# Can Artificial Intelligence (AI) Manage Behavioural Biases Among Financial Planners?

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## ABSTRACT

The main novelty of this paper is proposing artificial intelligence (AI) to manage behavioural biases in the financial decision-making process. An empirical study by Kahneman and Tversky identifies the evidence of behavioural biases in the investment decision-making process: a reversal of an established tenet in traditional finance. Financial planners are vulnerable to behavioural biases and are therefore unable to provide optimal investment solutions for their clients. Identifying the limitations of current practice, this research attempts to address how AI can help financial planners in subduing their behavioural biases and proposes the adoption of AI in financial planning services to circumvent behavioural biases. In recent years, AI has attained significant efficacy and has proven to be efficacious through supervised and unsupervised learning. Applying these AI techniques in mitigating behavioural biases, this study confirms that the backpropagation within the neural network and deep reinforcement learning can help overcome confirmation and hindsight biases.

### KEYWORDS

Artificial Intelligence, Cognitive Biases, Confirmation Bias, Decision Making, Deep Learning, Financial Advisors, Financial Planners, Hindsight Bias, Reinforcement Learning

## INTRODUCTION

Traditional economic theories assume that individuals act rationally, and the role of emotions or psychological issues is kept at bay in financial decision-making situations. In this decision-making process, the economic agents consider all the available information, process the collected information judiciously, and arrive at optimal financial decisions. The optimal decisions lead to the most desired

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outcome and help attain the financial goals of the individuals. However, behavioural finance and neuroeconomics research reveals that individuals are not entirely rational and susceptible to various biases. There are constraints in the decision-making process leading to biased decisions. The decision-making process occurs in the human brain through a mutual communication between the prefrontal cortex and hippocampus with neural connectivity (Weilbächer & Gluth, 2016; Moghadam, Khodadad & Khazaeinezhad, 2019). Wang (2008) suggests that the prefrontal cortex estimates the required information for the decision-making process and then obtain this information from the hippocampus. However, along with the cognition process for decision making, the hippocampus channels emotional experience during this procedure. Consequently, the decision-making process is susceptible to biases. In his ground-breaking research, Simon (1967) contends that the system will be incomplete without taking emotions and situational constraints into the decision-making process producing sub-optimal decisions. Financial planners who regularly take financial decisions for their clients also exert biases in their decision-making process (Akhtar & Das, 2020). Baker *et al.* (2017) assert that financial planners' psychological biases can lead to flawed economic decisions. Understanding personality traits and effective behaviour management techniques positively influence financial decisions, but unfortunately, this is not effectively explored (Pompian, 2012).

## Background and Research Gap

In our current fourth industrial revolution, Artificial Intelligence (AI) offers a new sense of hope to combine human intellect and machines to resolve the biases in the decision-making process. Several studies have already identified the use of AI for decision-making purposes. In a recent paper, Bogoviz (2020) shows that AI leads to a human-artificial intelligence framework and data intelligence and analytics for effective decision-making purposes for businesses. Duan *et al.* (2019) and Pillai *et al.* (2020) demonstrate that the integration of AI into a business setting offers tangible benefits through effective decisions. Although AI influenced human service jobs are well established (Huang & Rust, 2018), the authors find no research on how AI can help financial planners deal with biases. In this conceptual paper, we will reflect on the biases of the financial planners and propose AI as a possible solution to overcome biases in the financial decision-making process. In this case, the research will use two specific cognitive biases i.e., confirmation and hindsight biases and demonstrate how AI can resolve these biases.

Behavioural finance classifies the biases into two categories: cognitive and emotional biases (Baker & Nofsinger, 2002; Al-Dahan, Hasan & Jadah, 2019). Pompian (2012) defines that cognitive biases arise from faulty cognitive reasoning; whereas, emotional biases result from the emotions' influence. Unlike in traditional economics, bounded rationality is commonly assumed in behavioural economics in that decisions cannot be made rationally, thereby resulting in cognitive biases, as pointed out by Kahneman (2011), Tversky and Kahneman (1974) and Kahneman and Tversky (1984). Kahneman and Tversky (1984) stated that humans' cognitive information processing, conducted through either of the following processes. System 1, where the operation is quick, automatic, without much time consumption and intuitive, with little or no effort, and System 2, requires effortful, demanding and deliberate mental activities.

Nevertheless, a heuristic approach of cognitive information processing, adopted when there is a time constraint, is based on System 1 and is intuitive and straightforward. However, such methods frequently suffer from cognitive biases. Because of these cognitive and emotional biases, individuals cannot process the information optimally. Cognitive biases are hypothesised to distort decision making, thereby leading to human errors in judgment, decision making and behaviour, eventually (in the worst case), triggering incidents, crashes, collisions or disasters if the commitment to the biased judgment, decision making and behaviour is escalated (Murata and Nakamura, 2014; Leković, 2020).

## Literature Review

Our evaluation in the financial planning industry literature indicates two approaches taken to circumvent the behavioural biases for optimal financial decisions for the clients. These are psychographic classification of clients and digitalisation of financial planning by adopting Robo-advice (Piehlmaier, 2022; Shanmuganathan, 2020). However, these two approaches' primary purpose is not to overcome biases in the financial decision-making process. The clients' psychographic analysis intends to classify them based on their personality traits, beliefs, attitudes towards money and investment, interests, and other factors. This classification's main objective is to understand the clients' return objective and perspective towards risk so the financial planners can advise efficiently (Lin, 2002; Bhola & Zanvar, 2010). While understanding the clients using the psychographic classification, instinctively, financial planners identify the clients' potential behavioural biases; however, this technique cannot allow managing the biases.

On the other hand, digitalisation of financial planning, e.g. Robo-advice, automatically avoids human interaction to bypass biases (Bhatia, Chandani & Chhateja, 2020; D'Acunto & Rossi, 2021). However, the application of the Robo-advice is limited to certain areas of financial planning services-market timing for efficient trading, rebalancing the portfolio on time, constructing a tax-efficient portfolio and cost savings through transaction automation (Kaya, Schildbach & Schneider, 2017; Scherer & Lehner, 2022). Moreover, Robo-advice efficiently collects information from the clients and processes this information for decision-making purposes (Brenner & Meyll, 2020). However, the limitation of using Robo-advice is that most clients want their services from actual financial planners, not directly from computers or robots (Todd & Seay, 2020; Northey *et al.*, 2022; Athota *et al.*, 2023).

Considering the implications of biases in the financial decision-making process and understating the limitations of clients' psychographic classification approaches and digitalisation of financial planning in dealing with the biases, we propose incorporating artificial intelligence (AI) in financial planning services. AI attempts to extend human capabilities and accomplish tasks that neither humans nor machines could on their own (Jarrahi, 2018; Vrontis *et al.*, 2022). In this case, the financial planners will utilise AI in tackling human biases to achieve optimal financial decisions for the clients (Jarrahi, Lutz & Newlands, 2022). AI-powered financial planning services can assist financial planners in developing risk-efficient portfolios, availing the market timing by controlling the behavioural biases of both clients and financial planners themselves. AI can solve complex tasks through supervised, unsupervised, and reinforcement learning (Dhanaraj, Rajkumar & Hariharan, 2020; Sarker, 2021; Singh, Singh & Deka, 2021). Artificial neural network (ANN) has also been used in decision support system (DSS) in higher education system for advanced decision making and largely uses big data (Fayoumi & Hajjar, 2020).

Section 2 discusses the processes involved in financial planning services with the identification of behavioural biases' Section 3 introduces the current practices in mitigating behavioural biases in the financial planning industry; Section 4 proposes the use of AI in financial planning services. Finally, Section 5 outlines the practical implications and section 6 concludes the study.

## FINANCIAL PLANNING SERVICES

Financial planning involves a complex set of tasks that require financial planners' professional services. Financial planning service starts with understanding the clients' financial goals along with their risk capacity and risk tolerance, investing in an optimal portfolio and incorporating retirement planning, estate planning, and attaining tax efficiency. People find financial planning tasks are overwhelming, and they are fearful of making expensive mistakes. These mistakes could jeopardise their long-run financial wellbeing. Therefore, people take services of the financial planners. Altfest (2014) asserts that financial planners or advisers should assist individuals in developing a financial plan that incorporates a client's values, needs, and wants to reach their financial goals. Importantly, individuals cannot cruise their financial goals in a multifaceted financial world in the right direction. Financial planning services are supportive in this context. Barnes (1985) states that the complex economic environment, frequent changes in income and estate taxes, and new and varied ways to invest money have caused people to seek professional financial advice.

Financial planners and advisors assist individuals and clients in developing a financial plan to attain their financial goals and wellbeing. Harris (1998) states that financial planners influence the decision-making process and behaviours of the clients. Clients require complex financial advice or decisions from the financial planners, which involve financial objectives, risk tolerance, economic prospect, tax structure, age, saving behaviour and others. In addition to these factors, clients are susceptible to mental mistakes and emotional responses (Athota *et al*., 2023; Chhapra *et al*., 2018). One of the most outstanding services a financial advisor can provide to clients is ensuring that reason, discipline, and objectivity triumph over emotions such as fear, greed, and regret in times of market turbulence.

As evident in the literature, behavioural biases are rampant among people (see Kahneman and Tversky, 1979; Thaler, 1980, Thaler, 1999 and others), and financial clients exhibit cognitive and emotional biases (Dervishaj, 2021; Baker *et al*., 2017). The biases evident throughout the financial planning services include understanding the clients, developing capital market expectations, portfolio construction, and maintaining client-advisor relationships. For example, clients' information at the beginning of financial planning services is often filled with emotions rather than objective information. Therefore, experienced financial advisers know that defining financial goals is critical to creating an investment program appropriate for the client. To best define financial goals, it is helpful to understand the psychology and emotions involved in the decisions underlying the goals. Again, during portfolio formation or asset management, clients frequently exhibit biases. For instance, clients show inertia and status quo bias in asset allocation by not changing their portfolio construction even though they need it for attaining their financial goals (Amerkis and Zeldes, 2000). Benartzi and Thaler (2001) observe naïve diversification among the investors by allocating the same weights in their various investments. Clients also show overconfidence in the same portfolio management by excessive trading (Barber and Odean, 1999) and home bias by investing only in familiar assets (French and Poterba, 1991). Financial planners are advisors aware of these biases and work with clients to manage these biases. Yeske and Buie (2014) state that financial planning clients are prone to behavioural bias, and advisers must mitigate these tendencies. Consequently, appropriate financial planning policies can play a decisive role in keeping clients committed to a consistent and disciplined course of action and avoiding such biases. Ignoring or failing to grasp this concept can negatively influence investment performance.

Successful financial planning and investing are more than crunching numbers, listening to popular opinion, and understanding the latest market trends. As much as clients need to know about financial markets and investments, they also need to know about their behaviours. A large part of investing involves investor behaviour. Emotional processes, mental mistakes, and individual personality traits complicate investment decisions (Kubilay & Bayrakdaroglu, 2016). Lerner *et al*. (2005) stated that emotion outweighs rationality in decision making. Emphasising the importance of managing emotions, Baker & Ricciardi (2015, pg. 23) mentions a quote from Ben Graham, the father of value investing; "individuals who cannot master their emotions are ill-suited to profit from the investment process". Despite this sage advice, investors often allow others' greed and fear to affect their decisions and react with blind emotion instead of calculated reason. Emotions can help explain asset pricing bubbles and related market behaviour. According to the old investment adage, investors can make money as a bull or a bear but not as a pig. In short, investors need to understand the psychology of financial planning and investing.

For providing effective financial services to clients, a financial planner or adviser requires an understanding of an investor's psychology. Sometimes data are no match for human emotions. In support of financial planners, in this case, Fisher (2014) notes, "One of the greatest services a financial adviser can provide to clients is helping to ensure that in times of market turbulence, reason, discipline, and objectivity triumph over emotions such as fear, greed, and regret." (Baker & Ricciardi, 2015, pg. 24).

In financial planning services, financial planners also exhibit behavioural biases. Baker *et al*. (2017) contend that financial planners and advisors exhibit various psychological and cognitive biases. These biases can create a barrier to their sound judgment and lead to suboptimal investment decisions for the clients. In analysing the financial advisors losing clients, Pompian (2012) states that financial advisors do not fully comprehend the clients' financial needs and cannot engage with clients' psychology. The failure in effective engagement with the clients yields poor relationships. Pompian (2012) suggests that the main reason for failing to understand the clients is the financial advisors' psychological biases. To attain a robust relationship between financial advisors and clients and produce optimum investment decisions for the clients, Pompian (2012) also suggest that financial advisors and planners need to understand their biases and give the best effort to manage these biases. Although psychological biases are difficult to contain, the cognitive biases are correctable.

## CURRENT PRACTICES IN MANAGING BIASES

As Sahi *et al*. (2013) note, understanding individual investment decisions also requires understanding the various behavioural biases associated with their decision-making. Financial therapy blends knowledge from financial planning and mental health services to better understand economic behaviour and implement interventions to improve financial and relational wellbeing. The development of financial therapy's concept reflects the strong acknowledgment from a subset of practitioners and researchers that money affects relationships and overall wellbeing—additionally, psychological and relational wellbeing influence one's financial management. For example, Stolz (2009) notes that more financial planners seek training to acquire skills and knowledge on preventing or decreasing marital discord from causing a financial plan to fail.

### Psychographic Classifications

In recent decades, financial service professionals and researchers have been attempting to classify investors by their psychographic characteristics—e.g., personality, values, attitudes, and interests—rather than classifying based on demographic characteristics (Sahi & Arora, 2012; Yankelovich & Meer, 2006). Psychographic classifications are particularly relevant concerning individual strategy and risk tolerance. An investor's background, past experiences, and attitudes can play a significant role in decisions made during the asset allocation process (Ngcamu *et al*., 2023). If investors fitting specific psychographic profiles are more likely to exhibit particular investor biases, practitioners can recognise the relevant behavioural tendencies before making investment decisions. In this case, the literature identifies three models: Barnwell two-way model, b) Bailard, Biehl, and Kaiser (BB&K) five-way model, and c) Behavioural investor type by Pompian (2008).

Barnwell two-way model identifies clients into two categories, i.e. passive and active. Passive investors, defined as those investors who have become wealthy passively. In contrast, active investors are individuals who have been actively involved in wealth creation through investment, and they have risked their capital in achieving their wealth objectives. Barnewell's work suggests that a simple, non-invasive overview of an investor's personal history and career record could signal potential pitfalls to guard against in establishing an advisory relationship. Her analysis also indicates that a quick, biographical glance at a client could provide an essential context for portfolio design. Like the Barnwell two-way model, the BB&K model classifies the clients into five groups based on investors' confidence and whether the investor is methodical, careful, and analytical in his approach to life or emotional intuitive and impetuous. Pompian (2008) identifies four behavioural investor types. This categorisation scheme's objective, similar to BB&K and Barnewall, is to help advisers and investors better understand investors' behaviour. For an adviser or investor to diagnose and treat behavioural biases, they must first test for all behavioural biases in the client. This testing helps to determine which biases a client has before being able to create an appropriate investment policy statement and a behaviorally modified asset allocation like those presented in the reading, "The Behavioral Biases of Individuals." Pompian and Longo (2005) explain how to plot bias type and wealth level information on a chart to create a "best practical allocation" or "best behaviorally modified allocation" for the client. However, some advisers may find this bottom-up approach too time-consuming or complicated.

Although there is wide use of psychographic classification in the financial advising industry to understand the client better, this system does not effectively mitigate behavioural biases. It only facilitates detecting the biases, but the system does not efficiently tell us how to manage them. Moreover, psychographic classification happens when the client-advisor relation is established, but then the clients demonstrate a change in behavioural patterns in various circumstances. Therefore, the clients exhibit variants of behavioural biases on multiple occasions. In this case, the psychographic classification cannot capture the biases correctly. An individual may generally behave one way but at times may act unexpectedly. Different and irrational behaviours are exhibited randomly, usually during the financial market or personal stress periods. Because of inconsistencies in behaviour, financial decision-making is not always predictable, or financial decision-making expectations are not reliable.

## Automated Financial Services

Since the emergence of the information technology and automation system, some financial service industries have embraced this technology to provide clients with financial services. It is a data-driven software, which runs on specific algorithms. The logic behind these algorithms is arrived at by analysing data gathered from the investors by inducing them to answer a set of questions. The main intention of introducing the automated services is to attain efficiency in various facets of financial advising, including efficient portfolio formation, market timing, reducing transaction costs and more importantly, circumventing human interactions to manage biases (Tao *et al.*, 2021; Fares, Butt & Lee, 2022).

The design and purpose of Robo advice are to provide automated and fast financial advice to the clients. It uses a set of rules and importantly avoids human interaction. Since it is not prone to have cognitive and emotional biases, it can provide optimal advice to its clients. For example, Jung *et al.* (2018) report that optimally designed Robo advisory services can neutralise decision inertia bias. The Robo advice facilitates efficient market timing, rebalancing the portfolio on time, and building a tax-efficient portfolio and cost savings through transaction automation. The total amount of assets under management (AUM) in the Robo-advisory segment equals USD 980,541million in 2019 globally (Netscribes, 2019).

Financial DNA started in 2001, is an online system using behavioural insights to provide financial advice to clients. This system argues that traditional risk profiling processes are insufficient to fully grasp how clients make decisions and importantly circumvent the biases. The Financial DNA can discover all dimensions of a client's financial personality. It also unveils the client's automatic decision-making biases. It has been used in 50 countries over ten languages. In another example, Vanguard, a financial advising firm, offers a platform that includes a combination of Robo technology and human advice and has been widely successful in drawing attention from clients. Another Robo-investing pioneer, Betterment offers options where clients can interact with a human advisor and a platform that allows human advisors to use Betterment's platform for their clients. However, Betterment's Robo-advisor is mainly limited to recommending the optimal portfolio for the customers and automating the investment process to save time and avoid human clerical error. With the emerging super-smart society (Fiorini, 2020) which is an evolution of the current autonomous system (AS) together with the symbiotic autonomous system (SAS), automated financial system will be a focal point.

Since Robo-advisors are a class of financial advisors with minimal to no human intervention, specific concerns plague an investor when availing these services and platforms (Phoon and Koh, 2017). As of yet, Robo-advisors have limited capability in the financial advising industry. It is mainly involved in forming an efficient portfolio; executing trading based on market timing. Based on the analysis of available Robo-advice products, it is not evident how this system can manage behavioural biases. Notably, there may be times when investors would prefer to consult with someone, especially during the bearish phase in the market (Zhang, Pentina, & Fan, 2021). The human consultation enables the investor to converse about their emotional and behavioural concerns with advisors looking after their portfolios (Athota *et al.*, 2023). Lack of the ability to consult and voice their views may make investors insecure and biased during distress. Behavioural biases are inaccurate and potentially harmful to investors' behaviours by erroneous decisions.

Based on the above literature and framing, we now aim to propose how AI can successfully intervene in reducing biases by financial planners. We argue how we can minimise the physiological and other reasons for biases by the intervention of AI and how this can address the root causes of biases.

## METHODOLOGY

### Reducing Biases Through AI

We analysed existing literature and identified that financial planners are subjected to various cognitive biases that can impact the financial decisions taken by the planner and the investor. In general, errors in human cognition lead to cognitive biases, whereas emotions and feelings pave the way to emotional biases. Literature identifies that when people need to make financial decisions, they face difficulty devising rational approaches (Adil, Singh & Ansari, 2022; Mittal, 2022). In the decision-making process, they require considering uncertainty coupled with the abundance of information (Hastie & Dawes, 2009). In most cases, they do not know what information to use and how to assign a probability. Individuals cannot describe problems, identify the correct information to focus on, and integrate all the information to create rules for making decisions. Individuals use mental shortcuts or heuristics to arrive at conclusions to circumvent these problems. Hence, the human mind lacks optimisation for taking optimal financial decisions.

This is a research gap that we address and suggest AI as a possible solution due to its ability of deep reinforcement learning. We thereafter propose our conceptual 'backpropagation' model which we believe will be helpful to financial planners in overcoming Confirmation bias and Hindsight bias specifically.

### Cognitive Biases in Financial Planners

In this section, we will reflect on the nature of the cognitive biases, i.e. systemic loopholes in the decision-making process leading to biases. When financial planners use numbers, mathematical modelling, and probability estimation, they assume that their financial decisions for the clients are optimal. However, the financial planners can have cognitive illusions (Reeves and Pinna, 2017), make mistakes in understanding the complex mathematical process to update probabilities, and become victims of a false understanding of association among the variables (Korteling *et al*., 2018). Importantly, in cognitive bias, individuals presume they act rationally and logically; however, they use faulty reasoning, apply spurious variables, and use the wrong information set. Considering the nature of the cognitive biases, we can possibly classify them into belief perseverance bias and information processing bias. A belief perseverance bias appears when the financial planners stick to their previously held beliefs without sufficient justifications. Financial planners often exert cognitive dissonance in belief perseverance bias when new information is discordant with current views or opinions. The belief perseverance biases include hindsight, confirmation, representative, and the illusion of control bias. In belief perseverance biases, e.g. confirmation and hindsight bias, the financial planners have selective retention ignoring information inconsistent with existing belief, and selective exposure focusing only on the information of interest. On the other hand, information-processing bias occurs when financial planners use information irrationally or unreasonably. In this case, the financial planners tend to apply faulty reasoning while processing the decision-making process information. The processing biases include anchoring and adjustment, mental accounting, framing, and availability bias.

### Managing Cognitive Biases

In managing biases, the literature suggests that we need to 'moderate' the cognitive biases since this type of bias stems from the subconscious mind and faulty reasoning (Pompian, 2006). Moderation suggests reducing the impact of biases through better information and education. Although financial planners are aware of these biases, it is not easy to manage since it requires human effort. In most cases, people are reluctant to exert that effort to moderate cognitive biases. Hirshleifer (2001) contends that human effort involved in processing information and updating belief, inversely correlated with new information processing. The previous section highlights the use of psychographic classifications and Robo-advisors in dealing with the biases of the financial planners. Although digital or Robo-advising facilitates financial planning decision-making, it cannot be the ultimate companion for financial planners because of its inherent limitations. Robo-advice does not have human interactions, and it is not efficient enough to address most behavioural biases. Publicis Sapient, a company provides digital transformation services to financial institutions, undertakes a study to understand the perception of the retail investors on various digital investment programs. The study confirms that many people are unwilling to allow a robot to perform decisions without human oversight (Zhang, Pentina, & Fan, 2021). For example, three out of four clients agree that a Robo-advisor can perform some tasks, such as explaining option differences; however, they are unwilling to utilise the Robo-advisor since it lacks human interactions.

## Confirmation and Hindsight Bias

Since the sub-optimal financial decisions due to cognitive biases are difficult to manage efficiently, AI has immense potential. AI augments human intelligence. We argue that AI will retain human interactions and, at the same time, manage human biases. It helps make data-driven decisions. In its report, McKinsey & Company, a world leading consulting firm defines AI as “the ability of a machine to perform cognitive functions we associate with human minds, such as perceiving, reasoning, learning, and problem-solving” (McKinsey & Company, 2018, pg.1). By offering machine learning and deep learning, AI goes beyond the basic automation process to complete more complex tasks. AI provides client-facing tools, such as self-service on boarding, portals and interactive dashboards. However, it also goes deeper, targeting both its operations and the entire ‘wealth management value chain’. This model unlocks new levels of client-centricity, organisational efficiency, and cost savings by targeting both front- and back-office functions and infusing AI within the wealth management process. Also, Monarch Butterfly Optimization (MBO) algorithm was developed and tested by Alweshah *et al.,* (2020) for feature selection thereby reducing computing time and improving accuracy of feature classification.

Now we will demonstrate how AI can manage cognitive biases. In this case, we will investigate two common biases in financial planning scenarios: confirmation bias and hindsight bias, identify the physiological reasons these two biases occur and provide AI’s linkage in dealing with these cognitive biases. Confirmation bias tends people only to consider new information if it complies with their existing belief and discount if it contradicts. This biased nature relies on selective exposure, perception, and retention of a specific type of information. Gilvich (1993) contends that financial planners are susceptible to confirmation bias since it is easier to deal with cognitively. As physiological reasoning, this bias can arguably link to individuals’ attitudes to accept information according to their perception and understanding of what they already know. There could be a possibility that there is a connection of this confirmation bias to the compatibility principle (Korteling *et al.*, 2018).

The compatibility principle suggests that human brains do not store any information without associating it with existing knowledge. It implies that when new information hits the human mind, its acceptability or adaptability depends on its compatibility with existing values. In understanding the reason for confirmation biases, Korteling *et al.* (2018) suggest that humans see, recognise, and accept any new information according to their perceived mindset, understanding of the situation, expectations, and values. When the human brain receives a new piece of information, it does not keep it separately from other information; instead, it maintains an associative network. In the associative network, if the new information is not compliant and consistent with the existing information, the human mind rejects the latest information. Nickerson (1998) contends that humans tend to focus on and interpret information in a way that confirms their existing perception, which ultimately yields a confirmation bias. Human brains cannot keep the information separately, and it regularly applies compatibility principles to evaluate information. Therefore, the financial planners place greater weight on information that supports their beliefs in estimating probability. This biased approach, placing higher weights on confirmatory information and ignoring or placing no weights on negative information, leads to an under-diversified portfolio for the clients by the financial planners.

### Backpropagation for Mitigating Biases

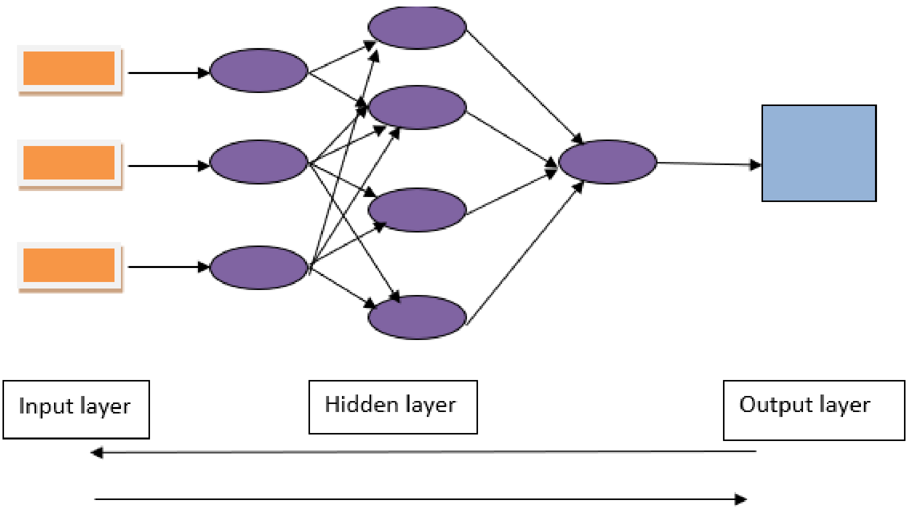
The human mind lacks optimisation for the efficient processing of information without biases. To address this confirmation bias, AI can assist through a neural network. In this event, AI will work with the human mind and avoid the compatibility principle so that judgment happens independently. When a human mind struggles with accepting information as the existing belief does not endorse it, AI will enable humans to evaluate the information according to its merit without falling into confirmation bias. An artificial neural network is a collection of smaller units called neurons, which are computing units modelled on how the human brain processes information. A group of neurons is named a layer, which takes in an input and provides an output. Any neural network will have one input layer and one output layer. It will also have one or more hidden layers that simulate the types of activity in the human brain. Hidden layers take in a set of weighted inputs and produce an output through an activation function.

This study suggests that the backpropagation within the neural network will enable the financial planner to overcome the confirmation bias. Zaras *et al*. (2022) contend that in a backpropagation process, an input vector to a resulting output vector through a model inspired by neurons and their connectivity in the brain. The model consists of layers of neurons interconnected through weights that alter the importance of specific inputs over others. Each neuron includes an activation function that determines the output of the neuron. In this case, its weight vector multiplies a function of its input vector. Computation of the output happens by applying the input vector to the network's input layer, then calculating the outcomes of each neuron through the network (in a feed-forward fashion). The computational error happens by comparing the actual output and desired output and then backpropagated to adjust the weights and biases from the output to the input layer. Figure 1 shows a backpropagation process using an artificial neural network. The system offers three layers: input layers (orange boxes), output layer (light blue boxes), and hidden layers (purple ovals). The process shows that new information comes as inputs, and the backpropagation computes the output. The backpropagation process does not apply the compatibility principle when further information comes in; instead, it treats information independently. The neural network can appraise the acquired knowledge without any prejudice. Figure 1 shows three inputs, and there is no overlap among the information. So, there is no confirmation bias in this instance since the system does not evaluate new information based on perceived understanding about the same.

## DISCUSSION

The study focuses on hindsight bias and proposes how AI can manage this bias. Hindsight bias is information-processing bias with selective perception and retention aspects. The individuals find that past events, which already occurred, are more predictable than those that did not happen. People may see past events as having been predictable and reasonable to expect. Also, people tend to remember their future predictions as more accurate than they were because they are biased by knowing what has happened. Understanding the physiology of this bias, Korteling *et al*. (2018) link the hindsight bias to the retainment principle. The retainment principle implies that the human brain captures necessary and irrelevant information. It cannot ignore the information gathered from experience, which can be irrelevant as inputs for future decisions. Highlighting the reasons for the hindsight bias, Kosslyn and Koenig (1992) state that when the human brain perceives and processes information, it also retains the information, and it is difficult to erase or ignore. Therefore, this persisting effect of information influences human decision-making, yielding hindsight bias and suboptimal outcomes in financing decisions. Biased reasoning then occurs when irrelevant or deceptive information associatively interferes with this process. Pompian (2006) study identifies that the hindsight bias provides a false

**Figure 1.**
**Backpropagation**




sense of confidence among financial advisors. In addition, this incorrect level of confidence is detrimental to attaining optimal decisions for their clients.

This study proposes that deep reinforcement learning can overcome hindsight bias using AI. Matsuo *et al*. (2022) and Singh *et al*. (2022) state that deep learning and reinforcement learning are significant factors in the AI system. In addressing the hindsight bias, the system needs to separate individuals' existing perceptions or understanding of previous information, as they do not influence the new set of information. Deep reinforcement learning unites artificial neural networks with a reinforcement learning framework that helps software agents learn how to reach their goals. It implies that the system uses function approximation and target optimisation, mapping state-action pairs to expected rewards. Reinforcement learning refers to goal-oriented algorithms, which learn how to achieve a complex objective (goal) or maximise along a particular dimension over many steps. Reinforcement learning solves the difficult problem of correlating immediate actions with the delayed outcomes they produce. Like humans, reinforcement-learning algorithms need to wait to see the results of their decisions. They operate in a delayed-return environment, where it can be challenging to understand which action leads to which outcome over many time steps. When choosing from an arbitrary number of possible actions, reinforcement learning algorithms are slowly performing better and better in more ambiguous real-life environments. Reinforcement learning judges actions by the results they produce. It is goal-oriented, and it aims to learn sequences of actions that will lead an agent to achieve its goal or maximise its objective function. Applying the features of AI's deep reinforcement learning technique, hindsight type bias is manageable. When the financial planners' experience dominates their future decisions, leading to sub-optimal results, the reinforcement-learning approach will allow them to maximise their objective function. Since this system is goal-oriented, it does not allow a hindsight type bias to interrupt in desired decision making by the financial planners.

## IMPLICATIONS

### Theoretical Implications

Our conceptual piece adds to the body of literature that has identified behavioural biases in both financial planners as well as investors as a hindering factor in taking effective financial investment decisions. Prior studies have looked at human-AI collaboration and suggested AI as well as robo-advisors as effective ways of dealing with human cognitive biases. However, literature showed that robo-advisors have limitations and are therefore not very successful (Todd & Seay, 2020; Northey *et al*., 2022). Our research provides an advanced AI solution to specifically overcome hindsight and confirmation biases through a backpropagation model. Through our proposed model, we contribute to the literature strands of AI in financial planning, AI in overcoming cognitive and behavioural biases, deep neural networking and reinforcement learning. We hereby prove that reinforcement learning is an effective AI technique that can help financial planners and investors in taking optimal investment decisions.

### Practical Implications

Financial planning involves a large set of tasks- understanding the clients' financial goals, risk capacity and risk tolerance, investing in an optimal portfolio and incorporating retirement planning, estate planning, and attaining tax efficiency. This study contends that AI will overcome cognitive biases so that financial planners can take optimal decisions for their clients; however, the use of AI is not limited to this aspect only. The adoption of AI can have practical implications in most financial planning areas.

This research proposes that the deep reinforcement learning of AI can efficiently deal with the hindsight bias. Deep reinforcement learning integrates artificial neural networks with a reinforcement learning framework that helps software agents reach their goals of augmenting AI applications. Reinforcement learning refers to goal-oriented algorithms, which learn how to achieve a complex objective (goal) or maximise along a particular dimension over many steps. Software companies can develop software with programs using the backpropagation model and provide data analysis software to financial planners. Moreover, this model can be extended by combining with other AI techniques to target and eliminate other behavioural biases of planners and investors.

Through the use of AI in data analysis, financial planners can improve their services by providing more accurate solutions to their clients thereby increasing their client base. They can further use AI in forecasting which is crucial in financial planning and improve the efficacy of forecasting. Since AI can analyse a large data set, financial planners can generate significant insights for investment options that are otherwise not possible to human capacity. AI can also explore different asset classes using sentiment analysis. Cheishvili (2021) argues that AI tools have the ability to generate precise sentiment analysis. This sentiment analysis is beneficial to momentum traders. Cheishvili (2021) also reports that AI tools can create summaries of various news and allow financial planners to compare economic forecasts from different sources. Jayawardena *et al*. (2022) have also highlighted the use of AI based data visualization in fintech services. AI Sedik *et al*. (2022) suggest that AI can be applied in identifying digital forgery so the clients can have the confidence in the financial planning industry. But, Saavedra-Rivano (2020) also brings to the attention of policy makers that the impact of 'man-machine symbiosis' will not be uniform in the current heterogenous world and that this transition needs to be unwavering across all geographical regions. This avoids domination of the world by the minority who will be privileged to benefit from this symbiosis. Finally, AI will allow the robotic process automation in financial planning to mechanise repetitive tasks without intervention by the planners. This process will save significant costs to the financial planning business.

## CONCLUSION

The main novelty of this paper is to propose artificial intelligence (AI) to manage behavioural biases in the financial decision-making process. The literature on behavioral finance confirms the existence of cognitive and emotional biases and their influence as a significant challenge to the financial planners in making optimal decisions for their clients (Baker *et al*. 2017). In order to overcome these challenges, our research attempts to address how AI can help financial planners in overcoming such behavioural biases. Our study considers two common biases- confirmation and hindsight bias, and proposes an AI method to overcome these biases. In recent years, AI has attained significant efficacy through supervised and unsupervised learning (Dhanaraj, Rajkumar & Hariharan, 2020; Sarker, 2021; Singh, Singh & Deka, 2021). By applying this AI technique to mitigate biases, our study confirms that the backpropagation model within the deep neural network and deep reinforcement learning can manage confirmation and hindsight biases, respectively through the layers in the model that do not overlap with each other and therefore do not allow previous information to influence the outcome. We propose that there is a greater need for financial planners to employ AI technology to overcome cognitive biases in the financial decision-making process that can help them in taking optimal investment decisions.

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