Overcoming financial planners' cognitive biases through digitalization: a qualitative study

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Abstract

The purpose of this paper is to present an investigation of whether financial planners are aware of the cognitive biases that affect both them and their clients and of whether and how digital transformation through Artificial Intelligence (AI) can help them overcome such biases while making financial decisions. Although the literature does establish that investors exhibit cognitive biases, it does not evidence whether financial planners understand such cognitive biases in clients and whether they 'attempt' at all to address them while providing financial planning services. By utilizing attribution theory, our study contributes to the literature by exploring the gap related to the cognitive biases affecting financial planners and providing a future research agenda through a qualitative investigation. Our study was designed over two stages involving in-depth interviews (21 in the first stage and 10 in the second) conducted with financial planners based in Australia. Our findings suggest that financial planners are indeed subject to cognitive biases while making financial decisions. Further, we suggest that digital transformation through AI technology, albeit combined with human intelligence, can help overcome such biases. To the best of our knowledge, no qualitative research had been hitherto conducted on the association between cognitive biases and AI among financial planners.

Keywords: *Cognitive biases; Decision making; Artificial Intelligence, Financial planners*

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Introduction

Research suggests that the psychological biases affecting financial planners can lead to flawed decisions (Baker, Filbeck, & Ricciardi, 2017). According to Humphreys (1979), an individual's cognitive ability is defined as "*the resultant of the processes of acquiring, storing in memory, retrieving, combining, comparing, and using in new contexts information and conceptual skills...*" (p. 115). The individual cognitive ability of employees may be swayed by cognitive biases in their decision-making processes, potentially leading to systematic errors (Kahneman, 2011) due to blind spots. This is a serious concern in relation to making financial decisions. Cognitive abilities can be impaired by the decision makers' workplace perceptions and emotional states. The fundamental attribution error (FAE) defined as "*the tendency to underestimate the role of situational determinants and overestimate the degree to which social actions and outcomes reflect the dispositions of relevant actors*" (Ross, Amabile, & Steinmetz, 1977, pg. 491) also affects various decision-making processes in the workplace through cognitive biases. Therefore, it is important to employ mechanisms or techniques suited to overcome or mitigate any biases that predominantly and unknowingly influence human thinking, whether while arriving at decisions or voicing opinions.

We know that the right way of making any decision involves considering all the scenarios and available data. But this can be time consuming and exhausting. Therefore, we sometimes resort to shortcuts (Haselton, Nettle & Murray, 2015) or heuristics that are based on previous experience (Juliusson, Karlsson, & Gärling, 2005), age differences (Bruine de Bruin, Parker & Fischoff, 2007), alignment towards the opinion of the majority (also known as herd behavior) (Bikhchandani & Sharma, 2000), cognitive biases (Stanovich & West, 2008) or sometimes maybe just on taking a chance. Biases are very closely related to the gambler's fallacy (Tversky & Kahneman, 1974), whereby a person feels that the next opportunity will nullify any wrong decisions taken previously (reverting the mean), and the conjunction fallacy (Haselton et al., 2015), whereby a person is influenced by a few specific conditions, rather than by just a single one. Sometimes, there is no good reason behind an investor's decision to invest large amounts of money in the market. Historically, stock markets have crashed due to huge investments or to financial crises triggered by excessive money lending. These behaviors are also seen in people involved in gambling and gaming, who cannot really explain their decisions on rational grounds.

The literature establishes that investors and financial service clients also exhibit cognitive biases (Cordell, Smith & Terry, 2011; Gerhard & Michayluk, 2008; Laing, 2010; Pompian, 2011; Choudhary, Yadav & Srivastava, 2021). Although both financial planners and their clients are influenced by cognitive biases, the subject has not been empirically explored, thus resulting in a research gap. Exploring these biases will help us understand why people behave the way they do. Moreover, it is unclear whether financial planners understand and detect these cognitive biases among their clients and 'attempt' to address them while providing financial planning services. Our research was aimed at investigating these issues by focusing on whether and how financial planners attempt to detect cognitive biases in the provision of their financial planning services. There is a need to employ computational support to improve decision-making competencies, and AI is a promising strategy in this regard (Callaway et al., 2022). Human-machine collaboration in making risky decisions has been suggested by Xiong et al. (2022), and the aim of our study was to empirically investigate how digitalization can positively influence financial planners' cognitive biases in relation to financial investment decisions. In our study, we explored the impact of cognitive biases on financial planners and investigated how digital transformation through Artificial Intelligence (AI) can help overcome these biases.

However, from a practical point of view, many financial planners may resist the adoption of AI based on the assumption that it may make them redundant. As in every instance in which a breakthrough technology becomes widespread, people fear that it will take away their jobs. On the other hand, the success of AI technology in the realm of financial planning depends on its successful adoption—which, in turn, depends on how financial planners perceive it. Notably, the technology inherent to AI is complex and financial planners may therefore be reluctant to embrace it. We are specifically looking at AI as a medium for digitalization because it facilitates sustainable business activities and helps to maintain a competitive advantage in globalized arenas (Di Vaio et al., 2020; Li, 2018). Throughout the world, organizations have been significantly transformed by digitalization through AI (Athota, 2021; Li, 2018), which is playing a pivotal role in the digitalization of data processing aimed at achieving any desired goals through flexible adaptation (Kaplan and Haenlein, 2019). This was the primary focus of our study, as we proposed the use of AI to assist in data analysis. In practice, digital or robo-advice enhances a financial planner's decision-making capabilities and the use of these technologies is believed to potentially be able to help reduce bias, as they significantly reduce human operation or interaction. However, the inherent limitations of these technologies make them unsuitable to be the ultimate resource for financial planners. Robo-advice does not involve human interactions, and most clients do not feel comfortable dealing with robots in relation to money matters. Publicis Sapient (Poole, 2018, May 3), a digital transformation partner to some of the world's leading financial institutions, recently conducted a study of 235 retail investors to gauge their attitudes in regard to digital investment platforms. That study confirmed that many people are unwilling to trust a robot to make decisions without human oversight. The emergence of AI, which combines human interaction and digital power, may overcome the limitations of robo-advice and offer the ability to manage cognitive biases. In this scenario, financial investors may trust financial planners.

Under the above-mentioned circumstances, it is essential to understand the cognitive biases that influence the decisions of financial planners and their perceptions toward the adoption of AI for assistance. Consequently, our study was aimed at answering the following research questions.

RQ1 – How do cognitive biases influence decision making processes in financial planning?
RQ2 – How does digitalization—e.g., AI—assist financial planners in their decision-making processes?
RQ3 – What experiences do financial planners' report in relation to the use of AI to reduce cognitive biases?

With our first research question, our study makes a major contribution in terms of helping financial investors and planners understand that they are affected by cognitive biases that influence their decisions, thus potentially directing their investments into the wrong channels. Furthermore, through our second research question, we propose the use of AI as a medium suited to digitalize the data processing activity in order to remove the influence of such cognitive biases and to make it possible for decisions to be thereafter made only on the basis of past and present data, without any scope for emotions while analyzing them. However, once AI has analyzed the data, financial planners will make decisions for their clients, thereby providing the human and emotional touch through the exchange of investment ideas with their clients. This way, both financial planners and investors can be sure of making the right, bias-free decisions. Through our third research question, we aim to learn the current experiences and understanding of financial planners in relation to using AI and if at all they believe that AI can help reduce cognitive biases. The novelty of our study is that we bring to light the various cognitive biases experienced by financial planners while taking investment decisions and how AI can assist them in reducing these biases. In terms of theoretical contribution, our paper has implications for future researchers in terms of developing scales for the measurement of cognitive biases in financial planning and in practice, programmers can develop algorithms suited to mitigating cognitive biases—especially in regard to financial planning—and bringing about the digital transformation of the financial planning sector. Financial planners can use these algorithms or tools as suitable to business as (Ferraris et al., 2019) and adopt ambidextrous work environment (Ferraris, Erhardt & Bresciani, 2019) but the growth of a firm also depends on the regional, economical, institutional and social attributes (Pereira et al., 2020).

Theoretical Underpinning and Literature

Cognitive biases among financial planners

The cognitive biases that affect financial advisors can be broadly categorized into two types—i.e., cognitive and emotional ones (Pompian, 2011). Cognitive biases cause reasoning fallacies whereas emotional ones influence reasoning based on certain feelings (Pompian, 2017). Further, Pompian (2017) classified cognitive biases into two categories. The first is the belief-perseverance bias, wherein people refuse to accept facts, despite the availability of any body of proof, rather preferring to stick to their beliefs (e.g., confirmation, representativeness, hindsight bias, etc.). Second is the information-processing bias, whereby people rely on estimations, rather than considering facts (e.g., framing, self-attribution, availability, anchoring, etc.). Overconfidence, loss-aversion, and affinity biases are emotional ones. Mistakes made due to cognitive biases can significantly and negatively affect financial investments (Baker & Puttonen, 2017). Prospect Theory (Kahneman & Tversky, 1979) helps us to understand the decision-making process, which focuses on behavioral economics and behavioral finance. Among the heuristics generally exhibited by people are: a) representative heuristics (RH), whereby people opt for the most recognized option; b) availability heuristics, which influence people to make decisions based on the most readily available information; and c) anchoring and adjustment heuristics, whereby people first establish a base estimation and then adjust it to obtain a satisfactory answer (Shah & Oppenheimer, 2008; Dietrich, 2010). Haselton et al. (2015) identified ‘increasing costs’ as a reason behind heuristics.

The need for digitalization to overcome biases

Cognitive biases are unavoidable and unconscious. Every person, irrespective of his/her profession, is subjected to biases in relation to any kind of decision making (Simon, Houghton & Aquino, 2000; Acciarini, Brunetta & Boccardelli, 2020). Here, in the context of financial planning, such biases can lead to flawed decisions (Baker & Ricciardi, 2014a) and loss of business clients, which makes understanding them and using technological support (Collino & Lauto, 2022) to mitigate them essential to improve the decision-making process. The adoption and use of technology or non-human methodologies, which are exempt from the influence of emotions is quite evidently needed to avoid biases. Moreover, technological upgrading is the new way to compete in business. This comes with highly accurate machine learning algorithms (Pagliaro et al., 2021; Wasserbacher & Spindler, 2021) suited to analyze the scenarios, and the resources needed to build such complex algorithms require needs huge investment. Also, a systematic review conducted by Hentzen et al., (2021) shows that AI research in financial planning and investment is dominant. Specifically, Bhatia et al. (2020) study the use of mitigating retail investor's behavioural biases and Brenner and Meyll (2020) found that demand for human advice can be reduced with robo-advisors.

Another aspect pertains to the timeliness and accuracy of any decision made. People make quick decisions when time is of the essence and they cannot wait for an algorithm to process the data or when a high degree of accuracy is not really a concern (Haselton et al., 2015). Moreover, employee willingness to accept new technologies is a primary factor in digital transformation. Digitalization, which can sometimes involve replacing people with machines in organizations (Athota, 2021; Lennox, 2020), is the outcome of humans feeding information into such machines. AI can also sometimes outperform human intelligence in terms of workplace performance (Athota, 2021). A study conducted in Germany has found that public sector employees tend to exhibit resistance to technology (Oschinsky, Stelter & Niehaves, 2021). Making employees aware of the benefits of a new technology and upgrading their competencies could thus help to foster greater acceptance in them (Oschinsky, Stelter & Niehaves, 2021).

There have been attempts to develop programs aimed at helping reduce biases in decision making. For example, Otuteye & Siddiquee (2015) developed a heuristic algorithm that considers profitability, financial stability, and bankruptcy together with safety margins. Further, Bonaccorsi, Apreda & Fantoni (2020) found that experts who are involved in technological development are also affected by various biases such as framing, desirability, advocacy, overconfidence, planning fallacy, anchoring, hindsight, and false consensus. The authors further called for research to be conducted to measure these biases and explore strategies suited to mitigate them. This means that, although we rely on machine learning algorithms to help us make non-biased decisions, the very data used to train AI programs are themselves affected by biases. Therefore, Harris (2020) developed a machine learning algorithm aimed at helping to mitigate the algorithmic biases that invariably are transferred from humans to an algorithm's training data. Bearing in mind these different biases, we studied how AI can be put to best use in countering the cognitive biases of financial planners.

Theoretical Lens: Attribution Theory

As human beings, we tend to assign and argue causal explanations for our actions and behaviors. In other words, we tend to 'attribute' our actions and behaviors to processes that causes lead to them as outcomes. Attribution theory is based on this explanation, one that assumes that we try to determine why we ourselves do what we do, or the way in which we interpret the causes of an event or behavior (Heider, 1958). Attribution theory posits that people mostly attribute their successes to 'internal' factors, such as their own skills and personal attributes. In comparison, the very same people will mostly attribute their 'failures' or mistakes to 'external' factors, thereby assigning their causes to situational factors (rather than blaming themselves or attributing them to internal factors) (Monson & Snyder, 1977).

Within psychology, this phenomenon is called 'self-serving bias' (Canary & Spitzberg, 1990), and it serves the purpose of protecting our egos and our self-esteem by blaming external factors for our failures (Sillars, 1980). Interestingly, when we attribute other people's actions and behaviors (Jones & Nisbett, 1971), the reverse is evident. Thus, when we assign reasons and causes to other people's successes, we tend to credit them to external factors (such as good luck, or favorable market conditions), rather than to any internal skills possessed by the people themselves. Yet, when assigning causes or reasons to other people's failures or mistakes, we are more likely to attribute them to the internal personal characteristics of those persons. This actor-observer effect is defined as "*the pervasive tendency for actors to attribute their actions to situational requirements, whereas observers tend to attribute the same actions to stable personal dispositions*" (Jones & Nisbett, 1972, p. 80).

Thus, people encounter the concepts of perception and attribution in their workplace every day, without even realizing it or giving thought to it. People do not normally attempt to actively or critically think about the reasons underpinning their interpretations of things, or about how such interpretations pertain to the situation at hand. Thus, within a working environment, people can significantly affect how things are played out, both by themselves and others. Researchers have used attribution theory to understand the dual perspectives of Indian Railways HR professionals both as implementers and internal customers (Pereira & Fontinha, 2016), the effects of socially responsible human resource management (SRHRM) on employee wellbeing (Zhang, Wang & Jia, 2022), people's reciprocation toward the sharing of knowledge (Kim & Choi, 2022), the performance drivers of Ghana's advertising firms (Boateng et al., 2022), and the public blame game for the spread of COVID-19 in New Zealand (Nguyen et al., 2021).

In the field of finance, investors (with their high attribution biases) tend to downplay the risks involved in financial decisions because of their self-confidence and high optimism (Tan, Audrey & Cheah, 2021). Thus, financial advisors have a major role to play in many investment decisions. For example, Heinemann et al. (2014) studied the ways in which financial advisors can influence investments in sustainable financial products. A few other researchers (Nilsson, Nordvall & Isberg, 2016; Martenson, 2008) also found that private investors look up to financial advisors as their primary information sources for sustainable investment. A study conducted in the UK on millionaire investors and their financial advisors showed that the portfolio recommendations the latter made for investments were based on the former's characteristics (Baeckström, Marsh & Silvester, 2021). Moreover, gender bias was also observed, with female investors being considered less knowledgeable by advisors and hence directed to invest in lower risk portfolios. Additionally, advisor characteristics were also seen to play a role in investment recommendations. Some advisors would recommend investments depending on their own needs and based on the wealth of their clients. Baeckström et al. (2021) therefore concluded that advisors are influenced by the profiles of investors and by their own biases. Furthermore, overconfidence has been seen to be higher in male investors than in their female counterparts, increasing with experience and education (Mishra & Metilda, 2015). From the above studies, we know that biases affect investment decisions; however, would financial advisors accept this or blame external situations for any bad decisions and take credit only for successful ones? De'Armond (2011) showed that the perceived success of financial planners depends on their relationships with their clients and their wealth, their own empathy and ethics, experience, and referrals. It would be interesting to understand whether financial planners would behave differently as planners and as customers. Would they accept the existence of biases when questioned from a client's point of view?

We thus witnessed the manifestation of the aspects of attribution theory playing out in a working environment. In our study, we utilized and tested attribution theory by investigating, in the first instance, whether financial planners in Australia think of their own biases and how these biases play out in the decisions they make for their clients. We then delved deeper by probing these financial planners' thoughts on avoiding biases, and asking what their expectations would be if they were clients themselves. We further asked these financial planners whether they thought that the intervention of AI would counter their biases and, similarly, how they thought their clients would feel about it. In more specific terms, we investigated, in both the cases and scenarios that we designed and set up for them, what reasons they gave for any biased behaviors or actions. Conducting such a deep investigation was only possible through a qualitative method of analysis. It also brought out any concerns, both from planners' and their clients' points of view, pertaining to the use of AI in making financial decisions.

Research design

As stated in our research questions, our primary aim was to understand whether financial planners are aware of their own cognitive biases while making decisions for their clients, and whether they would agree that AI could help them avoid biased decisions. "Quality refers to the what, how, when, where, and why of a thing—its essence and ambience. Qualitative research, thus, refers to the meanings, concepts, definitions, characteristics, metaphors, symbols, and descriptions of things" (Lune & Berg, 2017, p. 12). To this end, we employed a qualitative research method that would involve seeking our answers only through open ended questions. To understand the influence of cognitive biases on the decision making processes of financial planners and how AI could help overcome such biases in greater detail, we viewed a qualitative enquiry as reasonable and suitable (McCracken, 1988; Glaser and Strauss, 1967). As Lune & Berg (2017, p. 12) say "Quantitative work leans toward "what" questions, while qualitative tends toward "why" and "how"", we preferred the qualitative over quantitative method since we needed to explore deeper into understanding the biases that financial planners were unconsciously subjected to. We considered in-depth interviews to be a method suited to gain from our participants rich and detailed responses (Ghauri and Gronhaung, 2002) on their potential cognitive biases and on mitigating them in their decision making (Lee, 2020). We also probed further to understand whether our participating financial planners would have been open to the use of new technologies, and AI in particular. The results of our first round of interviews were found to indicate that cognitive biases do exist and that our sample financial planners did support the idea that AI could help compensate for them. For our second round of interviews, we drew upon attribution theory to give our sample financial planners a feel of how they would react if they were clients and to gauge their opinions on accepting biases and using AI for unbiased decision making. This also helped us understand the extent to which AI could help both financial planners and their clients.

Data collection

For this study, we collected interview data from 31 financial planners and advisors in Australia. The data collection process, which was approved by the Human Research Ethics Committee (HREC), was held in two stages through two sets of in-depth interviews. In stage one, 21 in-depth interviews were conducted in July 2020, with financial planners to gain an understanding of the cognitive biases they faced while taking financial decisions. A semi-structured interview style was employed to collect the responses, but probes and prompts were also employed when greater clarity was needed. An interview guide was developed based on a thorough critical and in-depth literature review. The questions were related to cognitive biases, decision making processes, and AI. The guide included (1) introductory questions (e.g., the years of experience working in the sector), (2) general questions about cognitive bias (e.g., “What may be some biases that financial planners carry?”), and (3) specific questions about the use of AI (e.g., “How can AI help in specific biases for e.g., emotional processes?”, “How will AI help in overcoming biases and aid in an improved undertaking of investor psychology?”, and “How can AI help in overcoming biases and aid rational thinking that minimize psychological/cognitive biases?). In stage two, 10 in-depth interviews with scenario questions were conducted in January 2022, with our sample financial planners to elicit detailed responses about whether and how AI would help in overcoming cognitive biases. Considering the nature of our study, we selected our participants purposively (Patton, 2002) based on their extensive experience as financial planners; we did so in order to get reliable data on cognitive biases, as inexperienced financial graduates may have a lesser understanding of them. One way of determining a sample’s size is by a identifying a number that will be sufficient to achieve a study’s aim (Kuzel, 1999, Patton, 2014) and reach saturation. However, according to Malterud, Siersma, & Guassora (2016), a smaller sample size is sufficient for a study with a narrow aim, dense specificity, applied theory, strong interview dialogue, and in-depth case analysis; therefore, we determined our sample size based on our knowledge and experience. From our 31 interviews, we gathered sufficient information to obtain theoretically supported findings. The financial advisors in our sample all had between 14 and 31 years of experience in the sector, with an average of 19. Our sample financial planners’ academic qualifications varied, and ranged from advanced diplomas to postgraduate qualifications. Among our participants, 25 were male and six female, which is representative of the Australian financial service industry and of the high percentage of males in the industry (77%). In terms of their geographical distribution, 42% were from New South Wales, 26% from Victoria, 16% from Queensland, 10% from Western Australia, and 6% from South Australia. Figure 1 (below) summarizes the overall data collection process.

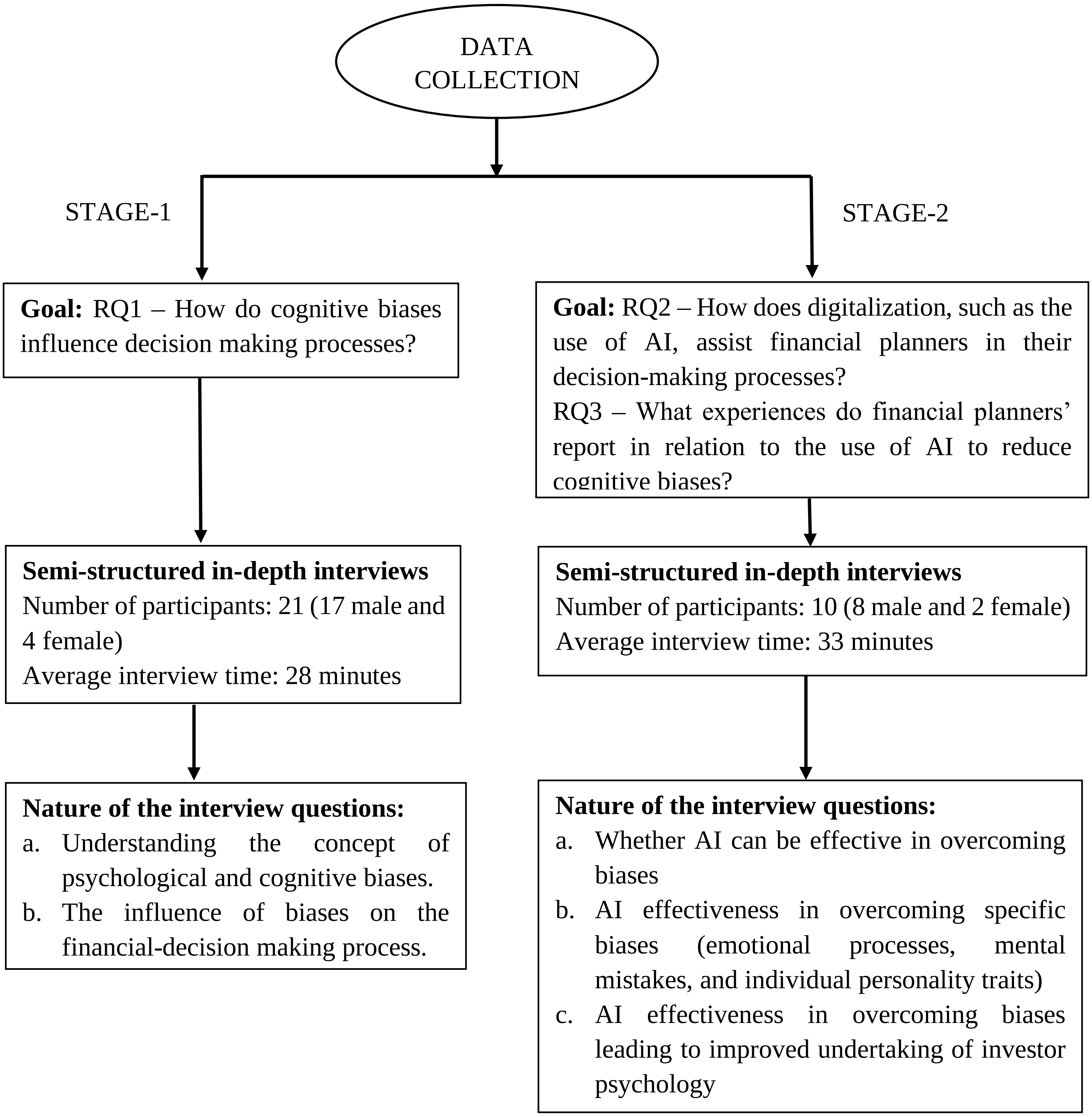

Figure 1: Data collection process

Due to the COVID-19 lockdown that was being enforced in Australia at the time, the interviews were conducted over Zoom. We created a relaxed environment for participants, who expressed their opinions without any hesitations. The interviews, which lasted between 30 and 40 minutes, were recorded and later transcribed for analysis through Microsoft Word's dictation function. We also took notes and maintained a digital diary, which was used as a primary data source.

Data Analysis

To analyze our data, we performed a thematic analysis using the six-phase approach illustrated by Braun & Clarke (2006) and Clarke, Braun, & Hayfield (2015)—i.e., familiarization, coding, searching for themes, reviewing themes, defining and naming themes and writing the report. We did not use any software for data analysis, preferring to rely upon the authors' expertise in qualitative analysis. The purpose of this robust analysis was to achieve theoretical saturation in regard to the research problem we were addressing (Eisenhardt, 1989; Glaser and Strauss, 1967). We read and discussed the transcripts during research meetings, which led to codes and to the identification of larger themes in the financial planners' responses. We cross-coded the transcripts for interrater reliability. We jointly discussed the results of the analysis and sought a mutual agreement on the codes.

Our research validity and reliability were ensured by employing an appropriate methodology and an analytical data process. There was logical consistency between the data, analysis, and findings (Carcary, 2009). We explored the patterns in the participants' responses and found meaningful themes. Our research met the scientific criteria for reliability and validity and was conceptualized through rigor and integrity applied to the methodology and analysis (Eisenhardt, 1989; Silverman, 2001; Yin, 2009). As per the evidence, our findings are expected to be consistent over time (Creswell, & Miller, 2000; Patton, 2002). This method of data analysis was followed for both interview stages.

Findings and Discussion (Stage 1 - financial planning, biases, and AI)

The first stage interview data, which was of an exploratory nature, was analyzed as detailed above. Below, we present our key findings and discussion, linking them back to the literature reviewed above. In doing so, we reproduce our findings and discussion with evidence and identify emerging themes based on the following eight topics.

Topic 1: understanding the concept of psychological or cognitive bias

Investors or clients share sensitive information regarding their wealth, property, and investments with their financial planners. The clients' vulnerability is thus linked to their financial planners' trustworthiness (Joiner, Leveson & Langfield-Smith, 2002) and to the expectation that the latter will devise investment plans devoid of any bias. However, this depends on whether the planners are aware of being influenced by any biases and whether they consciously make the decision of not giving into them. When we asked our 21 respondents about their understanding of the concept of psychological and cognitive biases, most reported that they were aware of being subject to cognitive biases in the process of making professional decisions on behalf of their clients (refer to Table 1, Theme 1). While drawing out investment plans for their clients and making critical decisions, financial planners need to be aware of any biases they may be subject to. Baker & Ricciardi (2015) stated that financial decisions are affected by cognitive and emotional biases, along with household (Bogan, 2013), socio economic (Farrell, 2011), personality traits (Baker & Ricciardi, 2014b), demographic (Farrell, 2011) and religious attributes (Mansour & Jlassi, 2014). in this regard, two of our 21 respondents said that they had neither knowledge nor awareness of cognitive biases (refer to Table 1, Theme 2). We think this may be due to the generalized lack of understanding of biases.

Insert table-1 here

Topic 2: the possible (psychological/cognitive) biases identifiable in financial planners' decision-making processes

We probed deeper by asking our 21 respondents about any possible cognitive biases they may have identified in regard to their professional decision making. Baker & Ricciardi (2014a) listed eight behavioral biases and concluded that most investors are influenced by overconfidence or status quo. Baker & Ricciardi (2014a) further stated that investors may not be able to overcome all their biases, but can definitely contain their effects by understanding those to which they are subject by following investment strategies and rules. Nofsinger (2017) asserted that the finance sector assumes that people make rational decisions and are unbiased. This is basically because people do not acknowledge that they are biased in the first place. Nofsinger (2017) categorized behavioral biases in relation to their source—i.e., self-deception (people overrating themselves), heuristic simplification (complex analysis being cut short due to cognitive inability), and personal moods (which hinder reasoning abilities).

Our analysis showed that some of our respondents (6/21) were fully aware and showed an advanced knowledge of the various biases cognitive/psychological to which they could be subject when making key investment decisions on behalf of their clients (refer to Table 2, Theme 1). In comparison, most respondents (10/21) had only some knowledge and awareness of such biases (refer to Table 2, Theme 2). We thus probed them even further in questions that followed. The remaining respondents (5/21) either totally lacked any knowledge or awareness of cognitive biases or misunderstood them (refer to Table 2, Theme 3).

Insert table-2 here

Topic 3: the most common biases identified

When asked to give examples of the biases they might be able to identify, our 21 respondents referred to 10 of the 11 categories. These were as follows: confirmation bias (5/21) (Table 3, Theme 1), affinity bias (4/21) (Table 3, Theme 2), unconscious bias (3/21) (Table 3, Theme 3), priming bias (2/21) (Table 3, Theme 4) and one each for overconfidence bias, framing bias, self-serving bias, belief bias, anchoring bias, and embodied cognition (Table 3, Themes 5, 6, 7, 8, 9, and 10, respectively).

Confirmation bias emerged as the most prominent amongst our respondents. One of the reasons for this could be that their previous experiences or choices affected their interpretation of new evidence or data (Talluri et al., 2018). A second reason could be that they were extremely confident of the choices they made (Rollwage et al., 2020) as they had become experts in their field. Confirmation bias is also considered to be a gradually harmful bias (Peters, 2022) as it makes people overconfident (Mercier, 2016), thus causing them to place undue faith in their own beliefs (Mercier & Sperber, 2017; Steel, 2018) and in less reliable information (Peters, 2020). Confirmation bias has also been proven to derail forensic investigations (Kassin, Dror & Kukucka, 2013) even in the presence of strong evidence. Moreover, information overloads can also lead to confirmation bias (Goette, Han & Leung, 2020). Though most of our respondents mentioned at least one common bias, one of them (R6) did not give any response.

Insert table 3 here

Below, we present the different biases we identified amongst our sample financial planners.

Confirmation bias. This involves financial planners or investors holding pre-conceived beliefs about an investment. These are reinforced when the information arising from the scenario seems to be aligned with their thought processes. Such information may be true or false, but the financial advisors consider it to be true and to use it in support of their decisions (Glick, 2017; Çalıklı & Bener, 2013).

Affinity bias. It is in play when investors make decisions believing that their choices of investment will reflect their own value. This is purely irrational and may not favor them economically. An example is HR hiring candidates who will get along with the team as they belong to the same cultural background (Nalty, 2016).

Familiarity bias. This is expressed when financial planners decide to invest in platforms with which they are familiar and therefore are not diversified in terms of investment ideas (Ricciardi, 2008).

Priming bias. When under the influence of priming bias, people tend to connect two objects or conditions based on their previous experiences. For example, if the stock market once crashed due to a sudden spike in stock purchase, financial planners may tend to relate stock market crashes with such spikes in the future. However, stock markets may crash due to a number of other reasons (Cherry, 2021, Jun 18).

Unconscious bias. This bias involves making judgements or decisions with no evidentiary support. It is also known as implicit bias and results in unfair judgements being made toward any non-favored group of people or things (Gordon & Overbey, 2022).

Overconfidence bias. It is defined as "*a particular form of miscalibration, for which the assigned probability that the answers given are correct exceeds the true accuracy of the answers*" (Skala, 2008, pg. 34). Investors affected by increased confirmation bias are also subject to high degrees of overconfidence (Park et al., 2010; Ricciardi & Simon, 2000).

Framing bias. This bias is defined as the "*process of culling a few elements of perceived reality and assembling a narrative that highlights connections among them to promote a particular interpretation*" (Entman, 2007, pg. 164). The decisions made under the influence of framing bias are based only on the presented data, which may be factual or not, rather than on all of the available ones.

Self-serving bias. People under the influence of self-serving bias claim responsibility if the outcome of a decision is favorable. But blame external factors for any non-favorable outcomes (Shepperd, Malone & Sweeny, 2008).

Belief bias. Financial advisor place their belief in an assumed conclusion or result long before being faced with the related outcome of logical reasoning (Morley, Evans & Handley, 2004).

Anchoring bias. This is exhibited when a person is anchored to the first information made available. In other words, the first information available is considered as a reference point or a benchmark for the processing of successive information when forming a decision (Lieder et al., 2018).

Embodied bias. This results in decisions taking shape in a person's mind due to their various senses and experiences, following intuitive reasoning (McNerney, 2011).

Topic 4: confidence in AI's effectiveness in overcoming biases

Having investigated the respondents' knowledge and awareness of the different types of cognitive biases that may affect them in making financial decisions for their customers, we proceeded to investigate whether AI was deemed to be potentially effective in overcoming such biases. We further enquired how, when, and under what circumstances and situations AI could help financial planners.

The bulk of the respondents expressed a strong belief that AI could be effective in overcoming biases. They opined that this result could be achieved either with the help of data or through the use of the latest technology. Seven of our 21 respondents unreservedly believed that this would happen (Table 4, Theme 2). However, despite expressing strong confidence in the potential of AI, one respondent doubted whether financial planners would be prepared, in practice, to totally rely on AI-based decision making. While supporting the idea of relying on data for unbiased decision making, this respondent maintained that the final decision should rest with the financial planner (Table 4, Theme 1). The reason for this opinion could be the existence of what Bhatia, Chandani & Chhateja (2020) termed 'robo-advisors', which have hitherto proven not to be very efficient, as they have not been totally successful in reducing investors' biases and conducting risk profiling.

Another set of four respondents expressed partial belief in AI and its relevant training data. They opined that the AI's programmers would also need to be unbiased for their product to be effective in assisting financial planners in overcoming their biases (Table 4, Theme 3). This argument is in line with the findings of Ntoutsi et al. (2020), wherein programmers and decision makers are assumed to be aware of their own biases, choices, and assumptions. Hence, the point made by these respondents was that any AI utilized would need to be logical and factual both in its design and final application, and that care would need to be taken by its programmers to avoid any manipulation or the influence of their own biases. In this regard, Schwartz et al. (2022) found that AI can invariably and unconsciously pick up bias beyond the computational level.

Seven respondents also expressed partial confidence in the effectiveness of AI in overcoming biases (Table 4, Theme 4), stating that AI would not be fully capable of countering biases. They further opined that AI's lack of emotions and of a detailed understanding of the clients' needs—together with other typically human characteristics such as wisdom, judgement, morality, goals and objectives, imagination, etc. (Braga & Logan, 2017)—would limit its ability to make effective decisions. These respondents also further expressed their belief that AI support could however be effective in short term investments as it would help in making the necessary complex calculations (Kunnathuvalappil Hariharan, 2018). Finally, this set of respondents also stated that AI would be helpful only in specific applications and should not be totally relied upon in financial planning decision making.

Finally, two of the 21 respondents stated that they did not believe that AI could support them in overcoming their biases in financial planning (Table 4, Theme 5).

Insert table 4 here

Topic 5: AI effectiveness in overcoming specific biases (emotional processes, mental mistakes, and individual personality traits)

We delved deeper to seek answers as to whether and how AI could be effective in overcoming certain specific biases—such as emotional processes, mental mistakes, and individual personality traits. Almost 50% (10/21) of our respondents felt that it was possible for AI to suggest certain solutions devoid of bias (Table-5, Theme 1). These respondents argued the case that AI could suggest an array of outcomes based on the consideration of certain aspects and make the user aware of what would be best for the client based on their personality traits and on the risks involved. These respondents further stated that AI could suggest possible personalized solutions and could be used as a tool for the objective profiling and assessment of customer needs aimed at providing reliable solutions. They also suggested that AI data and factual analysis could swiftly tackle huge data sets and therefore help in making timely unbiased decisions. Lastly, this set of respondents expressed the belief that AI could provide unbiased solutions due to its lack of emotions and that, as it cannot think, it would not consider prior experiences before making decisions. This can be related to the use of AI in recruitment (Black & van Esch, 2020) and the initial screening of applications, which eliminates human intervention and biases.

The next set of respondents, also the bulk of the remaining (9/21) argue that AI can suggest possible solutions but these respondents were not fully satisfied that the final decisions should be fully dependent on AI (refer table-5, theme 3). These respondents argue that the financial planners should make the final decisions with the client only after reconsidering the data and initial decision suggested by AI. These results are in line with the study by Zhang, Pentina & Fan (2021) which showed that consumers also prefer expert human financial advisors over robo advisors due to lack of trust. More specifically, these respondents believe that AI can start the initial process so that emotional biases are avoided and thereafter humans (financial planners) can take over. This set of respondents also suggest that it should be a combination of unbiased AI and logical reasoning of humans. They consider AI to assist in sorting out initial traits before taking decisions. These respondents feel they can take it ahead after AI has finished categorizing data. They further believe that AI can be only used as an indicator giving pros and cons for an outcome. These respondents believe that AI can only help and not totally avoid these mistakes as AI needs to be properly trained to avoid cognitive biases, because AI can be a guide to financial planners in taking decisions to avoid emotional bias.

Lastly, we had one respondent who believes AI can help only if programmed in unbiased manner (refer table-5, theme 2). This result corresponds with previous research that claim demographics (Cowgill et al., 2020) and cultural background (Johansen, Pedersen & Johansen, 2020) to be influencing programmers of AI. Additionally, the respondent thinks that AI can help financial planner take decisions avoiding emotional aspects and taking facts and data into consideration. Another single respondent had several doubts if AI could ever be helpful (refer table-5, theme 4). This respondent was not sure how AI could help in overcoming specific biases. Please refer table 5.

Insert Table 5 here

Topic 6: AI effectiveness in overcoming biases leading to improved undertaking of investor psychology.

We further quizzed the respondents in regard to how, in the process of countering biases, AI could aid in the development of an improved undertaking of decision making by taking onboard investor psychology. In regard to aiding investor psychology, most of our sample financial planners (16/21) expressed the belief that AI could help by providing evidence-based rational decisions (Table-6, Theme 1). These respondents were convinced that, as AI is data driven, its decisions would be realistic and unbiased by default. This conviction may be borne by the belief that AI could provide rational decision-making opportunities and understand human needs. They stated that AI is based on interactive educational videos and tools that could be useful to financial planners. These respondents shared the opinion that, as an evidence-based system, AI would be effective in unbiased decision making. In this regard, researchers have built intelligent models endowed with sentiment analysis, which helps investors make better decisions (Ren, Wu & Liu, 2018).

Another set of respondents (3/21) expressed the belief that human intervention would still be required in decision making and that AI could not make any decisions independently. These respondents argued that human interactions were very important, and rejected a total reliance on AI in dealing with clients (Table-6, theme 2). They specifically referred to reading clients' body language, understanding investors' emotions and needs, etc. (Kunnathuvalappil Hariharan, 2018). These respondents concluded that, although AI could be useful, the human aspects are essential.

Finally, two of our 21 respondents expressed doubts and a lack of conviction that AI could help at all (Table-6, Theme 3).

Insert table 6 here

Topic 7: AI effectiveness in overcoming biases and helping rational thinking by minimizing cognitive biases.

We tried to understand whether AI was considered capable of aiding the rational thinking of financial planners by not merely supporting their personal preferences but making decisions based solely on AI relevant data. We further investigated whether AI could help financial planners with sets of possible solutions.

Some of our respondents (7/21) stated that, through rational thinking, AI could help in overcoming any biases and personal preferences, which would be very helpful in the decision-making process (Table-7, Theme 1). These respondents expressed the belief that AI could be useful in compensating for overconfidence and improving intuitive reasoning. Rastogi et al. (2020) used machine learning algorithms to minimize the effects of anchoring bias in decision making, which would also improve human-AI interaction. In this regard, our respondents suggested that financial planners could compare their decisions with those produced by AI and thus take a realistic perspective. They also stated that, due to its ability to challenge the human thinking process with its fact-based positivism, AI could be used to assist planners in not overriding any facts on the basis of gut feelings and emotions. Kim (2020) suggested the use of AI and machine learning in support of decision making. Furthermore, Financial Literacy and overconfidence bias are known to positively and significantly influence investment intentions (Jain et al., 2022).

Moreover, four of our 21 respondents opined that AI uses superior algorithmic techniques and could thus assist financial planners with rational decision-making processes for both the present and future (Table 7, Theme 2). These respondents further expressed the belief that AI would also challenge the financial planners' thought processes and help with evidence-based decision making.

Some respondents (6/21) were convinced that AI could provide an evidence-based platform for investment decisions, furnish them with sets of possible options, and help avoid any preconceived perceptions (Table 7, Theme 3). These respondents strongly argued that AI uses only factual data for decision making.

Finally, a few of our respondents (4/21) were unsure and doubted whether the data used in AI programming would be useful (Table 7, Theme 4). In this respect, Karunakaran (2018) also found low levels of trust in AI decision making (platform-based services) due to uncertainty.

Insert table 7 here

Topic 8: AI effectiveness in overcoming overconfidence, improving intuitive reasoning, ability, and judgement, thus minimizing cognitive biases.

We dug deeper to learn whether AI was seen as potentially useful in overcoming the overconfidence and unconscious biases of financial planners, thereby helping in evidence-based decisions. Most of our respondents (14/21) expressed the belief that AI could indeed help by making fact-based decisions (Table 8, Theme 1). They argued that AI would need to work with financial planners and not against them by means of a decision tree approach. Financial planners could thus avoid making decisions based on emotional biases. Araujo et al. (2020) found that people trusted AI decisions more than human ones in specific contexts. Accordingly, this set of respondents opined that AI makes informed decisions by taking an objective, fact-based approach, enabling business leaders to avoid taking excessive risks through empirically-driven analyses in which AI data provides the appropriate guidance and challenges the thought processes of both investors and planners. As AI provides enough information to avoid surprises, it could help financial planners overcome their confirmation bias.

Further, one of our respondents stated that a practical decision-making approach involving comparison would be helpful to financial planners (Table 8, Theme 2). This would involve AI being used in practice and for testing and comparison purposes. In this way, financial planners could reinforce their investment ideas and start trusting AI recommendations. This is in line with Wood (2019), who suggested that technology can phased in, with adaptive learning as the final stage.

While most of our respondents strongly suggested that AI could be used to overcome overconfidence and to improve intuitive reasoning, two of them expressed the opinion that its effectiveness in doing so would be contingent on the financial planners themselves (Table 8, Theme 3). They argued that it all depended on the financial planners' rationales and capability to deal with AI, despite the latter's ability to help individuals self-improve (Rossi & Utkus, 2020).

Finally, four respondents were found to be unaware of to have no idea of how AI could help in overcoming these biases (Table 8, Theme 4).

Insert table 8 here

As per our study design, having analyzed the exploratory areas, we engaged in stage 2 of our research based on the above findings and discussion.

The utilization, operationalization, and testing of our attribution theory lens is visible in our investigation. More specifically, for stage 2 of our research, we developed seven further areas/topics involving ten financial planners. Based on the analysis presented above, we designed an interview guide for the second round of interviews with the aim of delving deeper into the ways in which AI can help to overcome financial planners' cognitive biases. In stage 1, the respondents were asked to answer questions as financial planners, therefore expressing 'their own views'. To complement this, and invoke attribution theory, our design of the second round interview questions was aimed at understanding the perspectives of financial planners as clients. This was done to gauge whether our sample financial planners understood that they were influenced by biases from the perspective of a client. Moreover, we used scenarios to understand the kind of biases the financial planners would exhibit, which included the top four biases from stage 1—i.e., confirmation, affinity, priming, and unconscious biases. We then probed the respondents to ascertain whether they thought that AI could help them in their financial planning by compensating for their biases, and whether they would support the use of AI in their field. The reverse was also tested—i.e., whether they would be supportive of this idea if, as clients, they were to benefit from AI's bias reduction effect.

Findings and discussion (Stage 2 – In relation to attribution theory)

We selected 10 financial planners out of our previous sample of 21. Our choice was based on the responses they had given in stage 1, which were representative of our analysis.

This second set of 10 interviews was focused on cognitive biases and on the kinds of techniques used by financial planners to overcome them, and incorporated scenarios and the use of AI to do so. The interview questions were thus aimed at exploring the cognitive and psychological biases of financial planners. We clearly explained that psychological and cognitive bias is an umbrella term that refers to the systematic ways in which the context and framing of information influence individuals' judgment and decision-making.

Building on stage 1, topic 1 (i.e., 'understanding the concept of psychological or cognitive bias'), we designed and asked the following more in-depth questions.

1a. If you used the services of a financial planner, would that person understand your bias?
1b. Where is the evidence that you are/are not biased? In other words, have you reflected on any decisions that could have been biased?
1c: Do you employ a process of checks and balances in your dealings to avoid cognitive/psychological bias?'

After analyzing the interview transcripts, three major themes emerged from the responses for the first two questions, each of which is discussed below.

Theme 1. Financial planners are subject to biases.

Respondent R2 did not hesitate in answering question 1a. This respondent clearly described how biases could be avoided by giving specific examples. Respondents R3 and R10 were also forthcoming in explaining what they would expect from a financial planner in terms of bias avoidance. However, these respondents also very honestly stated that Australian financial planners were unaware of bias. They candidly declared that, in the near future, they would consider taking a course on understanding financial planning biases. To summarize, the argument made by these respondents was that financial planners themselves are unaware of their biases, which makes it difficult for clients to gauge the existence of biases and thereafter avoid them.

Theme 2. Vague and inconclusive

Respondent R1 expressed some considerations about how he/she would actually behave or think about biases as a client. This provides evidence that financial planners clearly think differently of themselves when they put themselves in the position of a client. This respondent's answers also portrayed the difficulties of putting oneself in such a position, but expressed the certainty that an unbiased decision would be in the interest of both the client and the financial planner. Respondents R5, R6, and R8 echoed R1 in that their answers were vague, merely stating the obvious in regard to how an ideal financial planner is expected to behave.

Theme 3. Philosophical response

Respondents R7 and R9 came across as more philosophical. They made the point that no financial planner is conscious of being biased and, further, that neither they nor any client would expect biases to be at work. To summarize, these respondents explicitly affirmed that biases may or may not occur, but always unconsciously.

The third question (1c) revealed that our sample financial planners did not have a process aimed at dealing with biases. This may have been because the Australian financial planning industry does not offer any tools suited to manage biases. Notably, the discussion of biases is a relatively new phenomenon; as such, no formal step has hitherto been taken to address cognitive or emotional biases by preparing a Statement of Advice (SoA) for the clients.

In conclusion, it is quite obvious that financial planners are subject to biases while making decisions for their clients. Although the second and third sets of respondents gave vague and philosophical answers, it was evident that, as clients, they would have nevertheless preferred to consult financial planners consciously or unconsciously devoid of biases. This implies an admission that financial planners are, in fact, subject to biases. The extant research has found that financial planners tend to be overconfident (Cordell et al., 2011) and to be subject to various psychological biases (Nofsinger, 2017). As a result, they should be heedful while advising their clients on financial matters.

For these interviews, to ascertain whether our sample planners held biases, we framed scenarios and asked them to comment upon them. We then conducted a scenario analysis that evidenced the top four biases—i.e., confirmation, affinity, priming, and unconscious bias.

Further to stage 1, topics 2 and 3 (i.e., '*the possible (psychological/cognitive) biases identifiable in financial planners' decision making processes*' and '*the most common biases* *identified*') involved scenarios in order to avoid asking direct questions and instead understand the decisions that the respondents would make in this context, in order to gauge whether they were influenced by biases.

Scenario 1. Stock market investing

Raj has inherited some shares from his father's ABC company. Now, the ABC company is struggling financially and his financial planner has advised him to sell the shares. However, Raj does not want to do so because he is emotionally attached to his shares. Raj is thus not making any effort to sell the shares. What is going on in Raj's mind?

Scenario 2. Property investment

Rocky wants to buy an investment property. He has two options to do so. Option one involves buying a house in a seaside town. This is a lifelong dream of his, but the future prospects do not seem promising. The second option is buying a property in a regular suburb, for which the expected return on the investment is lucrative. Rocky has decided to buy an investment property in the seaside town.

In both scenarios, the financial planners observed the biases at work in the clients. The interviewees noticed that both clients were exhibiting emotional bias in their financial choices. They also stated that such form of bias is common and that they often dealt with similar situations. However, seven out of the 10 interviewees suggested that clients' goals are not always of a strict financial nature. Sometimes, the emotional aspect is essential for the overall wellbeing of the clients.

Overall, our sample financial planners expressed the need to highlight any biases that may cause emotional desire to outweigh financial goals in an individual event or scenario. However, from a holistic perspective, most of our interviewees suggested that a focus on emotional desire at the expense of financial gains is not always bad. This is in line with the importance, affirmed by McCarthy (2020), of addressing emotional preferences for the clients' overall wellbeing. Clients also often do not agree with the monetary plans devised by financial planners solely as a result of emotional attachments and perspectives (Carter, 2006). Such conflicts of opinion between financial advisors and clients can result in unhealthy arguments. However, tackling such situations falls within the duties of planners, which is why Luskin, Aberman, & DeLorenzo (2005) proposed emotional competence training for financial advisors. This would suggest that, in order to achieve the highest degree of effectiveness, AI ought to be combined with human intelligence (La Torre, Colapinto, Durosini & Triberti, 2021).

Further to stage 1's topic 4—i.e., '*confidence in AI's effectiveness in overcoming biases*'—we designed the following three questions.

4a. If financial planners were to benefit from the use of AI, would they support it? (Attribution lens)
Based on our analysis, we found that the financial planners would support any technology that could benefit their profession overall. We found all interviewees willing to adopt AI. However, most of our sample financial planners contended that they did not fully understand how AI works in general. Also, a minority of interviewees suggested that if AI supported both them and their clients, they would not have a problem in adopting it.

4b: If financial planners were to be negatively affected by the use of AI, whereas their clients were to benefit from it, would financial planners support it?
We found that all interviewees would agree to adopt AI in principle, even if it were not to benefit them. A few of our interviewees stated that, were AI to be found to benefit clients, but not the financial planners, it would not survive/could not be adopted in the long run. However, most interviewees did not believe that financial planners would risk losing their jobs because of AI. Additionally, a majority of interviewees further contended that their practices would change as a result of the adoption of AI. Indeed, most of our participants deemed that AI would bring about significant structural transformation in many professions, including the financial planning industry. However, our sample financial planners did not claim to have a technological understanding of how AI works. Most of them affirmed the need for sufficient training before the wholesale adoption of AI in the industry. Interestingly, all of the older financial planners among our interviewees stated that they were not fully confident that they would be able to fully reap the benefits of AI. This demographic group also felt that AI might create divisions among financial planners, as the relatively younger ones would be more likely to adopt it.

4c: As a financial advisor, you say you would/would not want AI. But, as a customer, would you be in favor of AI aiding a financial planner?

All the participants were overwhelmingly in favor of adopting AI, as they believed it would aid their profession. They agreed that there was a need for repetitive tasks to be automated, and that AI's superiority in this regard would make automation more efficient. Most of the interviewees mentioned that clients generally sought human interaction in their dealings with financial planning. When asked about robo-advice (the use of robots for financial advice), all our interviewees unanimously agreed that clients would prefer it if not all of the advice were to be supplied by robots. The interviewees also contended that financial planning is not a purely cognitive process; it also requires an emotional touch. As such, clients would not entirely prefer the use of technology. There is therefore the need for a suitable blend of technology and emotional processes. In general, we found that, although they would have unhesitatingly adopted AI, our sample financial planners were concerned about its excessive use, as it might defeat the whole purpose of financial planning.

Our current findings, which complement the existing literature on digital strategy, digital transformation, and digitalization (e.g., Bertello et al., 2020; Hess et al., 2020; Scuotto et al., 2017), could potentially influence the adoption of AI in various industries (Vasiljeva, Kreituss, & Lulle, 2021). We observed that most of our sample financial planners were interested in the adoption of AI and considered this technology suited to help financial planning from the perspectives of both planners and clients. Although, in stage 1 of our analysis, a few respondents stated that they did not support AI, their opinion changed in stage 2, when they were asked to imagine themselves as clients. But it should be noted that, although the sample planners all unanimously expressed their support for the adoption of AI, they did not endorse entrusting the entire decision-making process to it. Their view was that a human touch was needed to devise the best plan for clients, considering the latter's emotional needs (Carter, 2006). Moreover, our findings, the implications of which can benefit future organizations (Brougham, & Haar, 2018), show that financial planners require training in order to use AI, and that the scope for robo-advisors has increased as financial planners aim to remedy overconfidence (Piehlmaier, 2022).

Discussion and Conclusion

With our investigation on overcoming cognitive biases in financial planners, we tried to answer three research questions. We hereby discuss them one by one. The first was aimed at understanding how cognitive biases influence decision making processes. First, we identified that virtually all our sample financial planners were affected by biases (Cordell et al., 2011;

Nofsinger, 2017), although a few of them did not accept this. Some of the most common biases of which the financial planners were aware were the confirmation, affinity, unconscious, priming, overconfidence, framing, self-serving, belief, anchoring, and embodied biases, which extends the list of biases and personality factors laid down by Choudhary et al. (2021). Of these, confirmation bias was found to be the most prominent, which is in line with the findings of previous research (Talluri et al., 2018; Rollwage et al., 2020). This shows that financial planners are subject to cognitive biases, which leads them to make investment decisions that may be based on their prior experience or to the best of their knowledge, being thus potentially not actually based on their clients' profiles but on their own ideas of the future. Financial planners should therefore have healthy discussions with their clients regarding any biases involved and investments planned (Pompian, 2017).

Our second research question pertained to whether digitalization through AI can assist financial planners in their decision-making process by helping them to overcome any cognitive biases. In this regard, we found evidence that financial planners are interested in overcoming their biases in the best interest of their profession and of their clients. Understandably, people fear losing their jobs to technological progress, thus exhibiting depression and turnover intentions (Brougham & Haar, 2018) and therefore a certain resistance toward the adoption of new technology; however, the financial planners agreed that AI, being totally based on data and calculations, could assist them in making unbiased decisions. Their main concern pertained to any bias passed on to AI from its programmers (Ntoutsi et al., 2020). Their second concern was that, lacking of the human touch (Carter, 2006), AI would be unable to sense any nervousness felt and reservations held by the clients before making any investment decision. However, AI's lack of emotion is what enables it to be unbiased; therefore, the conclusion was that AI should only assist financial planners in making decisions, but not make any by itself.

Our third research question was aimed at understanding whether financial planners were open to the use of AI for financial planning on the basis of its ability to reduce cognitive biases and whether they were ready to utilize it in serving their clients. Our analysis showed that our sample financial planners were open to use AI in their profession and did not view it as a threat, but as an aid capable of curbing any overconfidence (Piehlmaier, 2022). They viewed AI as a useful tool to perform complex calculations (Kunnathuvalappil Hariharan, 2018) and to take over any redundant tasks, leaving the decision making to them. Overall, most of our sample financial planners responded positively toward the adoption of AI, albeit with the caveat that training on the use of AI would need to be imparted to all financial planners.

In conclusion, our findings suggest that biases occur unconsciously. In their clients' best interest, financial planners are now opening up and showing positive attitudes toward the use of AI in the data analysis that precedes financial decisions. In this regard, they seem to have positive perceptions of digitalization, which builds their trust in AI (Caputo et al., 2019). Openness toward the adoption of AI may vary across industries and its current level of adoption. Employees who are already exposed to digitalization tend to respond differently from those in organizations in which the AI concept is relatively new and far from being implemented (Vasiljeva et al., 2021). Moreover, technological, organizational, environmental (Tornatzky et al., 1990; Baker, 2012), and social factors (Vasiljeva et al., 2021) contribute to forming the attitudes of employees and organizations toward the adoption of AI technology. The team formation model proposed by La Torre et al. (2021), which incorporates technology acceptance, technology self-efficacy, and source credibility, can help the development of teams that accept digital transformation. Smart Technology, Artificial Intelligence, Robotics, and Algorithms (collectively known as STARA) are known to have effects such as depression, cynicism, and lower career satisfaction and organizational commitment (Brougham & Haar, 2018). Moreover, managers tend to be more willing than staff members to use AI (Huang et al., 2022), although factors such as peer influence, facilitating conditions, attitude, and perceived threats can impact such willingness (Cao et al., 2021).

Pompian (2017) suggested that, in order to ensure the satisfaction and long-term retainment of their clients, financial advisors should distinguish between various biases and discuss the related psychological issues while advising them on investments. The notion here is that the existence of an asset suited to assist in decision making and provide guidance in making recommendations, while not letting emotions influence decisions, can ensure the attainment of the best of both worlds. One of the respondents mentioned that *"I still believe in the human touch, but I believe in the tech; using the technology if it's an advantage",* another response was *"now we buy a lot online—it could be anything close or whatever it is—but, sometimes, it's nice to go into a store and actually speak to someone"* and *"I can't see there is anything wrong with doing that but… just working with AI technology, but I think that, with further more structured advice, I believe… you know, the human touch is something that should still be going. So, you see a place for both AI and people. I do absolutely".*

The role of AI in overcoming biases seems suited for financial planning. AI comes with the advantage of having low operational costs and high operational efficiency (La Torre et al., 2021); it is therefore a most useful and effective platform for financial planning assistance. To strengthen the decision-making process, we thus propose the design of machine learning algorithms able to predict certain patterns. By doing so, we would provide investors—both those who are overconfident (and overestimate their abilities and skills) and status quo-inclined (who do not pay attention to detail and stick to any prior stock selling or holding decisions)—with a strong solution suited to avoid investment decisions based on emotions and biases (Baker & Ricciardi, 2014a). The desirability of designing a heuristic algorithm with high-quality decision-making abilities had already been proposed by Otuteye & Siddiquee (2015), who claimed that it would contain the influence of cognitive bias. By gathering empirical evidence related to identifying the cognitive biases affecting financial planners and to the mitigation of such biases through digitalization, our research closes the gap we had identified.

Theoretical implications

Theoretically, our study extends the extant research in the area of the cognitive biases found in financial planners or advisors (Cordell et al., 2011; Gregory, 2010; Pompian, 2011; Gerhard and Michayluk, 2008). Our study has identified the different biases that affect financial planners, thereby pushing the literature beyond the biases related to overconfidence and over optimism (Thomas, 2018; Cossette, 2014). By means of scenarios and rigorous data analysis, we have provided strong evidence for the existence of cognitive biases in both planners and their clients, and for the perception that AI has the potential to counter the effects of such biases (Rastogi et al. 2020). Our study provides evidence to Acciarini et al., (2020), who stated that decision making is influenced by perception and digitalization and that cognitive biases lead to shortcuts in decision making (Ehrlinger, Readinger & Kim, 2016). We have further established that an attribution theory lens helps identify how a respondent might behave when questioned from two different perspectives (Heider, 1958).

AI has major implications for decision making processes, and not only in the financial sector. It can help in overcoming human thought process fallacies and provide data driven solutions to existing problems. Our findings, which provide in-depth insights into how digitalization complements the financial sector, are also important to strengthen and to serve effectively in benefiting organizations from a strategic perspective (Tabrizi et al., 2019). Evidence based knowledge can positively influence the digital transformation of organizations. (Benson et al., 2002, Sousa and Rocha., 2019); in this vein, our qualitative analysis has provided a case for digital transformation in the financial industry.

Practical Implications

Beyond providing an evidence-based case for a digital transformation in the financial industry, our qualitative study has bridged the gap between cognitive biases and practical insights. Although AI did not appear to have the potential to be of any help in financial planning due to reasons of non-cognitive abilities, we found that it can assist planners in streamlining the initial data analysis processes and provide unbiased step by step solutions that planners can then take forward. This provides start-up companies with opportunities for the design of financial planning algorithms suited to help financial planners or individual investors. A survey conducted by NewVantage Partners and published in the MIT Sloan Management Review (Davenport & Bean, 2022, Feb 17) shows that 92% of the large organizations surveyed had started accruing returns on their investments in AI. Another study conducted by Pereira & Temouri (2018) shows that high growth firms are crucial in emerging Central and Eastern European (CEE) countries and that bureaucratic quality has high impact on institutional environment for a high growth firm. These firms especially the financial services can adopt AI to be ahead of the race. If governments outline regulations for firms, suppliers will also comply to the safety and quality norms (Srivastava et al., 2021). Since AI is widely used in developed countries, MNE's from developed economies can later expand into emerging economies thereby exploring knowledge and assets of the acquired subsidiaries (Munjal et al., 2021). Also, since most AI programmers are from Gen Y and Z, organizations must align their HR policies to the expectations of these employees (Pereira et al., 2017).

Our research also opens the door for organizations to develop training programs aimed at providing financial planners with the tools they need to contain their various cognitive biases while making investment decisions for their clients. Such programs can effectively influence attitudes and behavioral interests toward the employment of AI technologies (Cao et al., 2021). Another field in which financial planners need to be trained is collaboration with AI so as to make them comfortable with the technology regardless of their age groups. This can build up the financial planners' trust in AI and also make them more open to its use for their benefit and ease of planning. Financial literacy training programs can also improve the knowledge held by individuals in regard to financial products and services (Carpena et al., 2019).

Limitations and scope for future research

Despite its numerous implications, we hereby identify a few limitations of our research. We conducted our study only in Australia and considered highly experienced professionals. This study could thus be replicated in other countries by engaging professionals of mid and low-level positions, as age has an effect on the attitudes held toward AI implementation (Vasiljeva et al., 2021). This study could also be replicated in domains other than that of finance in order to understand how cognitive biases influence professionals in other sectors. The findings may also be affected by geographical considerations (Murata, 2018; Hershey, Henkens & Van Dalen, 2007). The Chinese, for example, are known to be less risk-averse than Americans, with any such differences being attributed to cultural differences (Weber & Hsee, 1998). The Chinese rank object value higher than Americans and any financial decisions differ between the two nationalities based on their respective cultural backgrounds (Levinson & Peng, 2007). In a stock market game, Asian students were also found to be more overconfident than their British counterparts; however, both were equally prone to self-attribution bias (Acker & Duck, 2008).

Researchers could also explore advanced applications of AI or alternate technological solutions suited to overcome the cognitive biases of financial planners. We believe that our study can form a basis for research to be conducted in other disciplines. Although we identified AI as the technology through which cognitive biases can be overcome, we did not explicitly state which of its related techniques could be used. Programmers could take the opportunity to explore machine learning and deep learning techniques to develop algorithms suited to assist financial planners.

Also, further to our proposition of using AI in financial planning, we would invite researchers to identify the details of the financial data—which could be provided by highly experienced financial advisors—to be fed into an algorithm designed to be screened and analyzed before any financial decision can be made. Such a task would be fraught with multiple challenges, particularly those identified by Xiong et al. (2022) in relation to team organization, mutual enhancement, and communication for human-machine collaboration.

We found that financial planners are subject to various biases, but we did not link such biases to specific investment decisions; we limited our exploration of the concept of cognitive bias to generalized financial planning situations. However, specific biases may come into play in relation to specific investment plans; an aspect that would require more in-depth investigation.

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