaction through the impact of reliable third parties (Dupont and Karpoff, 2020). When first exposed to new things, individuals could generate initial trust, which is particularly important for businesses attracting clients (McKnight *et al.*, 2002). Accordingly, trust in FinTech services is multidimensional, and it is necessary to consider the potential influence of other stakeholders on individuals' trust in robo-advice, including robo-advice providers and governments.

For this study, technology trust is related to robo-advice itself. The reputation of the service provider, user feedback and relatives' recommendations can affect firm-specific trust (Grayson *et al.*, 2008). Additionally, robo-advice in Australia is regulated by the government (ASIC, 2019). System trust can be established through unified rules, such as laws and regulations, as well as guarantees and protections (Zucker, 1986). Therefore, in this study, trust involves three dimensions:

(1) technology trust (Xia *et al.*, 2023);

(2) firm-specific trust (Grayson *et al.*, 2008); and

(3) system trust (Grayson *et al.*, 2008; Xia *et al.*, 2023).

2.2 Trust transfer theory

Trust transfer theory posits that "transfer occurs from better-known to less well-known targets, and perhaps an unknown target could increase perceived trustworthiness by sending a link to a trusted target" (Stewart, 2003, p. 14). Technology itself is not a moral issue, but it does participate in social relationships, and people can build trust in it (Belanche *et al.*, 2014). Trust transfer theory offers a comprehensive explanation of how various entities and contexts related to new technologies influence people's trust. Trust can be transferred within the same channel, for example, when trust in one website extends to an unfamiliar site through hyperlinks (Xiao *et al.*, 2019). Alternatively, trust can transfer freely between offline and online contexts (Shao *et al.*, 2022). For instance, people's trust in public administration influences their trust in public electronic services (Belanche *et al.*, 2014). Additionally, word-of-mouth serves as an informal source of information, making individuals more likely to trust online retailers before directly engaging with them (Kuan and Bock, 2007). Trust transfer theory has been well applied in areas such as e-commerce (Kuan and Bock, 2007; Xiao *et al.*, 2019), blockchain (Shao *et al.*, 2022) and public electronic services (Belanche *et al.*, 2014), but limited application in the field of robo-advice. This study will also address that gap.

2.3 Technology trust

The current low adoption rate of robo-advice among Australians (ASIC, 2019) indicates that most people lack the prior experience needed to build trust in this technology (Kim *et al.*, 2009; Koufaris and Hampton-Sosa, 2004). For new digital advisory services, individuals' initial trust is typically grounded on instinctive irrational emotions, increasing their likelihood of trust (Kim *et al.*, 2009). A positive attitude reflects an affective tendency to trust (Yang and Wibowo, 2022), suggesting that individuals believe that they will be treated reliably (McKnight *et al.*, 1998). Optimistic clients tend to have positive attitudes towards new investment opportunities, like robo-advice (Flavián *et al.*, 2022). However, negative attitudes towards potential unsatisfactory performance or fraud of robo-advice (Brenner and Meyll, 2020; D'Hondt *et al.*, 2020) could lower individuals' propensity to trust robo-advice (Gillath *et al.*, 2021; Schoorman *et al.*, 2007).

Unlike traditional financial services, which involve emotional interaction, robo-advice lacks personal touch and face-to-face interaction, making it difficult for clients to generate affect-based trust (see McAllister, 1995). While robo-advice can avoid the negative effects of human emotions on financial decision-making (Bai, 2021), robo-advice is unable to sensitively recognise and respond to clients' emotional needs, nor adjust portfolios based on sudden emotional issues (Bhatia *et al.*, 2021). Furthermore, the absence of human involvement may cause clients to panic during uncertainties and emergencies (Isaia and Oggero, 2022), increasing clients' concerns about decision risks (Dalla Pozza *et al.*, 2017) and lowering trust in algorithm-driven services (Gulati *et al.*, 2019).

Security is crucial for individuals evaluating a new technology (Belanche *et al.*, 2023), with perceived security positively affecting individuals' trust in robo-advice and shaping their adoption intentions (Roh *et al.*, 2023). Robo-advice requires mandatory authorisations to access individual information (Xia *et al.*, 2023). Consequently, clients are concerned about potential threats such as data breaches, abuse, hacking and fraud (Belanche *et al.*, 2023; McKnight *et al.*, 2002), which can undermine their trust (Gulati *et al.*, 2019).

If individuals can perceive the innovation or benefits of new technologies before and during their adoption, it helps them establish a trust relationship (Koufaris and Hampton-Sosa, 2004) and reduces their perceived risks of using robo-advice (Xia *et al.*, 2023). For example, individuals will begin to trust robo-advice if they perceive it as easy to use and useful (Nourallah, 2023). However, because robo-advice assesses risk profiles only through a survey with limited questions for specific time periods (Bhatia *et al.*, 2021), there is room for error, potentially resulting in an inappropriate portfolio. This would make it difficult for the clients to recognise the usefulness of robo-advice, potentially reducing their likelihood of trusting robo-advice (Koufaris and Hampton-Sosa, 2004).

2.4 Firm-specific trust

Firm-specific trust can develop from information gathered through direct interactions and second-hand sources (Grayson *et al.*, 2008), such as company-related news, government endorsement and user feedback that can affect individuals' attitudes (McKnight *et al.*, 2002). When individuals lack experience with new technology, the provider's reputation becomes crucial for building trust (Kim *et al.*, 2009; McKnight *et al.*, 2002), because a strong reputation reflects a trustworthy history and public recognition, increasing individuals' confidence in the future activities (Karbowski and Ramsza, 2017). A positive reputation can transfer trust in the provider to its services and products (Johnson and Grayson, 2005; Koufaris and Hampton-Sosa, 2004). This is also important for AI providers, where a positive reputation serves as a crucial precursor in establishing trust, signifying their commitment to meeting clients' needs (Yang and Wibowo, 2022). The positive relationship between reputation and trust, in turn, impacts preferred choices (Dupont and Karpoff, 2020). Given that many individuals have limited experience with robo-advice or even traditional financial advisory services, a provider's reputation could be essential in initial trust.

The strong capacities of providers can positively affect individuals' trust in the technology, such as the ease of use and usefulness of the platform (Koufaris and Hampton-Sosa, 2004) and the expertise exhibited by AI services (Yen and Chiang, 2021), which is reflected in the ability to provide accurate, effective and complete information content (Kim *et al.*, 2021). For robo-advice, different providers use varying algorithms, resulting in disparities in the content and quality of robo-advice. Some robo-advice providers may offer only general financial advice, while other providers use advanced algorithms enabling their robo-advice service to personalise financial advice tailored to clients' input and needs (Tiberius *et al.*, 2022). When individuals perceive a high level of expertise and tangible performance, such as financial advice provided by robo-advice move them to a better situation, will enhance their trust (Gulati *et al.*, 2019; Johnson and Grayson, 2005; Roh *et al.*, 2022).

As mentioned before, individuals value secure technology, and the essence of these threats (potential financial losses) lies in the leakage and misuse of clients' private information (Koufaris and Hampton-Sosa, 2004; Roh *et al.*, 2023). Privacy issues are particularly significant in the context of AI, where clients cannot identify whether algorithms misuse their information for learning or if employees with access unethically use their personal information (Zhu *et al.*, 2020). Providers who proactively address privacy issues and formulate protection policies are perceived as more trustworthy (Roh *et al.*, 2022) because individuals perceive the security control from providers towards the platform can increase their firm-specific trust (Koufaris and Hampton-Sosa, 2004).

2.5 System trust

In Australia, FinTech firms providing robo-advice are regulated under existing traditional financial service frameworks and specific regulatory guidelines, such as RG 255 (ASIC, 2019). System trust complements individuals' trust in technologies (Yang and Wibowo, 2022). Dupont and Karpoff (2020) highlight that government regulations and supervision can reduce speculative behaviours and help potential clients build *ex ante* trust. When clients understand that AI's data collection complies with legal requirements, they are more inclined to trust the provider and its services (Lobschat *et al.*, 2021; McKnight *et al.*, 2002). This is because regulations-backed legal protection gives clients confidence that their finances and information are secure during the robo-advisory process (Kim *et al.*, 2009; Luo *et al.*, 2010).

3. Methodology

3.1 Design

Lourenço *et al.* (2022) empirical research indicates that individuals with a bachelor's degree or higher are more predisposed to accept digital finance advice. Moreover, Figà-Talamanca *et al.* (2022) empirical research indicates that gender differences in accepting robo-advice among the highly educated population have been eliminated. In a context where the adoption rate among Australian adults stands at 1% (ASIC, 2019), this study aligns with previous research (Zhang *et al.*, 2021; Figà-Talamanca *et al.*, 2022; Nourallah *et al.*, 2022; Nourallah, 2023), setting inexperienced young university students as the research sample to focus on individuals who are most likely to become the primary client base of robo-advice. Aw *et al.* (2023) focus on non-robo-advice users as "the primary aim of the study is to understand factors of robo-advisor resistance" (p. 8). Similarly, this study's purpose is to investigate and explain why some individuals do not trust robo-advice, and trust serves as a prerequisite for engaging with robo-advice (Gillath *et al.*, 2021). If an individual has already used or is currently using robo-advice, the trust could naturally underpin these behaviours (Nourallah *et al.*, 2022). We followed Nourallah *et al.* (2022) screening criteria, setting young university students aged from 18 to 29 as the sample, to ensure demographic homogeneity and reduce bias (Sarstedt *et al.*, 2018).

We developed open-ended semi-structured interviews based on literature reviews (DiCicco-Bloom and Crabtree, 2006; Tiberius *et al.*, 2021), facilitating participants in freely offering and complementing their insights, while also providing explanatory notes (Graebner *et al.*, 2012). Existing studies on the trust relationship between young people and robo-advice reveal either a positive or negative correlation through the verification of hypotheses (see Nourallah *et al.*, 2022; Nourallah, 2023). Qualitative research enables researchers to explore the worldview of specific minority populations rather than focusing solely on hypotheses from large samples (Boddy, 2016; Azungah, 2018). This study seeks to achieve a deeper understanding of the reasons behind the factors influencing young people's trust in robo-advice and the process of building trust, offer a more comprehensive explanation of the existing literature and contribute to the further development of a theory (Jacobides, 2005; Graebner *et al.*, 2012).

Based on Lee *et al.*'s (1999) theory elaboration, our study is both deductive and inductive. Collecting data within a theoretical context allows for the reflection of the research theme (deductive), the data collection process is designed to be open to capture new insights or expanding insights through participants' social knowledge and experiences (inductive). This approach assists researchers gain a deep comprehension of and explaining which reliable sources individuals can depend on to build trust in robo-advice.

Hennink and Kaiser (2022) conduct a systematic review analysis focusing on data saturation and find that saturation can be achieved with a minimum of nine interviews. However, qualitative research focuses on the explanation of the phenomena of the specific groups, rather than the number of responses (Bhatia *et al.*, 2020). The previous sample experience can only serve as a reference range for the number of participants (Saunders and Townsend, 2016), as the purpose and context of each study are different (Braun and Clarke, 2021). Thus, this study prioritises data saturation over the number of participants. When no more innovative ideas, new concepts or codes are produced, the qualitative data reach saturation (Guest *et al.*, 2006). This study conducted a total of 15 individual interviews and reached saturation in the sixth.

3.2 Data collection and participants

Given accounting, finance, FinTech and financial planning students are likely to have a better understanding of robo-advice and therefore may be more inclined to trust it, there could be a risk of bias. To address this, we ensured data was collected from students in different majors through purposive sampling. However, students in related majors were not completely excluded as they can have different perspectives from students in non-related majors (Bedué and Fritzsche, 2021). Further, international students were included to increase the diversity of descriptive responses (Nourallah *et al.*, 2022) as Australia is a multicultural country, with a 29.5% overseas-born population (ABS, 2023).

Interviews were conducted in Australian universities, offered in-person or virtually (via Microsoft Teams) depending on the participants' preferences. We also clarified the audio-recording requirements, the purpose of the interview and the interview process. At the beginning of the interviews, participants were able to receive detailed information about robo-advice, including how they work and their characteristics. Accordingly, participants' responses are based on their personal perspective of how their level of trust in robo-advice might potentially be influenced. Table 1 provides descriptive details of the participants.

All participants are university students, aged between 18 and 27. All participants expressed that they use digital technology daily and enjoy the ease and comfort that online shopping, online banking and mobile payments. Of the total of 15 individual interviews, 11 were conducted face-to-face and four were conducted virtually through Microsoft Teams. The total interview time was 340.8 min, which exceeded the duration of the previous robo-advice study (see Bhatia *et al.*, 2021).

4. Analysis

The interviews were conducted in English and transcribed. Based on Braun and Clarke (2006) thematic analysis framework and Al-Eisawi (2022) coding guidance, we generate

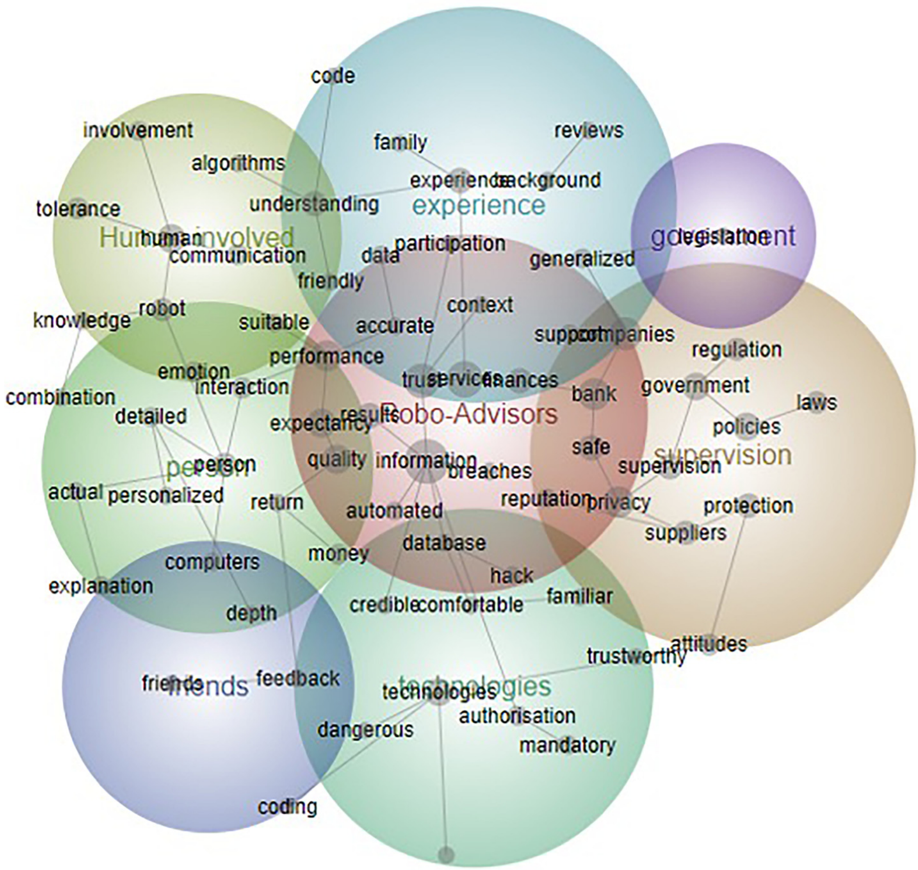
Table 1. Details of participants

ID	Gender	Age	Nationality	Major	Education	Delivery	Duration
1	M	23	China	Accounting	Master degree	Virtual	34:04
2	F	24	China	Accounting; Finance	Master degree	Virtual	24:16
3	M	27	China	Agricultural	Bachelor degree	Virtual	23:07
4	F	23	China	Laws	Bachelor degree	Virtual	28:35
5	F	23	Australia	Architecture	Bachelor degree	Face-to-face	20:00
6	F	19	Australia	Human resource management	Bachelor degree	Face-to-face	27:24
7	M	18	Australia	Exercise science	Bachelor degree	Face-to-face	19:36
8	F	22	Australia	Marine science	Bachelor degree	Face-to-face	17:07
9	F	20	Australia	Public policy	Bachelor degree	Face-to-face	22:37
10	F	24	Canada	Laws	Juris doctor	Face-to-face	20:44
11	M	21	Australia	Chemistry; Networks and security	Bachelor degree	Face-to-face	15:34
12	M	18	Australia	Physics	Bachelor degree	Face-to-face	21:29
13	F	19	Australia	Exercise science	Bachelor degree	Face-to-face	20:44
14	F	18	Australia	Social work	Bachelor degree	Face-to-face	26:48
15	F	18	Australia	Pharmacy	Bachelor degree	Face-to-face	18:44

Source: Authors' own work

theories through a three-stage coding process. In the first stage (S1), we read and familiarise ourselves with all the interviews' transcriptions, performing initial encoding. To avoid missing important information, we adhere to Strauss and Corbin (1998) line-by-line open coding method. Three participants (ID 1, 2 and 10) have educational backgrounds beyond undergraduate degrees (see Table 1), and they did not offer any innovative ideas.

In the second stage (S2), to clarify the relationships between codes and capture main concepts, we use Leximancer to semi-automatically analyse the relationships within the entire data set. Leximancer is considered a more objective analysis tool and is capable of automatically constructing a theoretical concept map, facilitating data visualisation (Sotiriadou *et al.*, 2014). In Figure 1, Leximancer identified eight concepts, some of which were related to each other, and all were identified through the initial coding process (S1). However, Leximancer's automation limits the comprehensive interpretation of data. Therefore, we through iterative manual analysis to gain a complete understanding of the data and generate detailed explanations. We compare the similarities and differences between codes, understand their relationships and close codes to extract the main concepts.



Source: Authors' own work

Figure 1. Contextual relationships

In the third stage (S3), we use selective coding (Glaser, 1978) to analyse whether the core concepts (obtained from S2) can be integrated into the theoretical framework based on literature (Sarker *et al.*, 2013) or if new themes are emerging (Walker and Myrick, 2006). This study aims to explain how other stakeholders of robo-advice affect individuals' trust in robo-advice. Based on the coding principles outlined by Sarker *et al.* (2013), the core factors in the theoretical framework – technology trust, firm-specific trust and system trust – serve as predetermined themes. These themes allow us to use explanatory data to confirm or refute the hypotheses and relationships proposed in previous studies (Bedué and Fritzsche, 2021). By further refining the themes, we renamed the broader themes to explain the factors that influence people's trust in robo-advice, focusing on dimensions such as social influence, psychological comfort, safeguarding and compliance and personal capacity (see Table 2).

Table 2. The output of analysis

Initial coding (S1)	Main concepts (S2)	Themes (S3)	Implications
Money Friends Feedback Government Brands Providers Interpersonal trust	Attitude Reputation of provider Technology trust Firm-specific trust	Social influence	• Trust and a positive attitude towards one technology product or service do not transfer to another • The government, as a recognised third party, has minimal positive influence on young people's trust in robo-advice • Firm-specific trust can transfer to trust in robo-advice
Unfamiliar Explanation Anxiety Empathy Privacy issue Customer experience Customer protection Human participant Interaction Ease of use Information quality Transparency of the algorithms Understanding capability Combination way	Familiarity Interpretability Emotional interaction Hybrid model Firm-specific trust Personalised	Psychological comfort	• Unfamiliarity hinders trust-building as individuals lack a psychological foundation • Familiar providers help transfer firm-specific trust to robo-advice • Transparent and interpretable algorithms foster trust in robo-advice. The absence of human involvement causes anxiety and limits personalised services • Individuals desire the hybrid model, which encourages them to build trust in robo-advice
Privacy issue Customer protection Customer experience Regulations Supervision Data protection	System trust Firm-specific trust	Safeguarding and compliance	• System trust, built on regulatory reliance, helps individuals trust robo-advice • Providers who actively supervise internal activities and robo-advice earn customer trust, further enhancing their trust in the robo-advice
Customer experience Mismatched advice Need extra assistance Lower satisfaction	Financial literacy Risk tolerance	Personal capacity	• Inaccurate inputs lead to mismatched financial advice, reducing satisfaction and trust • The investment comes with risks, and low-risk tolerance tends to result in low satisfaction and a lack of trust

Source: Authors' own work

The next section will explain how trust develops between people and robo-advice and how the various transfer processes occur.

5. Findings

5.1 Social influence

The study participants, with an average age of 21, have an open attitude towards technology. However, most of them expressed a lack of trust in robo-advice. To explore this, we added a question probing why participants viewed robo-advice differently despite it being a form of technology. The main reason was concerning future consequences:

> Especially with finances, being on the internet can get very risky, people get very talented with technology, especially when it comes to hacking (ID 6).

We find that recommendations or feedback towards robo-advice from trusted and reliable third parties, such as friends, can positively impact initial trust in robo-advice. As participants already have strong trust relationships with friends, this trust can effectively extend to robo-advice. One participant expressed:

> If my friends have been okay with robo-advice and told me that is okay, I will trust it. Because my friends, they are not going to lie to me and put me at risk of losing, like doing anything dodgy (ID 7).

The government could act as a reliable third party; however, only a few interviewees believed that:

> *if the government endorses it, then people would like to trust it more* (ID 15).

Over half of the participants indicated that even if the governments endorsed robo-advice, it would not positively affect their attitudes or willingness to use robo-advice. As one participant explained:

> The government does not know me, it might be the best thing for the government, but not necessarily for me (ID 5).

Consequently, the government's endorsement has minimal influence on young, educated individuals' trust in robo-advice.

Participants stated that large providers are more reliable than smaller ones, valuing their long-term operating records and financial resources. Such preference for larger companies is cognition-based trust, which can transfer to the robo-advice. As one participant explained:

> Robo-advice' performance depends on their internal technology [algorithms], so the stronger banks or companies can invest more in the technology, and then the more accurate information the robo-advice can provide. So, the strength of the company behind the robo-advice determines whether I should trust it (ID 1).

Although as digital natives, participants highlighted that online reputation cannot be fully trusted and they prefer word-of-mouth reputation and trust the brands that have stood the test of time. One participant explained:

> Because trust behind it. That would come with age because if it were not trustworthy, it would not stay around for exceptionally long (ID 7).

Some participants also consider the developers behind the robo-advice. If reputable experts develop the algorithm, they feel more confident in trusting robo-advice. Their cognitive and affective trust will be shaped by "*experienced and highly regarded people*" (ID 13), then transfer to the robo-advice. For example:

> Trust depends on the algorithm's strength, particularly if it has some big financial people behind it, like economists and proven financial advisors, which will definitely help increase trust (ID 12).

5.2 Psychological comfort

Trust is built on familiarity, one participant stated that:

> *I think in familiar things, there is already trust there and it's probably convenient as well* (ID 14).

Because familiar experiences can provide psychological expectations, reducing uncertainty and enhancing trust. For example, people could transfer their trust in familiar providers to robo-advice:

> It depends if I am super familiar with it. I would want to make sure that this was a credible process before I start putting information about my finances online, and I would feel I had already been comfortable with the processes. […] If the specific bank I used recommended it, it would be more likely for me to choose, just something that I'm already familiar with (ID 8).

The algorithms used by robo-advice can appear as black boxes to users because they cannot see the analysis process behind the final financial advice. People's trust in robo-advice could be boosted by providing sufficient explanations on how the algorithms work. One participant expressed that:

> If their algorithm actually has some kind of explanation as to how it works, like there will be transparency in that. I would not have any problem with that if it can make the analysis process and the decision-making process more transparent and there are enough decision explanations (ID 11).

In addition to explaining the decision-making basis of robo-advice, participants also expressed a desire for explaining the content of financial advice provided by robo-advisory. For example:

> […]*if it offered support, like constant support services to go along with it, like more explanation about the decision, it would make people trust them more* (ID 7).

Accordingly, the interpretability is important, which could be improved though an:

> […]*education program through it that would help teach you about what's going on and inform you, so that you don't feel left in the dark* (ID 8).

Accordingly, improving the transparency and interpretability of robo-advice could reduce clients' anxiety and provide more peace of mind, which in turn, help them build trust in robo-advice.

Another controversial point is the lack of human involvement in robo-advice. The positive aspect is that an online survey is easy to use, one said, "*I could do it on my own time, and I don't have to set up a meeting with somebody*" (ID 8). Without emotional bias, investors can benefit from the unbiased and data-driven nature of the advice because:

> […]*people's emotions and their own life experience, maybe change a little bit the advice that they give* (ID 14).

However, individuals need human touch and the lack of emotional communication and interaction may lead to challenges in understanding the context and providing personalised advice. This could negatively affect individuals' trust in robo-advice, because clients "would be easy to trust robo-advice with high quality" (ID 14). As explained by a participant:

> I choose a human because I think they can individualise it better, they can show more empathy, they can understand you, and so that will give better advice. I do not think a robo-advice would

> work as well as talking to a human advisor because I know there is not much information you can get out of a quick survey, and it would make them have to categorise you into broader categories, they cannot understand you clearly (ID 7).

In the case of a technical failure or security breach, clients may experience panic and anxiety. Participants expressed the desire to have someone behind the scenes providing support in such scenarios. For instance:

> I would want someone behind the scenes helping me just in case. If my software goes down, to whom do I talk? What if there is a problem here? What happens if the technology breaks down? Or there is a glitch? Or if there is something that goes on? (ID 13).

Accordingly, a hybrid model combining human advisors and robo-advice is favoured, which may yield optimal results in digital financial advice:

> I feel like probably a combination of humans and robo-advice. Because I feel that computers have algorithms, and they do maths well. But human interaction is important as well (ID 5).

5.3 Safeguarding and compliance

As detailed before, privacy security is crucial in shaping people's trust in robo-advice, regardless of whether data security (hacking) or personal privacy (leaks), which all lead to financial losses. Most respondents expressed a desire for their information to be securely protected and preserved and not shared without their consent:

> My only concern would be the privacy aspect since you have to upload so much information into one database. If there were a breach or if somebody hacked into that technology, so much information would be available for them, to take off your bank accounts (ID 10).

While some participants understand that robo-advice requires sufficient information for analysis, privacy concerns remain. One participant noted:

> It is pretty necessary to give robo-advice information because they need that to work. But I would worry about it being in databases that are potentially accessible to people that should not have access to it (ID 7).

We found that most participants rely on legal regulations and other protection from providers to build their trust in robo-advice. Because:

> […]*when talking about something that is profit-driven, you [clients] want to make sure that the users' interest is kept in mind. The legislations probably have helped towards that* (ID 11).

Such as:

> […]*more regulation against AI, [particularly] the amount of data in the process, to prevent data spilled out* (ID 12).

Interviewees also have positive attitudes towards the providers that actively supervise their products and services, clearly explain policies and prioritise clients' interests. One participant explained:

> […]*if they [the provider] tell you what they can and cannot do and why, because of these laws, I will trust a company more* (ID 8).

Another interviewee stated:

> *I would need the protection policy to be explained to me in detail before I can go. I do not trust it if it is just like 'don't worry, you're protected', there is no proof here* (ID 9).

Therefore, this perceived security from regulations and providers' protection could transfer their system trust and firm-specific trust to the robo-advice.

5.4 Personal capability

Robo-advice relies on online surveys to collect clients' data, making data quality crucial for accurate advice. Clients with limited financial literacy may feel stressed, as one respondent stated:

> I think it would require the users themselves to have a greater [financial] understanding. Otherwise, we are getting a different kind of experience, I am not that economically literate. I guess if the user does not really know what they want, it is difficult for the machine to tell them (ID 11).

Consequently, the advice provided may not be suitable for their actual needs, leading to a negative user experience.

Furthermore, as mentioned in Section 5.1, high-quality information helps individuals establish trust relationships with robo-advice, while low financial literacy hinders individuals from assessing the information quality of robo-advice. One participant expressed:

> *I would have to check with a financial advisor to get a nice baseline* (ID10).

When individuals struggle to perceive the usefulness and applicability of advice provided by robo-advice, building trust becomes challenging.

The participants indicated that their satisfaction was linked to their capacity to tolerate losses. Risk tolerance does not directly lower trust. Poor performance – whether due to limitations in robo-advice expertise, clients' financial literacy, or security issues – can weaken personal trust. Consequently, when unsatisfied performance occurs, individuals with lower risk tolerance are likely to express a lower level of trust. For instance:

> […]*if the loss exceeds the baseline, I will not trust it anymore and do not give it a second chance* (ID 3).

6. Discussions

6.1 The conceptual model of building trust in robo-advice

Our research identifies the key foundations for individuals to build trust in robo-advice, highlighting that this trust involves three dimensions:

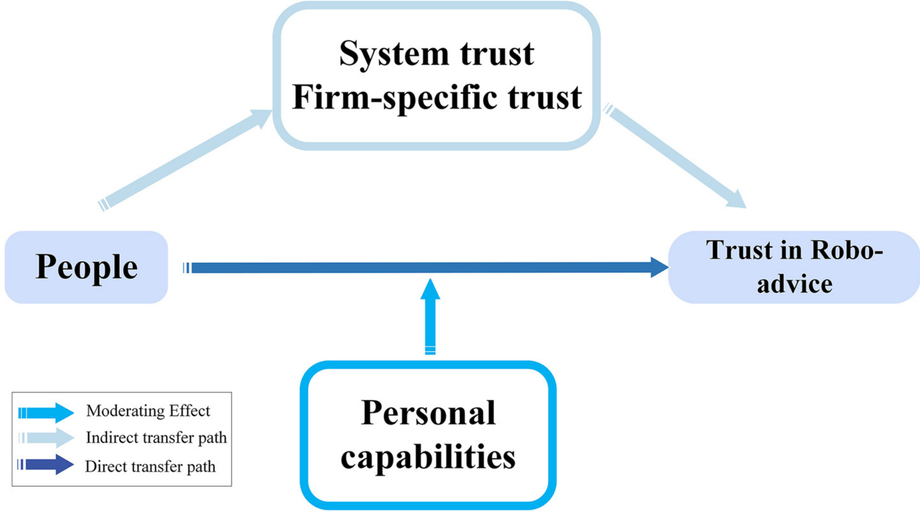
(1) technology trust (trust in the robo-advice itself);

(2) firm-specific trust; and

(3) system trust.

Based on our findings and trust transfer theory, we constructed the conceptual model (see Figure 2) to visualise the pathway of personal trust in robo-advice. We found that, in addition to the direct trust in robo-advice, their trust can also be transferred to robo-advice through firm-specific trust and system trust. Additionally, the level of individuals' financial literacy and risk tolerance can moderate their direct trust in robo-advice.

Contrary to the findings of Isaia and Oggero (2022), we find that young individuals with extensive experience in online shopping, online banking and mobile payments hesitate to trust robo-advice. This is because they are concerned about potential financial losses caused by their private information being hacked or leaked. Such anxiety could restrict individuals' trust in robo-advice. Moreover, consistent with previous FinTech studies (Xia *et al.*, 2023; Roh *et al.*, 2023), we underscore the positive influence of institutional protection and



Source: Authors' own work

Figure 2. The trust transfer process in the robo-advice

regulations on individuals' perceptions of security and privacy. These develop individuals' firm-specific and system trust, thereby indirectly enhancing their trust in robo-advice.

Nourallah *et al.* (2022) argue that young people's widespread access to online information contributes to the establishment of initial trust in robo-advice. However, our findings challenge that assertion. Participants in our study expressed scepticism regarding online reputation and, instead, exhibited greater trust in offline word-of-mouth reputation and recommendations from close social relationships. With related information about different stakeholders and robo-advice gathered and processed, their trust could increase or decrease, indicating the trust in robo-advice is process-based (see Grayson *et al.*, 2008).

This study emphasises the role of psychological comfort in building individuals' trust in robo-advice. Our findings show that the familiar providers offer a sense of security, which reduces perceived risks before and during the use of robo-advice. Individuals with low-risk tolerance tend to feel more concerned about the potential future consequences of robo-advice because the high costs can arise from misplaced trust in financial services (Bruhn, 2019). Aligning with Roongruangsee and Patterson (2023) findings, we also find that the lack of human involvement and interpretability lowers psychological comfort. However, our findings highlight low psychological comfort first reduces individuals' trust, rather than directly decreasing their intention to use robo-advice, which details the decision-making process of robo-advice adoption and shows the mediating effect of psychological comfort on trust.

Consistent with previous research (Jünger and Mietzner, 2020), our study highlights the significance of financial literacy in robo-advice. Individuals who possess certain levels of financial literacy and risk tolerance are more likely to place trust in robo-advice, which may positively influence their adoption intentions. However, young people generally have lower financial literacy (Lusardi *et al.*, 2010), and they are in the early stages of accumulating their financial foundation, displaying lower risk tolerance (Grable, 2000). This contradicts the existing research (Brenner and Meyll, 2020) suggesting that robo-advice is primarily suitable for young individuals and low-income groups.

6.2 Theoretical and practical implications

This study contributes to the research gap concerning trust between people and robo-advice by thoroughly exploring how various stakeholders influence individuals' trust in robo-advice. It extends the concept of trust in the robo-advice context into three dimensions: technology trust, firm-specific trust, and system trust.

Existing research on robo-advice lacks quantitative tests on firm-specific and systemic trust, this qualitative exploratory study provides foundational theoretical perspectives. Additionally, this study fills a gap in robo-advice literature from a client perspective (Belanche *et al.*, 2023) and highlights the positive role of psychological comfort in building individuals' trust in robo-advice. Aligning with Zhu *et al.* (2024) literature review, our study also finds that individuals would like to seek additional confirmation from human advisors and value empathy. This preference may be due to low financial literacy and risk tolerance, and human interactions provide individuals with greater peace of mind and help establish a foundation of trust in robo-advice. Further, Belanche *et al.* (2020) framework suggests that robot design, customer features and service encounter characteristics determine whether client engagement with AI-driven service robots. Our study extends it into the robo-advice context and provides insights into how each dimension influences trust and subsequently shapes individuals' engagement intentions.

This study highlights that the financial services industry may benefit from adopting a hybrid model that integrates both traditional and digital advisory services. Such a model may reduce the cost of obtaining financial advice while supplementing interaction and empathy in robo-advisory. Furthermore, this study finds that the transparency and interpretation of the algorithm positively affect individuals' trust in robo-advice, offering a direction for developers to improve the service systems. World-of-mouth reputation is also important for FinTech companies; however, small companies may face more challenges in establishing trust relationships with potential clients. Therefore, we recommend that the government take more responsibility in promoting robo-advice by supporting and educating individuals in its use. For instance, the government could collaborate with robo-advice providers to provide free financial seminars and attempt to connect traditional famous banks with the robo-advice industry. These could encourage more individuals to engage with affordable digital financial advice, helping to close financial literacy gaps and meet the growing need for financial advice among Australians.

6.3 Limitations and future research

The sample of this study does not represent all young, educated people, and the findings may not be applicable to other populations. Although all participants received education about robo-advice before the interviews, they lacked using experience, meaning their responses reflect their perceptions. All participants were aware we were discussing robo-advice within an Australian context and were living in Australia at the time of the interviews. However, including international students could introduce bias when analysing the responses to questions regarding system trust when from backgrounds where different regulations operate.

Despite these limitations, this study contributes to understanding the implicit expenses associated with the lack of trust in robo-advice, potentially improving accessibility to assist a larger population in obtaining affordable digital financial advice. This, in turn, could foster digital and financial inclusion and strengthen commitment to financial innovation. Although it seems reasonable not to completely trust robo-advice, understanding why people do not trust robo-advice is still crucial. Future research could address this research gap by supplementing quantitative works for different dimensions of trust in robo-advice.

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