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Cryptocurrency Investment Decisions in the Age of Artificial Intelligence: Behavioral Biases and Algorithmic Tools

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Abstract
The emergence of cryptocurrencies has transformed individual investment practices, exposing millions of investors to highly volatile markets where behavioral biases significantly influence decision-making. Simultaneously, artificial intelligence tools (robo-advisors, trading algorithms, and predictive analytics) have become increasingly accessible to retail investors, promising decisions that are more rational. However, the interaction between these two phenomena remains largely unexplored. This conceptual paper addresses the question: how does the use of AI tools moderate the influence of traditional behavioral biases on cryptocurrency investment decisions? Drawing on a systematic literature review at the intersection of behavioral finance, cryptocurrency studies, and human-computer interaction, we develop an integrative conceptual model. The model incorporates four cognitive biases (representativeness, overconfidence, herding behavior, loss aversion) as independent variables, cryptocurrency investment decision as the dependent variable, and AI tool usage as a moderating variable. We propose that AI exerts a contrasted moderating effect: mitigating certain biases (representativeness, herding, and loss aversion) while potentially amplifying others (overconfidence) and creating new vulnerabilities such as automation bias. Seven research propositions are formulated for future empirical testing. This conceptual framework contributes to the literature on behavioral finance in digital contexts and offers practical implications for investors, platform designers, and regulators concerned with responsible innovation and investor protection in the age of AI.

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1. Introduction

The emergence of cryptocurrencies has transformed the investment landscape for retail investors. With a global market capitalisation set to exceed $1 trillion in 2025, these digital assets are attracting millions of retail investors drawn by the promise of high returns against a backdrop of the accelerating digitalisation of finance. This phenomenon is part of a broader trend towards the democratisation of investment, where traditional barriers to entry like financial advisors, high minimum investments, specialised knowledge, are gradually disappearing.

Paradoxically, this democratization is accompanied by exposure to markets characterized by extreme volatility, glaring information asymmetry, and the absence of conventional valuation models. Unlike stocks or bonds, cryptocurrencies do not generate predictable cash flows, are not backed by any tangible asset, and are not subject to any centralized regulation. This structural opacity creates a particularly fertile ground for the manifestation of behavioral biases like overconfidence, confirmation bias, disposition bias, and herd behavior, among others. As Corbet *et al*. (2019) [5] and Al-Mansour (2020) point out; these biases are amplified by the radical uncertainty surrounding cryptocurrency valuations, making individual investors

vulnerable to suboptimal or even irrational decisions.

At the same time, artificial intelligence (AI) has entered investment practices through consumer applications: robo-advisors, trading algorithms, predictive analytics, and scoring tools. From fintech startups to traditional banking applications, these technologies promise more rational and efficient decision-making, theoretically capable of counteracting the cognitive biases extensively documented by behavioral finance since the seminal work of Kahneman and Tversky (1974, 1979) [11, 12]. AI promises to replace human intuition, the source of numerous biases, with systematic analysis based on objective data and robust statistical models. This promise has generated considerable enthusiasm among both professionals and individual investors, often seen as the primary beneficiaries of this technological democratization.

However, the literature on human-computer interaction warns against a major pitfall: automation bias. This refers to the tendency to place excessive trust in the decisions of automated systems, thereby suspending the user's critical judgment (Skitka, Mosier & Burdick, 1999) [15]. This phenomenon is well-documented in high-responsibility fields such as aviation and medicine, but remains understudied in the financial context. Applied to cryptocurrency investment, automation bias could lead investors to blindly follow the recommendations of an algorithm, even in the presence of obvious contradictory signals. Therefore, the very tool intended to mitigate behavioral biases could paradoxically create or reinforce new ones.

However, the relationship between the use of artificial intelligence tools and behavioral biases in investment decisions remains largely unexplored, particularly in the specific context of cryptocurrency markets. Existing literature addresses either cognitive biases in finance or the adoption of AI in investment, but few studies examine their interaction. This gap is all the more problematic given that cryptocurrencies and AI are two major technological phenomena of our time, whose convergence is often presented as a promise of increased efficiency, without its behavioral risks having been systematically assessed.

This research is situated within this context. Faced with two key observations, on the one hand, the vulnerability of individual investors to behavioral biases in cryptocurrency markets; and on the other hand, the growing but still poorly understood adoption of AI tools, we seek to address this gap. Therefore, this research aims to answer the following central question: to what extent does the use of artificial intelligence tools influence the relationship between behavioral biases and investment decisions in cryptocurrencies?

2. Literature Review

Behavioural finance emerged in response to the limitations of the classical finance paradigm and the efficient market hypothesis (Fama, 1970) [8]. This approach posits that investors are not perfectly rational and that their decisions are often influenced by systematic cognitive and emotional biases (Kahneman & Tversky, 1979; Barberis & Thaler, 2003; Shleifer, 2000) [12, 3, 14]. Prospect theory forms one of the major foundations of this approach by demonstrating that individuals evaluate gains and losses asymmetrically, with a stronger aversion to losses than a desire for equivalent gains. In contemporary financial markets, several behavioural biases have been identified as significantly influencing individuals' investment decisions, notably overconfidence, herd behaviour, representativeness and loss aversion (Statman, 2014) [16]. These biases are particularly likely to manifest themselves in cryptocurrency markets, which are characterised by high uncertainty, high volatility and the rapid dissemination of information through digital networks. The literature on behavioural finance has identified several cognitive biases that influence investors' decisions. For this research, we have selected four biases that have been particularly well documented in the context of financial markets:

2.1. Representativeness

Among the heuristics identified by Kahneman and Tversky (1974) [11], representativeness bias occupies a central place in understanding irrational financial decisions (Kahneman & Tversky, 1974) [11]. This bias leads individuals to assess the probability of an event based on the degree to which it resembles a familiar stereotype or past pattern, often to the detriment of base rate information (Tversky & Kahneman, 1983) [17, 11]. In the context of investment, representativeness manifests when an investor judges the future performance of an asset based on its superficial similarity to a previously successful asset, rather than on objective statistical evidence (Barberis & Thaler, 2003) [3]. For example, a retail investor might assume that a new cryptocurrency will replicate the spectacular rise of Bitcoin simply because it shares certain features like a limited supply, a charismatic founder, or a similar narrative of technological disruption (Liu & Tsyvinski, 2021). This heuristic, while cognitively efficient in certain everyday contexts (Gigerenzer & Gaissmaier, 2011), becomes particularly problematic in high-uncertainty environments such as cryptocurrency markets, where historical patterns are unreliable and volatility is extreme (Corbet *et al*., 2019) [5].

In cryptocurrency markets, representativeness bias takes on specific and amplified forms (Al-Mansour, 2020) [1]. First, the proliferation of new tokens and initial coin offerings (ICOs) provides fertile ground for pattern matching: investors often extrapolate past successes to fundamentally different projects, leading to speculative bubbles and subsequent crashes (Fry & Cheah, 2016). Second, representativeness fuels the tendency to see "trends" or "cycles" in price charts that are essentially random, a phenomenon known as apophenia (Shermer, 2008). Investors may convince themselves that a particular price movement resembles a previous pattern that preceded a major rally, thereby triggering impulsive buying decisions (Shiller, 2015). Third, this bias contributes to overreaction to recent news or celebrity endorsements (Bouri *et al*., 2019). When a well-known figure publicly supports a cryptocurrency, investors representative of past successful endorsements may assign disproportionate weight to this signal while ignoring broader market fundamentals (Klein, 2019). Unlike traditional financial assets, cryptocurrencies lack established valuation models (e.g., discounted cash flows), leaving investors with no objective anchor (Cheah & Fry, 2015). Consequently, representativeness often fills this vacuum, driving herd behaviour and amplifying market instability (Kristoufek, 2013).

The introduction of artificial intelligence tools into cryptocurrency investment creates a complex interplay with representativeness bias (Skitka, Mosier & Burdick, 1999; Parra *et al*., 2021) [15]. On one hand, AI – particularly machine learning models trained on vast historical datasets – might

mitigate representativeness by providing probabilistic assessments grounded in actual statistical distributions, thereby correcting the investor's tendency to rely on misleading analogies (Diks & Wolski, 2022). On the other hand, AI tools can paradoxically reinforce or even automate representativeness (Cummings, 2017). Many consumer-facing AI applications use pattern recognition algorithms that detect "similar" past configurations in price data (Nabiyev & Topaloglu, 2020). If investors trust these outputs without scrutiny (automation bias), they may delegate their representativeness-driven decisions to an algorithm that merely codifies the same heuristic at scale (Mosier & Skitka, 1996). Furthermore, the opacity of certain AI models (the "black box" problem) prevents investors from distinguishing between genuine predictive signals and spurious patterns (Lepri *et al*., 2018; Ananny & Crawford, 2018). In our conceptual model, representativeness is therefore positioned not simply as a bias that AI eliminates, but as a bias whose expression is transformed by AI usage (West & Allen, 2018). Depending on the transparency of the tool, the investor's level of financial literacy, and the degree of automation bias, AI may either attenuate or amplify representativeness (Hoffman & Novak, 2018; Lu *et al*., 2021). This moderation effect constitutes a key theoretical contribution of our research, distinguishing it from prior work that treats behavioural biases as static individual traits (Baker & Nofsinger, 2010).

2.2. Overconfidence

Overconfidence bias is one of the most robust and widely documented cognitive biases in behavioural finance (Kahneman & Tversky, 1974; Weinstein, 1980) [17, 11]. This bias refers to the tendency of individuals to overestimate their own knowledge, predictive abilities, and the precision of their information relative to objective benchmarks (Moore & Healy, 2008). Overconfidence manifests in three distinct forms: overestimation (believing one's true ability is higher than it is), overprecision (excessive certainty in the accuracy of one's beliefs), and overplacement (believing oneself better than others) (Moore & Schatz, 2017). In financial decision-making, overconfident investors tend to trade more frequently, underestimate risks, and attribute successes to their own skill while dismissing failures as bad luck (Barber & Odean, 2001) [2]. This bias is particularly persistent because it is reinforced by self-attribution and hindsight bias, creating a vicious cycle of escalating overconfidence following a series of successful trades (Gervais & Odean, 2001).

Cryptocurrency markets provide an exceptionally fertile environment for the expression of overconfidence bias (Al-Mansour, 2020) [1]. First, the extreme volatility and spectacular price increases observed in assets like Bitcoin and Ethereum create a context where early investors who made profits often attribute their success entirely to personal foresight rather than luck or market conditions (Liu & Tsyvinski, 2021). This self-attribution error fuels overconfidence, leading investors to increase their trading frequency and position sizes, often with detrimental consequences (Barber & Odean, 2001) [2]. Second, the technical complexity of blockchain technology and cryptocurrency trading platforms can paradoxically reinforce overconfidence: retail investors who acquire a superficial understanding of these technologies may believe they possess an informational advantage over other market participants, a phenomenon known as illusion of knowledge (Fry & Cheah, 2016). Third, the absence of conventional valuation models in cryptocurrency markets encourages overconfident investors to rely on their own subjective assessments and "gut feelings," which they systematically overvalue relative to objective indicators (Cheah & Fry, 2015). Consequently, overconfidence contributes to excessive trading volumes, increased volatility, and susceptibility to speculative bubbles (Corbet *et al*., 2019) [5].

The relationship between artificial intelligence tools and overconfidence bias in cryptocurrency investment is complex and potentially bidirectional (Parra *et al*., 2021). On one hand, AI-powered analytics and robo-advisors could theoretically mitigate overconfidence by providing objective, data-driven assessments that confront investors with the limitations of their predictive abilities (Diks & Wolski, 2022). By offering probabilistic forecasts with clearly communicated confidence intervals, AI tools may reduce overprecision and encourage more realistic risk perceptions (West & Allen, 2018). On the other hand, AI tools may paradoxically amplify overconfidence in several ways (Cummings, 2017). First, investors who use sophisticated AI tools may develop an illusion of control, believing that access to advanced technology confers a competitive advantage over other market participants (Hoffman & Novak, 2018). Second, the perceived precision of algorithmic outputs – often presented with high numerical specificity – can foster overprecision, as users mistake precise-looking outputs for accurate predictions (Ananny & Crawford, 2018). Third, automation bias (Skitka, Mosier & Burdick, 1999) [15] can combine with overconfidence: investors who trust automated systems may become overconfident in the system's recommendations while simultaneously becoming overconfident in their own ability to select and interpret the right AI tool (Mosier & Skitka, 1996). In our conceptual model, overconfidence is therefore hypothesized to be moderated by AI usage in a non-linear fashion: moderate reliance on transparent AI tools may reduce overconfidence, whereas overreliance on opaque or poorly understood AI systems may exacerbate it (Lu *et al*., 2021; Baker & Nofsinger, 2010).

2.3. Herding Behavior

Herding behaviour refers to the tendency of individuals to mimic the actions of a larger group, often abandoning their own private information or independent analysis in the process (Banerjee, 1992; Bikhchandani, Hirshleifer & Welch, 1992). In financial markets, herding manifests when investors buy or sell assets primarily because others are doing so, rather than based on fundamental value or personal analysis (Hirshleifer & Teoh, 2003). Several psychological mechanisms underlie herding: social proof (the assumption that others possess superior information), conformity pressure (the desire to avoid the regret of being alone in error), and reputational concerns (fear of being judged incompetent for deviating from the consensus) (Devenow & Welch, 1996). Information cascades occur when early decisions by a few individuals lead subsequent investors to ignore their own signals, resulting in collective behaviour that can become detached from underlying fundamentals (Bikhchandani *et al*., 1992). Herding is distinct from mere correlation of behaviour because it implies a causal social influence: investors actively choose to follow others rather than independently arriving at similar decisions (Christie & Huang, 1995).

Cryptocurrency markets exhibit particularly intense forms of herding behaviour due to several structural characteristics (Al-Mansour, 2020; Bouri *et al*., 2019) [1]. First, the absence of traditional valuation models for cryptocurrencies removes any objective anchor that might counteract social influence. Unlike stocks, where discounted cash flow models provide independent reference points, cryptocurrencies have no intrinsic value, making investors unusually susceptible to the observed behaviour of others (Cheah & Fry, 2015; Kristoufek, 2013). Second, the prominence of social media in cryptocurrency communities like Reddit forums, Twitter influencers, Telegram groups, and Discord channels creates powerful channels for herding. When influential figures endorse specific coins, rapid information cascades can trigger buying frenzies, as retail investors assume these figures possess superior information (Liu & Tsyvinski, 2021). Third, the 24/7 nature of cryptocurrency trading, combined with real-time price tracking applications, amplifies herding by providing continuous social comparison opportunities. Investors constantly observe which assets others are buying or selling, facilitating rapid contagion of sentiment (Fry & Cheah, 2016). Fourth, fear of missing out (FOMO) closely related to herding drives investors to join rallies without analysis, particularly during periods of sharp price appreciation (Corbet *et al*., 2019) [5]. Empirical studies confirm that herding is more pronounced in cryptocurrency markets than in traditional equity markets, especially during periods of high volatility and market stress (Bouri *et al*., 2019).

The relationship between artificial intelligence tools and herding behaviour in cryptocurrency investment is multifaceted and potentially transformative (Parra *et al*., 2021). On one hand, AI tools could theoretically reduce herding by providing independent, data-driven signals that allow investors to resist social pressure and information cascades (Diks & Wolski, 2022). A retail investor equipped with a reliable AI analytics tool may feel empowered to act against prevailing market sentiment if the algorithm indicates overvaluation, thereby breaking the herding cycle (West & Allen, 2018). Furthermore, AI systems that aggregate diverse information sources without weighting by popularity could counteract the social amplification effects characteristic of cryptocurrency social media (Nabiyev & Topaloglu, 2020). On the other hand, AI tools risk creating new forms of herding or amplifying existing ones (Cummings, 2017). First, if multiple investors use similar AI trading algorithms – a likely scenario given the concentration of fintech providers – these algorithms may generate correlated buy or sell signals, producing "algorithmic herding" that mirrors and potentially amplifies human herding (Mosier & Skitka, 1996). Second, AI-powered social trading platforms, where investors automatically copy the trades of successful peers, institutionalize herding by design (Hoffman & Novak, 2018). Third, automation bias (Skitka, Mosier & Burdick, 1999) [15] can transform herding: instead of following other humans, investors follow AI recommendations blindly, creating technology-driven information cascades (Ananny & Crawford, 2018). Fourth, the perceived authority of AI systems may intensify social proof effects: if an investor observes that "the algorithm" recommends a particular trade, and sees others following that recommendation, the combined pressure of social and algorithmic conformity becomes exceptionally powerful (Lu *et al*., 2021). In our conceptual model, herding is therefore hypothesized to be moderated by AI usage in a manner that depends critically on the transparency and uniqueness of the AI tool. Transparent, personalized AI tools may reduce herding, whereas opaque, widely adopted AI tools may create algorithmic herding that replicates the same inefficiencies as human herding (Baker & Nofsinger, 2010; Lepri *et al*., 2018).

2.4. Loss Aversion

Loss aversion is a cornerstone concept of prospect theory, developed by Kahneman and Tversky (1979) [12], and refers to the empirical finding that losses loom larger than equivalent gains. Specifically, individuals typically experience the pain of a loss approximately two to two and a half times more intensely than the pleasure of an equivalent gain (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) [12]. This asymmetric sensitivity to losses versus gains leads to systematically irrational decision-making patterns, most notably the disposition effect, the tendency to sell winning assets too early while holding losing assets too long (Shefrin & Statman, 1985). Loss aversion also manifests in risk-seeking behaviour in the domain of losses: when faced with a sure loss, individuals often prefer a gamble that offers a chance to avoid the loss entirely, even if the gamble has a negative expected value (Kahneman & Tversky, 1979) [12]. This bias is deeply rooted in human neurobiology and has been observed across diverse cultural and economic contexts (Camerer, 2005).

Cryptocurrency markets, characterized by extreme volatility and the absence of traditional safety nets, amplify the expression of loss aversion in distinctive ways (Al-Mansour, 2020) [1]. First, the dramatic price swings typical of cryptocurrencies create frequent situations where investors face paper losses. Loss-averse investors often respond by holding depreciated assets indefinitely, hoping for a return to break-even rather than accepting the loss and reallocating capital (Fry & Cheah, 2016). This behaviour, known as the "break-even effect," is particularly pronounced in cryptocurrency markets where the absence of fundamental valuation allows investors to maintain unrealistic recovery expectations (Cheah & Fry, 2015). Second, loss aversion fuels the disposition effect in crypto trading: investors systematically sell winning positions too early to lock in gains while retaining losing positions too long in the hope of reversal (Liu & Tsyvinski, 2021). Third, loss aversion interacts with the high volatility of cryptocurrencies to produce risk-seeking behaviour. When investors experience a substantial loss, they become more willing to take extreme risks such as investing in highly speculative tokens or using leverage in an attempt to "get even" (Corbet *et al*., 2019) [5]. This behaviour is amplified by the 24/7 nature of cryptocurrency trading, which prevents the cooling-off periods that occur in traditional markets (Bouri *et al*., 2019).

The introduction of artificial intelligence tools into cryptocurrency investment presents both opportunities and challenges regarding loss aversion (Parra *et al*., 2021). On the opportunity side, AI-powered robo-advisors can implement systematic stop-loss rules and portfolio rebalancing strategies that bypass the investor's emotional reluctance to realize losses (Diks & Wolski, 2022). By automating sell decisions based on pre-defined criteria, AI tools can effectively counteract the disposition effect and enforce disciplined risk management (West & Allen, 2018). Furthermore, AI-driven analytics can provide objective assessments of an asset's recovery probability, potentially correcting the overly

optimistic expectations that sustain loss-averse holding behaviour (Nabiyev & Topaloglu, 2020). However, several risks emerge from the AI-loss aversion interface (Cummings, 2017). First, automation bias (Skitka, Mosier & Burdick, 1999) [15] may lead investors to delegate loss-related decisions to AI systems without understanding the algorithms' limitations, potentially magnifying losses if the AI tool is poorly designed or backtested (Mosier & Skitka, 1996) [15]. Second, the opacity of certain AI models (the "black box" problem) can paradoxically increase loss aversion: if investors do not understand why an AI system recommends selling a losing position, they may hesitate to follow the recommendation, resulting in decision paralysis (Ananny & Crawford, 2018; Lepri *et al*., 2018). Third, AI tools that provide frequent performance updates may trigger more frequent loss realizations, intensifying the emotional impact of losses and potentially leading to avoidance behaviour (Hoffman & Novak, 2018). In our conceptual model, loss aversion is therefore positioned as a bias whose expression depends critically on AI transparency, automation bias, and the frequency of AI-generated feedback (Lu *et al*., 2021; Baker & Nofsinger, 2010).

Several recent studies have empirically validated the impact of behavioural biases in the specific context of cryptocurrencies. Al-Mansour (2020) [1] shows that representativeness significantly influences cryptocurrency investment decisions, particularly during bull markets where investors unduly extrapolate recent trends. Handoko *et al*. (2024) [9] demonstrate that herd behaviour and heuristic biases significantly predict investment decisions, with effects varying according to investors' experience. Shahani and Ahmed (2023) [13] confirm that representativeness, overconfidence and herd behaviour positively influence the intention to invest in digital assets, whilst loss aversion has a negative effect.

Furthermore, recent advances in the field of artificial intelligence have led to a gradual transformation of investment practices. Recent studies show that AI-based technologies, such as robo-advisors and machine learning algorithms, can influence investors' financial decisions by improving access to information and facilitating the analysis of financial data (D'Acunto, Prabhala & Rossi, 2019; Jiang, Kelly & Xiu, 2020) [6, 10]. However, some research also suggests that the use of these tools may give rise to new forms of technological dependence or excessive reliance on algorithmic recommendations.

3. Methodology

This research adopts a conceptual approach aimed at developing an analytical framework to understand the influence of behavioural biases on cryptocurrency investment decisions within a financial environment characterised by the rise of artificial intelligence. The conceptual model is developed based on a systematic review of the literature, drawing on three theoretical fields: behavioural finance, cryptocurrency studies and human-machine interaction.

The variables of the conceptual model were identified from empirical and theoretical work on the behavioural determinants of investment decisions. More specifically, the study considers several behavioural biases frequently analysed in the literature, notably overconfidence, herd behaviour, representativeness and loss aversion.

The proposed conceptual model also incorporates a variable relating to the use of artificial intelligence tools in financial analysis, in order to examine their potential role in the relationship between behavioural biases and investment decisions. This variable is considered as a moderating factor that may mitigate or, conversely, amplify the impact of behavioural biases on investors' decisions.

Table 1: Conceptual Model Variables

Variable Type	Variables	Authors
Independent	Representativeness	Tversky & Kahneman (1983); Al-Mansour (2020) [1]
	Overconfidence	Barber & Odean (2001) [2]; Shahani & Ahmed (2023) [13]
	Herding behavior	Bikhchandani & Sharma (2000); Handoko *et al*. (2024) [9]
	Loss aversion	Kahneman & Tversky (1979) [12]
Moderating	Use of AI tools	Skitka *et al*. (1999) [15]; Dolenc & Stropnik (2025) [7]
Dependent	Cryptocurrency investment decision	Behavioral finance literature

Source: Authors

4. Findings and Discussions

This literature review enables us to propose a conceptual model designed to analyse the behavioural determinants of cryptocurrency investment decisions in a financial environment characterised by increasing digitalisation. This model highlights the central role of behavioural biases in the decision-making process of individual investors.

More specifically, the model suggests that certain cognitive biases, such as overconfidence, herd behaviour, representativeness and loss aversion, can directly influence investment decisions in cryptocurrencies. In markets characterised by high volatility and uncertainty, these biases can lead investors to adopt irrational investment behaviours, overestimate their analytical abilities, or follow the decisions of the majority of investors.

The model suggests that four cognitive biases directly influence investment decisions regarding cryptocurrencies:

Table 2: Research Propositions – Direct Effects of Behavioral Biases

Proposition	Hypothesis Statement	Authors
P1	Representativeness has a positive effect on cryptocurrency investment decisions	Tversky & Kahneman (1983) [17]; Al-Mansour (2020) [1]
P2	Overconfidence has a positive effect on cryptocurrency investment decisions	Barber & Odean (2001) [2]; Shahani & Ahmed (2023) [13]
P3	Herding behavior has a positive effect on cryptocurrency investment decisions	Handoko *et al*. (2024) [9]
P4	Loss aversion has a negative effect on cryptocurrency investment decisions	Kahneman & Tversky (1979) [12]

Source: Authors

Furthermore, the conceptual model suggests that the use of artificial intelligence tools in financial analysis may act as a moderating factor in the relationship between behavioural biases and investment decisions. Technologies based on artificial intelligence can indeed help improve access to information and enhance investors' analytical capabilities. However, they may also alter the way individuals interpret market signals and introduce new forms of reliance on algorithmic recommendations.

Table 3: Research Propositions – Moderating Effects of Behavioral Biases

Proposition	Statement	Underlying Mechanism
P5a	AI use negatively moderates the representativeness-investment decision relationship (mitigation effect)	AI provides objective analysis that counteracts the tendency to extrapolate recent trends
P5b	AI use positively moderates the overconfidence-investment decision relationship (amplification effect)	Overconfident investors selectively seek AI signals that confirm their pre-existing beliefs (confirmation bias)
P5c	AI use negatively moderates the herding-investment decision relationship (mitigation effect)	AI offers independent analysis that reduces the propensity to imitate others' behavior
P5d	AI use negatively moderates the loss aversion-investment decision relationship (mitigation effect)	AI proposes more objective, emotionally-neutral investment decisions

Source: Authors

The proposed conceptual model sheds new light on the interaction between traditional behavioural biases and the use of artificial intelligence tools in cryptocurrency investment decisions. It differs from previous approaches by suggesting that AI has a nuanced moderating effect, far removed from a naïve view that sees technology as a miracle cure for human irrationality. On the one hand, AI could indeed mitigate certain biases: by providing objective analysis, it counteracts the extrapolation of recent trends (representativeness), offers an alternative to herd behaviour (herd mentality) and leads to decisions less influenced by emotion (loss aversion). On the other hand, AI could amplify other biases, notably overconfidence, when investors selectively choose algorithmic signals that confirm their pre-existing beliefs. More fundamentally, the model incorporates the possibility of a new bias induced by the technology itself: automation bias, that is, the tendency to place excessive trust in the recommendations of automated systems, particularly among novice investors. This conceptual framework thus contributes to the literature by opening the 'black box' of human-machine interaction in finance. It emphasises that AI is not a neutral tool but a cognitive artefact whose effects depend closely on the psychological profile of users and the contexts of use, calling for a responsible and ethical design of these technologies.

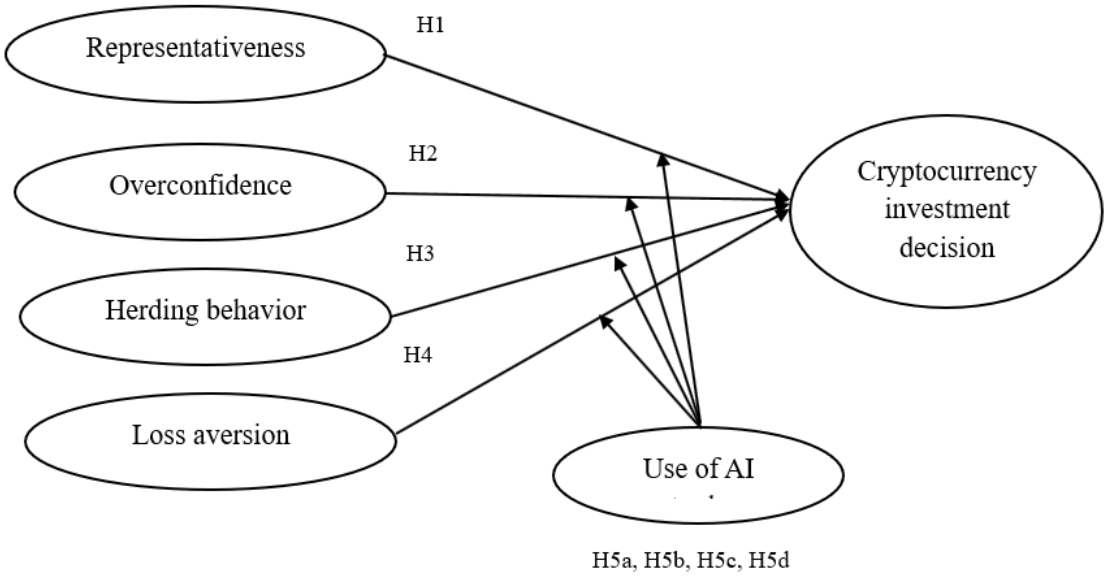


Fig 1: Research framework

5. Conclusion

This research proposes an original conceptual model designed to analyse the complex interaction between traditional behavioural biases and the use of artificial intelligence tools in cryptocurrency investment decisions. By drawing on a systematic review of the literature that combines behavioural finance, cryptocurrency studies and human-machine interaction, we have developed an integrative framework that highlights the contrasting moderating role of AI.

The model suggests that AI is not a universal remedy for human irrationalities, contrary to a certain prevailing techno-solutionist discourse. On the one hand, it can indeed mitigate certain biases: representativeness, herd behaviour and loss aversion could be tempered by the objectivity of algorithmic analyses. On the other hand, AI risks amplifying other biases, notably overconfidence, when investors select signals that confirm their beliefs. More fundamentally, the emergence of a new bias specifically linked to technology – automation bias – serves as a reminder that AI also creates new cognitive

vulnerabilities, particularly among novice investors.

This conceptual framework contributes to the literature in several ways. Theoretically, it constitutes the first attempt at a systematic integration of behavioural finance and human-machine interaction within the specific context of cryptocurrencies. It encourages us to move beyond a one-dimensional view of AI as a mere decision-support tool and to consider it instead as a cognitive artefact whose effects are mediated by the psychological characteristics of users.

In practical terms, our proposals open up concrete avenues for the various stakeholders. For individual investors, the challenge is to develop critical digital literacy enabling them to use AI without falling prey to automation bias. For platform designers, the aim is to develop explainable AI (XAI) that does not merely make recommendations but explains its reasoning, and to integrate alert mechanisms to address potentially biased behaviour. For regulators, our model highlights the importance of regulating these tools with a view to investor protection and financial stability.

This work has certain limitations, inherent to any conceptual approach: the absence of empirical validation at this stage, the non-exhaustive nature of the biases considered, and the failure to account for the diversity of AI tools. These limitations offer avenues for future research. Empirical validation through a quantitative survey of investors is already being considered as a follow-up to this paper. Comparative studies based on level of experience, digital literacy or geographical context would help to refine the model. Finally, the development of interface prototypes incorporating bias detection and explainability mechanisms would constitute an original contribution at the intersection of academic research and responsible innovation.

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