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Man vs machine: how artificial intelligence in banking influences consumer belief in financial advice

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Abstract

Purpose – This research set out to examine how financial advice provided by a human advisor (vs robo-advisor) influences investment intentions in a retail banking context.

Design/methodology/approach – In two experiments, between-subjects experimental designs were employed to test the primary hypothesis and identify the underlying causal mechanisms that influence consumer investment decisions.

Findings – The results from two experiments indicate consumers have more belief in financial advice provided by a human financial advisor (vs robo-advisor), when the level of involvement is high. The authors also identify customer belief in the information and the customer's perception of the bank's "customer focus" as the causal mechanisms that have downstream effects on investment intentions.

Originality/value – This research is the first to examine how financial advice received from a human advisor (vs robo-advisor) influences investment intentions in a retail banking context. Furthermore, this research identifies high involvement as a key boundary condition moderating the effects on investment intention and identifies consumer belief in the advice, as well as the bank's perceived level of customer focus as the causal mechanisms influencing investment intentions.

Keywords Artificial intelligence, Banking, Trust, Customer orientation, Robo-advisor

Paper type Research paper

Introduction

The global banking sector is huge. In 2022, despite the effects of COVID-19, annual revenue from the global banking system is expected to come in above US$5.5 trillion. Nonetheless, global banking revenues are under intense pressure and the global pandemic has made many banks rethink their strategy and tactics. As a result, there is a digital revolution occurring in the banking sector that is likely to reshape the industry considerably.

Following the 2008 GFC banking recession, innovation in the banking industry became subordinate to whatever product operations generated the most revenue. However, when COVID-19 hit the world in early 2020, social distancing, lockdowns and isolation sped up the digitalisation of the banking world. This is because bank customers around the world have moved to digital channels at increasing speeds. Since the outbreak of COVID-19, online banking has increased 23%, with mobile banking growing by 30% (Brackert *et al.*, 2021). For those banks leading the way with digital banking services, they are seeing efficiency gains up to double that of other typical retail banks. One area where banks have started investing heavily is with the use of artificial intelligence (AI) and automation.

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In the modern retail environment, consumers demand timeliness and efficiency, where the focus is on reducing time and effort and maximising convenience (Klaus and Zaichkowsky, 2020; Mogaji *et al.*, 2022). In this respect, Artificial Intelligence (AI) has taken convenience to a whole new level, because the consumer experience is becoming less human-dependent (van Esch *et al.*, 2021). First coined in the 1950s, "artificial intelligence" originally referred to the ability for machines to exhibit some form of intelligence (Helm *et al.*, 2020). Recently though, AI has been defined as a system's ability to interpret and learn from external data and use that learning to flexibly adapt to a situation in order to achieve specific goals (Kaplan and Haenlein, 2019).

What we now see is virtual bots replacing human service staff (van Esch and Black, 2021) to facilitate customer-controlled self-service (Huang and Rust, 2018), whilst service robots are being used to manage the dining experience in restaurants (Qiu *et al.*, 2020) and chatbots service customers for their needs (Mogaji *et al.*, 2021a). This is no different in the banking sector, where automated-teller-machines (ATM), phone-banking, tele-banking, EFTPOS, Internet banking (IB), mobile app-based banking and artificial intelligence (AI) have all had a profound effect on the consumers' banking experience (Payne *et al.*, 2021). Of those, AI promises to have a major influence on consumer behaviours in retail banking (Mogaji *et al.*, 2021b). This is because AI allows for robotic process automation that is a quick and simple way for banks to automate a wide range of processes and speed up the processing of big data (Mehdiabadi *et al.*, 2020; Perez-Vega *et al.*, 2021). Till recently though, the use of AI in banking and finance has primarily centred around areas such as asset management, algorithmic trading, credit underwriting and blockchain-based finance as a way to drive cost reductions and productivity enhancements (OECD, 2021). However, the past decade has seen a number of fintech companies leading a wave of disruption in the financial services industry (Rosenbaum, 2022). Central to this disruption has been the growth in robo-advisors, which are digital platforms that provide automated, algorithm-driven financial advice with little or no human supervision (Frankenfield, 2022). In the US alone, it is projected robo-advisors will soon be managing over $1 trillion of Americans' wealth (Iacurci, 2022). Part of this growth may be attributed to the fact the ease and usefulness of robo-advisors has a positive influence on attitudes towards and adoption of the technology (Belanche *et al.*, 2019). In fact, there is a large body of research that has examined why consumers are willing to adopt robo-advisors (see Hentzen *et al.*, 2021 for a review) across a range of countries including Germany (Seiler and Fanenbruck, 2021), Pakistan (Wang *et al.*, 2021), Malaysia (Gan *et al.*, 2021) and USA (Fan, 2021). However, recent research (Zhang *et al.*, 2021) has suggested consumers prefer human advisers with high expertise over robo-advisors. That said, there is currently limited understanding why this might be the case. One reason might be that humans are more trusting of advice from another human, rather than a machine. Certainly, evidence from developmental psychology that highlights the important role of social interaction in the human condition would support this (Baumeister and Leary, 1995; Hari *et al.*, 2015; Shumanov and Johnson, 2021). Another reason may also be the level of involvement people experience relative to the investment decision. Prior research (Castellini and Graffigna, 2022) indicates involvement can have a strong influence on consumer decision making. Moreover, in a finance situation, an individual's level of involvement can increase as the amount of funds being invested increases (Saqib *et al.*, 2010). To answer these questions, the current research set out to examine how financial advice provided by a human advisor (vs. robo-advisor) influences investment intentions in a retail banking context. The results from two experiments indicate consumers have more belief in financial advice provided by a human financial advisor (vs. robo-advisor), when their level of involvement is high. The findings also show information provided by an automated AI system reduces how "customer oriented" a bank appears to potential consumers, with this perceived customer orientation acting as a causal mechanism that reduces intentions to invest. The remainder of this paper sets out the conceptual model, describes the methodology and analysis and finishes by discussing the theoretical and managerial implications of this research.

Conceptual development and hypotheses

The need for human interaction

Humans are an incredibly social species with a hardwired need for social interaction (Baumeister and Leary, 1995). Before birth, babies perceive and respond to voices whilst in the womb. Similarly, after birth, devoting attention to another person is an important developmental milestone for human infants (Bakeman and Adamson, 1984). As early as 3 months of age, infants begin to engage in synchronous exchanges of gaze patterns, co-vocalisations, mutual expressions of positive affect and loving touch with caregivers (Feldman, 2012b). These earliest bonding memories are shown to influence the way we function and influence lifetime attachment with other humans (Feldman, 2012a). As a result, the human brain is shaped throughout life by social contact and communication (Gillin and Gillin, 1948; Hari *et al.*, 2015). Not only is brain structure influenced, but there are positive psychophysiological effects that come from social interaction. For example, the anti-stress effects of Oxytocin, responsible for inducing a feeling of safety, have been found to be released by our closest affiliations, and this same chemical effect enhances social affiliation through the sense of well-being associated with our closest bonds (Feldman, 2012a). As a result, even now in the digital age, some individuals will prefer to interact with sales employees simply because they value the human to human interaction (Shumanov and Johnson, 2021).

Social interaction in the digital age

Life in the modern, developed world involves frequent interaction with an ever-expanding array of lifelike technological and virtual agents (Epley *et al.*, 2007). As we interact with machines in increasingly complex and human ways, the psychological aspects of our relationships with technology takes on an increasingly important role (Burgoon *et al.*, 2000). Because of this, research (Bickmore and Picard, 2005) has examined how human-computer relationships influence specific benefits (such as trust) and task outcomes (such as improved learning) and how these can build long-term, social-emotional relationships between user and machine. Because of this, it is now not uncommon for people to have relationships with their computers including loving friendships with social chatbots (Abdulquadri *et al.*, 2021), whose opinions are perceived as credible, attractive, competent in communication, and interactional (Reeves and Nass, 1996; Skjuve *et al.*, 2021).

To understand how we have come to love interacting with machines, look no further than the extensive studies of Human Computer Interaction (HCI) (Burgoon *et al.*, 2000). Everything from politeness theory (Brown *et al.*, 1987), meta-relational communication (Dainton and Stafford, 1993; Stafford and Canary, 1991), affective facial displays (Levinson, 1983) and the anthropomorphism of human–computer interaction (Epley *et al.*, 2007) provide insights into conceptually designed machines that facilitate liking and create a virtual social connection. In addition, previous research has shown an increasing desire to turn non-human agents into human-like ones (Waytz *et al.*, 2010), even determining what level of subordination is needed to create the perfect, yet respectful tonality of greetings and messages to mimic social hierarchal norms (Bickmore and Picard, 2005). This is reshaping the banking industry.

Artificial intelligence in the banking industry

The past thirty years has seen a digital revolution in banking technology. Developments like automated-teller-machines (ATM), phone-banking, tele-banking, EFTPOS, Internet banking

(IB), mobile app-based banking and more recently artificial intelligence (AI), have all had a profound effect on the consumers' banking experience (Payne *et al.*, 2021). Of those, AI promises to have a major influence on consumer behaviours in retail banking. This is because AI allows for process automation that is a quick and simple way for banks to automate a wide range of processes and speed up the processing of big data (Mehdiabadi *et al.*, 2020; Perez-Vega *et al.*, 2021). At the same time, the growth in smartphone use, coupled with AI and 5G connectivity, banking has morphed from traditional bricks and mortar branches with the introduction of new offerings such as selfie-pay in China (Tomić and Todorović, 2018), blockchain in Africa (Kshetri and Voas, 2018), self-driving cars with their own bank accounts and augmented reality tech that informs the future design of banking systems (King, 2018).

At present though, the use of AI in banking and finance still appears to be focussing on cost reductions and productivity enhancements (OECD, 2021). Alternately, we also see AI used for client actions such as automated bill payments, fund transfers and transaction reminders, as well as higher value-in-use contexts such as personalised investment advice and fraud detection (Manser Payne *et al.*, 2021; Wexler and Oberlander, 2021).

Some notable advantages of AI are reduced human error and judgement bias and greater forecasting accuracy and precision (Duan *et al.*, 2019). However, even though AI may offer equally good, if not better, financial advice, consumers tend to consider the performance of AI objectively inferior to that of a human expert provider (Hildebrand and Bergner, 2020). For example, in the case of low-complexity tasks, customers considered the problem-solving ability of AI to be greater than that of human customer service. However, if the task has a high level of complexity (where too much information causes information overload), consumers viewed human customer service as superior and were more likely to use it than AI (Xu *et al.*, 2020). Despite the increasing presence of AI in the banking sector, academic and industry studies reveal that a broad consumer acceptance of AI —even amongst young, affluent investors—has been surprisingly low (Hildebrand and Bergner, 2020). What is more, even with rapid digitalisation is that consumers still prefer human interactions in industries characterised by high consumer involvement, such as health care and financial services (Gaspar *et al.*, 2020). These results corroborate earlier findings in medical and military operations contexts (Longoni *et al.*, 2019; Pearson *et al.*, 2018), showing that in important and high-risk domains, consumers may hesitate to use robo-advisor information if the information can instead be obtained from a human source (Zhang *et al.*, 2021). One "high risk" domain where this might influence consumer decisions is in personal banking, where amateur investors invest their life savings based on advice from a financial institution. What is more, as the amount of money they are investing increases, their involvement in the process is also likely to increase and influence their decisions.

The moderating role of involvement

The concept of involvement is complex, and its definition can be somewhat dependent on the context. Prior research has defined involvement as an individual's perceived level of importance or interest in a product, or their level of arousal when thinking about or experiencing a product (Laurent and Kapferer, 1985; McQuarrie and Munson, 1992). Importantly, it has been suggested involvement can influence an individual's response to advertising, their brand loyalty and their purchase decisions (Castellini and Graffigna, 2022). However, for the sake of the current research, we consider that a person's involvement at a given point in time can change depending on the individual's values or needs, or some other factor that might increase personal relevance. In a finance context, as the level of investment increases, the stakes become greater, thereby increasing the level of involvement (Saqib *et al.*, 2010). Effectively, the more money someone is looking to invest, the greater the involvement. This is critical, because we know that finance customers predominantly rely on expert advice (as opposed to benevolence) when they make risky financial decisions (Martenson, 2008). In this sense, expertise is the extent to which someone is perceived to be capable of making correct assertions (Eriksson *et al.*, 2020). As a result, the subsequent risk-return combinations make investment decisions a special kind of decision that includes vulnerability, reciprocity, and permanent feedback, which are all characteristics in trust situations (Ritzer-Angerer, 2019). These characteristics are evident in human-human social interactions but are much less discernible in human-computer interactions. Compounding the situation is that as the amount of money being considered increases, the threat of potential losses may influence investment decisions. This is because some individual's may focus on loss aversion, rather than gain maximisation (Kahneman and Tversky, 1979). Building on this, we propose the following hypothesis:

H1. In a finance context, human (vs. AI) investment advice will have a positive (negative) influence on intention to invest when involvement is high.

Our hypothesis proposes when the amount of money being invested increases, investors are more involved in the decision. When this involvement is high, investors are more likely to heed the financial advice given to them by a human, rather than advice generated by a robo-advisor. Ultimately, this will influence their investment decisions. To assist the readers, this does not mean the AI-enabled information is provided by a chatbot or some other AI-driven robot. It could be a simple report generated by an AI-enabled system, such as a robo-advisor software platform. Regardless, the hypothesised effects do not fully explain the psychological mechanisms that cause this change in investment behaviour. For this, we look to trust and the customer's perceived brand orientation as causal mechanisms within the model.

Do you believe that? The role of trust in human-computer interactions

Trust in financial advice is a complex, multifaceted construct based upon careful judgements of the quality of information and advice on offer (Sillence and Briggs, 2007). Whilst there is conflict in the literature on the definition of trust, most trust theorists agree that whatever else, trust is fundamentally a psychological state and needs to be conceptualised not only as a calculative orientation toward risk, but also a social orientation toward other people and toward society as a whole (Tyler and Degoey, 1996; Mayer *et al.*, 1995).

In a financial context, a useful approach is to develop a contextualist account that acknowledges the role of both calculative considerations and social inputs in trust judgements when transactional decisions are required (Hardin, 1991). Trust in financial services and advice can further be categorised to incorporate both a role-based and a rules-based trust aspect (Kramer, 1999). Together they represent "presumptive trust" where strong expectations are aligned with opinions that role occupants will fulfil the fiduciary responsibilities and obligations associated with the roles they occupy (Barber, 1983). Fundamentally, it is not the person in the role that is trusted so much as the system of expertise that produces and maintains role-appropriate behaviour of role occupants (Barber, 1983; Meyerson *et al.*, 1996; Kramer, 1999). This is important, because it means a customer's willingness to rely on financial advice is influenced by perceptions of the brand's ability to perform its stated function (Chaudhuri and Holbrook, 2001). Consequently, trustworthiness is ranked as the most important criterion when choosing a financial adviser (Lachance and Tang, 2012). What is more, belief in the financial advice provided is a proven predictor of investing, even after controlling for demographic characteristics and financial literacy (Burke and Hung, 2021).

From a psychological perspective, one way in which trust can function to reduce a consumer's transaction costs is by operating as a social decision heuristic (Gigerenzer and Goldstein, 1996). Essentially, people use heuristics to process a message quickly, but when a more careful judgement is required, they switch to analytic strategies (Chaiken, 1980; Tversky and Kahneman, 1992). Specifically for retail (i.e. non-expert) investors, the default option is to adopt an "advice taking" heuristic, where an investor's lack of experience and training increases their dependence and trust in financial advisors (Monti *et al.*, 2014). But what if the financial advisor is not human and instead the financial advice is delivered by a robo-advisor.? Which information are they likely to trust more?

Prior research (Parasuraman *et al.*, 2014) has shown when presented with information from both human and automated (computer-generated) sources, individuals may initially have more trust in automated information due to a powerful automation bias. However, over time people develop greater trust in information from humans, due to a higher degree of confidence the human adviser will perform the task based on the received feedback. At the same time, people are also "cognitive misers" and distrusting others can be cognitively demanding, meaning that individuals will often go with what they know (a simple decision heuristic) to minimise the cognitive effort required for any decision making (Liu and Goodhue, 2012). However, in relation to financial advice, the amount of funds being considered for any investment is likely to have an influence on the decision-making process and the level of trust in the information provided. This is because as the amount of financial resources being dedicated increase, the investor's involvement increases (Hedesström *et al.*, 2007).

Trust and belief in the information provided

When people trust the information they receive from any source, they are more likely to act in a positive manner to the information provider. In a business context, trust is directly connected to the brand name (Aaker, 1991) and for most customers, a strong brand is one that provides comfort and familiarity both offline or online (Ha and John, 2010). Strong brands are ones that provide customers with a degree of certainty about service and expected satisfaction. Because of this, strong brands play a special role in service companies – such as banks – by increasing consumers' trust of the invisible purchase (Berry, 2000). Customers find the intangible characteristics of financial services difficult to value, so by enabling consumers to better visualise and understand intangible products, this in turn reduces their perceived monetary, social, or safety risk in buying services, which are difficult to evaluate prior to purchase (Berry, 2000; Moin *et al.*, 2016). In situations where perceived risk is high, a brand engenders trust through making the products and services familiar to the customers, providing quality perceptions, reducing risk perceptions, creating emotional ties, and promoting trusting intention (Elliott *et al.*, 2015).

By contrast, lack of trust in financial brands is a long-standing problem in financial services (Robson and Farquhar, 2021). Distrust has been defined as a "lack of confidence in the other, a concern that the other may act so as to harm one that he does not care about one's welfare or intends to act harmfully, or is hostile" (Govier, 1994). The least successful financial services brands are characterised by considerable inconsistency (Ha and John, 2010). A variety of circumstances can trigger distrust and suspicion, including situations where perceivers believe that another might be insincere or untrustworthy, or their expectations have been violated, and when they recognise situational cues or possess contextual information that suggests another might have ulterior motives (Fein and Hilton, 1994).

Ultimately, though, credibility underlies consumer confidence in a firm's product claims. For this reason, the types of messages being communicated should be perceived as truthful and dependable, as they influence trust in the message source (Erdem and Swait, 1998). In the case of financial services organisations, if the brand's values and behaviour are incongruent with either the underlying or the espoused corporate values, then it is likely the brand will appear false and unconvincing to consumers (de Chernatony and Dall'Olmo Riley, 1998). Alternately, if the information received is dependable, believable, and trustworthy, customers are more likely to evaluate product offerings favourably, thereby increasing their willingness to invest. Part of that might be because dependable, trustworthy information influences customer perceptions of the brand, where the brand is perceived to be more customer focussed and have a more positive customer orientation.

Customer orientation: the mechanism that makes the magic happen!

A firm's customer orientation has been defined as the application of employees' specialised activities to identify, analyse, understand, and answer customer needs (Vargo and Lusch, 2004). In the financial services industry, customer orientation reflects the disposition of individuals working in the financial service industries to focus on and meet clients' needs (Halstead *et al.*, 2008). A crucial difference in a customer-oriented firm, is that the organisational culture shares a set of beliefs that puts the customer's interest first. Doing this can have a significant impact on customers' perceived service quality (Ha and John, 2010; Homburg *et al.*, 2011; Wallin Andreassen, 1994).

In a finance setting, customer orientation can also be seen as competence in service orientation, where a firm's competence includes the portfolio of skills and resources it possesses along with the way those skills and resources are used to produce outcomes (Menor and Roth, 2007). Building enduring customer relationships requires said competence and for financial services organisations like banks, employee conduct influences customers' perceptions of service performance and their subsequent behavioural outcomes (Lachance and Tang, 2012; Wasan, 2018). As such, functional clues like convenience, credibility, competence and compassion have been shown to be significant predictors of customers' discretionary behaviours (Wasan, 2018). Importantly, discretionary behaviours are indicative of a bank's performance and are based on a customer's own judgement of service quality behaviours. These discretionary behaviours include customers' recommendations of the bank to others or, possibly more importantly, investing in financial instruments or services provided by the bank (Wasan, 2018).

The influence of artificial intelligence on perceived customer orientation

Whilst prior research espouses AI's potential to engage with consumers (Chong *et al.*, 2022; Hildebrand and Bergner, 2020; Shanmuganathan, 2020), alternate research also shows conflict between AI administered advice and customer perceptions of trust and quality (Castillo *et al.*, 2021; Mogaji *et al.*, 2021a, b; Zhang *et al.*, 2021). Because of this, AI-enabled technology (such as robo-advisors) may not always help businesses service their customers more effectively (Mogaji *et al.*, 2021b). This conflict highlights a very real danger. When there is limited trust in the information source (or the brand), customers feel less trust toward the messaging, whether it is human or computer-generated advice (Eriksson *et al.*, 2020; Taylor *et al.*, 2007). This is critical, because In finance, a firm signals the value they place on customer orientation by supporting the brand's credibility as an information source and emphasising the resources spent to establish and maintain information credibility (Brady and Cronin, 2001; Ha and John, 2010; Halstead *et al.*, 2008; Wallin Andreassen, 1994). Thus, if a bank uses AI to service potential investors, those investors may experience less trust in the information provided. This will make them feel like the bank (the brand) is less customer focussed (has a lower "customer orientation") and as a result, they will be less willing to invest money or purchase financial products offered by the bank (see Figure 1 for the full conceptial model). From this, we propose the following hypothesis:

H2. In a finance context, human (vs. AI) investment advice will have a positive (negative) influence on perceived believability when involvement is high, which results in higher (lower) investment intention via customers' perceived customer orientation.

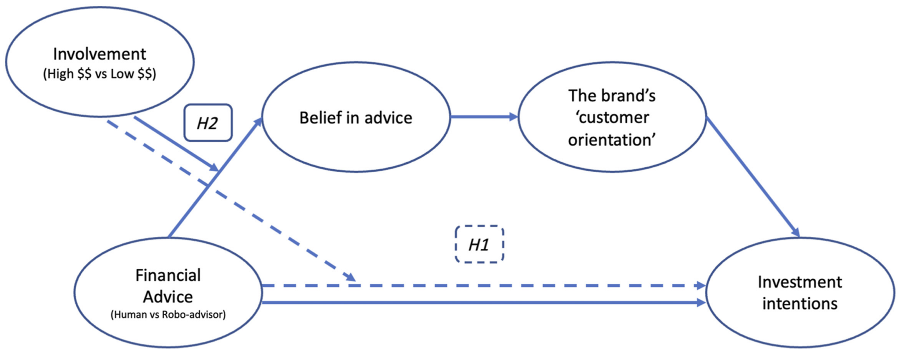

Figure 1.
Conceptual model

Methodology and analysis

Study 1

Methodology. Study 1 was a 2(Financial advice: human/robo-advisor) × 2(Involvement: high/low) between-subjects experiment. Participants (n = 165) were recruited through a research agency in the United States (mean age = 37years; 63.6% male). Two fictitious scenarios were created by the authors for the experiment, based upon the fictitious financial planning service provider "Moneymaker". In the "Human" (*robo-advisor*) condition, participants were asked to read the following:

(1) "Imagine you are a customer of the financial planning service provider, Moneymakers. You are looking to invest **$50,000** of your savings and you are seeking investment advice. Moneymakers financial and investment advice *will be provided by a member of their financial advice team*"

(2) In the robo-advisor condition, the last part was substituted to read "*…provided by their artificial intelligence (AI) software application.*"

Fictitious scenarios have been used in previous research (Belanche *et al.*, 2020; Hong *et al.*, 2021) involving artificial intelligence, whilst the use of a fictitious service provider (Moneymaker) is an accepted technique in consumer research (Stewart, 1992; Northey *et al.*, 2020). This is because the use of a fictitious brand avoids triggering any brand-related biases or pre-existing attitudes participants may have (Money *et al.*, 2006). Importantly, participants were asked to imagine that they are investing either $50,000 or $500 depending on whether they were in the high ($50K) or low ($500) involvement condition. To be clear, participants did not view any AI robots or chatbots. They were simply asked to imagine the information coming from a robo-advisory service. To measure investment intention, two items were used from a scale developed by Meyer *et al.* (2017), asking participants on 7-point semantic differential scales if they were likely to invest, with responses to each item recorded 1–7 as either very improbable/probable and unlikely/likely (α = 0.886).

Analysis and results. To test H1, a moderated regression analysis was run with intention to invest as the dependent variable using PROCESS Version 3.5, Model 1, with 5,000 bootstrap samples and a 95% confidence interval. For the independent variables, the authors included AI vs Human (1 = AI, 2 = Human) and Investment Involvement (1 = High [$50,000], 2 = Low [$500]), and their two-way interaction. The AI vs Human (B = 1.67, p < 0.007) and Investment Involvement manipulations (B = 1.55, p < 0.012) had significant direct effects on intention to invest as shown in Table 1. The results demonstrate a significant two-way interaction between the type of financial advice (human vs robo-advisor) and Involvement variables on intentions to invest ($B = -0.82$, $p = 0.037$), providing support for the hypothesis (H1). Specifically, when participants viewed information from a robo-advisor in a high-involvement condition (high-level investment) they reported the lowest level of intentions to invest ($M = 4.46$, SE = 0.19) (see Figure 2), and this was significantly lower than participants who viewed information supplied by a human employee in the high involvement condition ($M = 5.31$) ($p = 0.002$), as well as those who received information from the AI source in the low involvement condition ($M = 5.19$) ($p = 0.009$). Further, for participants receiving information from a human employee, no significant differences were observed between the high/low-involvement conditions ($p = 0.747$).

Study 2

Methodology. To ensure consistency, Study 2 replicated S1, designed as a 2(Financial advice: human/robo-advisor) × 2(Involvement: high/low) between-subjects experiment. Once again,

Relationship	*B*	SE	*P*
Study 1			
Human vs AI > intention to invest	1.67	0.61	0.007
Involvement > intention to invest	1.55	0.61	0.012
Human vs AI × High vs Low Involvement > intention to invest	−0.82	0.39	0.037
Study 2			
Human vs AI > belief in advice	0.9	0.36	0.013
Involvement > belief in advice	0.99	0.36	0.006
Human vs AI × Involvement > belief in advice	−0.54	0.23	0.019
Belief in advice > customer orientation	0.89	0.03	<0.000
Belief in advice > investment intention	0.49	0.11	<0.001

	Index	SE	CI
Index of moderated mediation	−0.22	0.11	0.02–0.46
Human vs AI > high involvement	0.14	0.07	0.01–0.31
Human vs AI > low involvement	−0.07	0.07	−0.22 – 0.05

Note(s): In both studies, age, gender, occupation, education and income were measured and had no significant effect on the model

Table 1.
Results

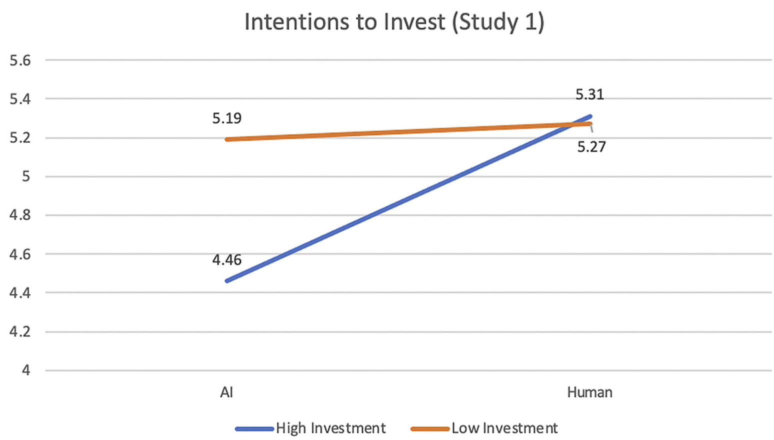

Figure 2.
Intention to invest

participants (n = 299) were recruited through a research agency in the United States (mean age = 36 years; 56.2% male). The procedure from Study 1 was replicated for Study 2, where two fictitious scenarios were created by the authors for the experiment, based upon the fictitious financial planning service provider "Moneymaker". As with S1, to measure investment intention, two items were used from a scale developed by Meyer *et al.* (2017), asking participants on 7-point semantic differential scales if they were likely to invest, with responses to each item recorded 1–7 as either very improbable/probable and unlikely/likely (α = 0.886). To measure the first mediator (belief in the financial advice), six items (α = 0.89) were used from a scale developed by Beltramini (1988). Scale items were measured on a 7-point semantic differential scales (1 = strongly disagree, 7 = strongly agree). To measure the second mediator (the firm's perceived customer orientation), six items (α = 0.93) were used from a scale developed by Saxe and Weitz (1982) and shown to have strong reliability and validity in banking and finance settings (see Tseng, 2018). Scale items were measured on a 7-point semantic differential scales (1 = strongly disagree, 7 = strongly agree).

Analysis and results. To test the proposed conceptual model in full and investigate the hypothesised moderated serial mediation, the authors used PROCESS Version 3.5, Model 85, with 5,000 bootstrap samples and a 95% confidence interval. The analysis examined the indirect effect of AI vs Human (1 = AI, 2 = Human) on investment intentions (the dependent variable), serially mediated by belief in financial advice and customer orientation, moderated by involvement (1 = High [$50,000], 2 = Low [$500]). The authors also again controlled for age, gender, occupation, and income as per Study 1.

The results demonstrate the type of financial advisor (B = 0.90, SE = 0.36, p = 0.013) and level of Involvement (B = 0.99, SE = 0.36, p = 0.006) had a significant negative direct effect on belief in financial advice. Further, as predicted the two-way interaction between financial advisor (Human vs robo-advisor) and level of involvement (high vs low) was significant (B = −0.54, SE = 0.23, p = 0.019), providing initial support for H2. Specifically, participants in a high involvement situation were less likely to believe in the financial advice from a robo-advisor(M = 5.01, SE = 0.11) compared to a human source (M = 5.38, SE = 0.11; p = 0.021). Similarly, participants in the high involvement situation were less likely to believe in the financial advice from a robo-advisor (M = 5.01, SE = 0.11) compared to those receiving information from a robo-advisor in a low involvement situation (M = 5.41 SE = 0.11; p = 0.007) (see Figure 3).

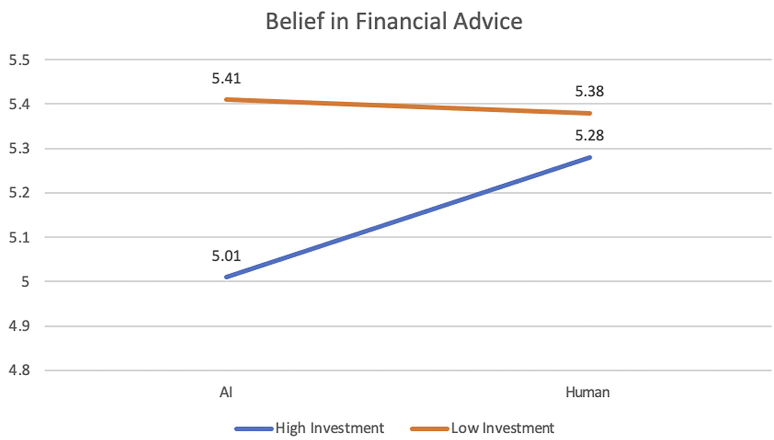

Figure 3.
Consumers' belief in the advice

In terms of the mediators, results show belief in financial advice (the first mediator) has a positive direct effect on customer orientation ($B = 0.89$, SE = 0.03, $p = 0.000$). Further, belief in financial advice was shown to have a significant direct effect on investment intentions ($B = 0.49$, SE = 0.11, $p = 0.000$). In addition, customer orientation (the second mediator) was shown to have a positive direct effect on investment intention ($B = 0.45$, SE = 0.03, $p = 0.000$). As predicted, the index of moderated mediation was significant, (index = −0.22, SE = 0.11, 95% CI 0.02-0.46). The effect of AI vs Human was significant for high-level investment ($B = 0.14$, SE = 0.07, 95% CI 0.01-0.31) but non-significant for low-level investment ($B = -0.07$, SE = 0.07, 95% CI −0.22-0.05). Of further note is the explanatory power of the model with moderate to high-level explanation of customer orientation ($R^2 = 0.69$) and investment intentions ($R^2 = 0.48$).

General discussion

The current research examined how the source of financial information received by an investor influences their investment decisions. The results from two experiments provide strong evidence that when consumers receive investment advice from an AI-enabled system (rather than from a human), it reduces their intention to invest. Study 1 set out to determine whether the information received from a human financial advisor, as opposed to information received from a robo-advisor digital platform, would influence consumer investment decisions and whether involvement moderated the effect. The findings from Study 1 show consumers are accepting of information from both human and AI sources, but only when their level of involvement (the amount they are investing) is low. However, in high involvement situations – when there are more dollars in play and stakes are higher – consumers are less likely to invest if the information is received from an AI-enabled system. Study 2 sought to further extend existing theory by identifying the underlying process acting as the causal decision-making mechanism. The findings from Study 2 show that consumers in high involvement situations are less trusting of (have less belief in) financial advice from a robo-advisor, compared to advice provided by a human advisor. What is more, this makes the consumer feel like the firm is less customer focussed, which has a negative influence on investment decisions.

Theoretical contributions

The findings from this research have several important theoretical contributions. First, we tested a novel prediction that financial information provided by a robo-advisor (rather than a human) would result in less willingness to invest. This is significant because most research has previously focussed on the antecedents of adoption (Zhang *et al.*, 2021; Belanche *et al.*, 2019; Seiler and Fanenbruck, 2021; Wang *et al.*, 2021; Fan, 2021). We add to this literature by showing that even if an individual was to adopt an AI-enabled system (robo-advisor), their intention to invest may be inhibited because they did not receive the information from a human advisor.

Second, our research identifies the boundary condition at which these effects occur. Specifically, we show that a consumer's level of involvement reduces their investment intentions when information is received from a robo-advisor. Prior research has shown the level of involvement is directly related to the level of funds being invested (Saqib *et al.*, 2010). Research by consulting firm Deloitte (2019) has suggested robo-advisory services are not likely to be favoured by high net worth individuals – effectively those with large sums to invest – as they are likely to have a greater appetite for risk and desire for control over their investments. Our findings support the suggestions by Deloitte and extend existing theory by demonstrating when involvement (where amount to be invested is a proxy for involvement) is high, investors are less likely to invest if the financial advice is received from an AI-enabled robo-advisory service.

Third our research identifies the underlying psychological processes that influence these effects. Our findings show the source of information influences a consumer's trust in the information, which affects the consumer's perception of the brand's customer focus. Together, these acts as causal mechanisms guiding a consumer's intention to invest. These findings are consistent with prior research that show belief or trust in the information influences consumer behaviours (Barber, 1983; Meyerson *et al.*, 1996; Kramer, 1999). Importantly, our findings extend existing theory by demonstrating an individual's belief in the information is what activates their perception of the brand's customer focus or orientation. What is more, our results show it is this perceived level of customer focus (effectively a brand's "customer orientation") that influences their investment decisions.

Managerial implications

The findings from our research could be beneficial for marketers and service providers in three important ways. First, the findings suggest financial institutions should use caution when employing robo-advisors to deliver financial advice. That said, we do know that robo-advisors are projected to soon be managing over $1 trillion of funds in the United States alone (Iacurci, 2022). However, much of those robo-advisory services are typically offered by specialised fintech companies that are not typical bricks and mortar retail banks. For retail banks that depend on savings and investments from "mom and pop" investors, it is critical to provide human service personnel, particularly if the amounts to be invested are significant enough to increase the level of customer involvement. Second, our results show trust in the information source is critical, so managers must ensure channels used to communicate financial advice are also trusted. These findings provide further support for research by Mogaji *et al.* (2021b) that suggests AI-enabled technology may not always help businesses service their customers more effectively. That said, our findings provide a more nuanced understanding of trust and its influence on customer perception. Prior research (Eriksson *et al.*, 2020; Taylor *et al.*, 2007) has shown limited trust in the information source results in less positive attitudes towards the brand, whether the information received is human or computer-generated advice. By contrast, the findings from our research indicate at low involvement levels, trust or belief in the advice is not an issue and it only becomes an issue at high involvement levels. Third, our findings demonstrate in retail banking, AI-enabled systems such as robo-advisors may have a negative impact on customers' brand perception. Prior research has shown us a brand's level of customer focus (or their "customer orientation") in the financial service industries effectively tells clients how likely the organisation is to focus on and meet clients' needs (Halstead *et al.*, 2008). Our findings reflect this and are consistent with current literature that suggests things that have a negative influence on customer judgements or expectations of service may negatively impact on investment behaviours (Wasan, 2018). What is more, for retail investors, if AI-enabled systems make them feel the brand is less customer focussed, they may feel less connection or attachment to the brand and much more willing to switch providers if they feel an alternate brand offers greater customer focus.

Limitations and future research

Together, the findings from this research suggest several interesting directions for future studies. First, the current study used the amount of money to be invested as a proxy for involvement. Future research could manipulate and measure involvement to conclusively test the causal mechanism.

Second, the current study tested involvement at two (high/low) points. Future research might look to test the effects across different levels of involvement to identify any threshold effects that might exist. Third, the current study examined consumer responses in the United States. Future research could look to replicate these findings in other countries, particularly those with different languages or cultural norms. Fourth, future research could look to discrete emotion theory (Roseman *et al.*, 1990) and investigate the influence an information source (human vs AI-enabled system) on an individual's emotional responses in a finance context.

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