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REGULAR PAPER

Context-adaptive intelligent agents behaviors: multivariate LSTM-based decision making on the cryptocurrency market

Dalel Kanzari[1,2]

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Abstract
Modeling human behavior offers substantial benefits to decision support systems, especially in intricate and ever-changing domains like the stock market. Such modeling allows for the knowledge extraction from a wide range of data sources that are diverse and subject to constant evolution. Human decision making is often influenced by internal factors such as emotions, intentions, and beliefs, as well as external factors like crucial environmental parameters and the behavior of others. Acknowledging and incorporating these factors enables decision support systems to operate more effectively in complex environments, leading to more informed and robust decision-making processes. In this paper, we first focus on examining the different types of human-like decision processes. In addition, we study the overall effect of crowd decision making on context dynamics. Specifically, we model autonomous intelligent agents' decisions based on rational, emotional, and mimetic behaviors in a cryptocurrency market. To validate our approach, we develop deep reasoning agents "DbrAs" that support the long-term memory method in their decision making. The "DbrAs" predict cryptocurrency prices on Yahoo Finance and react with buy, sell, or hold actions. We evaluate the impact of the DbrAs' actions on the prices changes and find that the DbrAs models as well as the DbrAs multi-agent system perform well in predicting cryptocurrency prices using out-of-sample data. This result provides a strong argument that context-adaptive agent behaviors impact context dynamics.

Keywords Deep learning · Multivariate LSTM · Multi-agent Systems · Decision support system · Rational behavior · Emotional behavior · Mimetic behavior · Stock market simulation

1 Introduction

Examining the dynamics of evolving contexts and identifying the key influencing factors are crucial for making timely and informed decisions. The challenge is to intelligently adjust behavior and decision based on the surrounding situation. It implies the perception and understanding of the environment's changes and then the subsequent decision making. For example, modeling the stock market price changes to make, in real-time, the appropriate decision is crucial to ensure investment profitability and overcome market instability. In this context, tracking cryptocurrency prices during a financial crisis is interesting given the gains that this new asset class can generate at a low cost. According to Arsi et al. [1] during the COVID-19 crisis, the price kept rising, recording daily performances between 8 and 16%. The latter remains a top issue for many researchers who seek to find theoretical and logical explanations for price variation. In [2], authors determined factors that can explain cryptocurrency excess returns and their implications for investors to determine optimal portfolio decisions.

Other research based on computational mathematical approaches [3] studied the linkage between dependent variables and studied their dynamic behaviors such as price series variation and the inter-dependencies between cryptocurrencies and the volatility index [4]. Poyser [5] found correlative associations between the cryptocurrency market price and several internal and external factors using the Bayesian structural time series approach. Michel Ballings et al. [6] evaluated the performance of ensemble methods (Random Forest, AdaBoost and Kernel Factory) versus single-classifier models (neural networks, logistic regression, support vector machines, and K-nearest neighbor) to predict

✉ Dalel Kanzari
dalel.kanzari@issatso.u-sousse.tn

1 Higher Institute of Applied Science and Technology, University of Sousse, 4003 Sousse, Taffela, Tunisia

2 LARODEC, University of Tunis, Liberte, Bardo, 41, Tunis, Tunisia

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stock prices using financial data from European companies. Zhang and Qi [7] carried out a comprehensive study of efficient time series modeling with seasonal and trend models. They explored the impact of data pre-processing techniques, such as seasonal adjustment and untwisting, on the modeling and forecasting performance of neural networks. All of them assume that financial markets are free of endogenous anomalies and that investors are fully rational in their strategy. This makes them unsuitable for explaining financial dynamics and crises [8, 9].

Brock and Hommes [10] proposed an asset pricing model with diverse beliefs, in which agents choose predictors based on their past performance. In a market with rational traders, the model is simplified, but with heterogeneous beliefs, it exhibits complex dynamics, including persistent deviations from the fundamental price and chaotic asset price fluctuations when the intensity of change is high. However, the model has certain limitations in capturing the realities of an evolving, dynamic market. For example, the assumption that agents rely solely on past performance to select predictors may not reflect the complexities of real financial markets. In addition, the model may overlook key behavioral factors, such as market sentiment and risk aversion, which can influence asset prices.

Fama [11] has highlighted the emergence of long-term return anomalies and presented a balanced perspective by examining different anomaly models, such as trader overreaction or under-reaction, post-event continuation, and abnormal return reversal. However, this approach faces challenges relating to empirical evidence, subjectivity, and scope.

Lo [12] proposed the "Adaptive Markets Hypothesis" (AMH) approach to reconcile market efficiency with behavioral factors such as survival in financial markets. He considered behavioral biases as simple heuristics aiding adaptation in a dynamic environment, with implications for portfolio management. However, this approach is still under development and requires more research to validate its hypotheses and empirical evidence.

Against this backdrop, a significant number of studies have focused on the importance of sentiment-based behaviors that tend to emerge in times of crisis. These behaviors play an essential role in investor decision making, and consequently have a significant impact on stock market dynamics. For example, Yutao Chen et al. [13] have studied the impact of investor sentiment on the stock market and asserted that when the influence rate of mutual communication of agent-based investors increases or when the rate of emotional calm decreases, investor emotions begin to diffuse, leading to an increase in the probability of a serious rush or fervent overbought condition in the stock market.

Eachempati et al. [14] and Debata et al. [15] proposed a Twitter machine-learning approach to analyze and track the investor sentiment that guided the market to the new low during the first 150 days of the COVID-19 era.

Lazzini et al. [16] and Wang et al. [17] explored the impact of investors' social networks on stock price dynamics and showed the impact of social networks in manipulating investors' feelings and decision making.

In this context, a growing literature has developed to represent the behavioral market that emphasizes the importance of investors' rationality combined with their emotions [18, 19] and mimics [20] to enhance decision making and explain market dynamics. Tools based on artificial intelligence have emerged to explain and predict stock prices based on the agent's behaviors [21, 22]. Researchers developed agent-based models (ABMs) to model heterogeneous investor behavior and showed the importance of agent interactivity on financial market dynamics [23–25].

Agent-based market simulation allows the reproduction of realistic market features, creates unobserved market states, and explains hidden patterns, to model the impact of an investor's investment actions on the market. It is a decision support system for investors, especially in crisis periods.

Several research studies developed multi-agent systems to explain complex phenomena and predict market dynamics. For example, Said et al. [8] proposed an agent-based decision-making model to represent the dynamics of the stock market during the crisis period. The authors focused on three main biases: overconfidence, loss aversion, and mimetic behavior. They conclude that overconfidence and loss aversion have relevance in explaining the formation and bursting of bubbles and that mimetic behavior has an amplifying role in stock market disruptions.

Kanzari and Ben Said [26] proposed an agent-based investor model adapting their behaviors to changing market conditions (stability vs. instability) and explained the dynamics of price securities formation in the financial market. The authors showed that the dynamic behavior of the rational adaptive agent, which becomes irrational during instability periods, is a relevant determinant of crisis periods. While these studies focused on agents' behaviors and their impact on market volatility, they did not address accurate market price forecasting.

In the volatile and noisy cryptocurrency market, making suitable decisions for agent-based investors can be challenging due to the complex and nonlinear nature of the data. To address this issue, the integration of a deep neural network (LSTM) into the reasoning process [27, 28] offers distinct advantages. LSTM's ability to abstract data features from intricate and nonlinear original data proves beneficial in this context. Additionally, LSTM considers new input features [29] derived from the changing cryptocurrency data, leading to enhanced prediction performance for agent-based models.

Accordingly, we aim to model “DbRAs” agents that simulate humans’ behaviors in the stock market, they have rational, chartist, and mimetic behaviors with deep decision-making reasoning based on LSTM to accurately predict the cryptocurrency price during and after a period of financial instability.

In this work, we present two major contributions:

1. The initial contribution of this research is the introduction of a pioneering decision modeling approach called “DbRAs.” This method enables the simulation of heterogeneous human behaviors and decisions within a dynamically evolving environment, specifically within the context of the cryptocurrency market. Leveraging the power of deep learning techniques, DbRAs accurately captures the intricate dynamics of human decision-making processes in response to the ever-changing landscape of the cryptocurrency market. By employing DbRAs, we gain a comprehensive understanding of the diverse range of behaviors exhibited by individuals, thereby shedding light on the complex dynamics that drive decision making within the cryptocurrency market.
2. The second contribution consists of environment modeling by a DbrAs-based multi-agent system. Through this approach, we elucidate the intricate dynamics within the cryptocurrency market, attributing them to the collective behaviors of DbrAs. Furthermore, we provide empirical evidence showcasing the profound influence exerted by these DbrAs on market prices, solidifying their role in shaping the overall market landscape.

The remainder of the paper is organized as follows. A review of related literature is presented in Sect. 2. Section 3 introduces the DbrA approach and the stock market modeling. The results are outlined in Sect. 4 and discussed in Sect. 5. Finally, Sect. 6 concludes.

2 Related literature

The growth of literature reviews on the importance of multi-agent systems to study the evolution of complex contexts such as the stock market is significant [30–32], especially during and after the crisis. Researchers are using multi-agent system models to emulate complex and diverse market phenomena [33], simulate the consequences of multilateral interactions between agents and their environment, and propose decision support systems to overcome the crisis [34, 35].

Advanced methods based on machine learning have been combined with multi-agent systems to better present the market and accurately predict the financial market dynamics has achieved some level of recent success [31, 36, 37].

Gyeongho Kim et al. [38] proposed a self-attention-based multiple short-term memory method (SAM–LSTM) to predict cryptocurrencies, which consists of several LSTM modules for the groups of variables on the chain and the attention mechanism, for the prediction model. An experimental study on real data of Bitcoin (BTC) prices proved the effectiveness of the proposed method for predicting the price of BTC.

However, training machine learning may suffer from overfitting because the stock market is affected by several external factors like other market trends, political events, market sentiment, and the stock price data are inherently noisy, complex, and nonlinear [39]. To overcome overfitting, Wu et al. [40] suggested an adaptive stock trading strategy based on deep reinforcement learning, which used the gated recurrent unit (GRU) to extract financial feature information that reflects the internal characteristics of the stock market and make adaptive trading decisions.

Oliveira et al. [41] implemented the State-Action-Reward-State-Action (SARSA) reinforcement learning algorithm to learn and decide whether to trade in the market and achieve maximum profit. Salvatore Carta et al. [42] proposed a Q-learning-based agent trained several times to learn how to maximize the return function and study its behavior on real stock markets to improve its performance.

Xiaoming Yu et al. [43] integrated in their study deep reinforcement learning models to optimize decision making in different market environments. The experimental results shown that the annualized return, cumulative return, and Sharpe ratio values of the proposed agents’ strategies were higher than those of the baselines.

Existing work focused on the predictive model’s performance without considering the investor’s internal factors that could influence his final decision making such as rationality, emotions, and mimetics as well as the impact of the multi-agent system on stock price variation. They did not provide a reliable approach that would overcome the complexity of markets and fully predict stock market price fluctuations.

To overcome these limits, Achref Mtir [44] proposed an “Intelligent Stock Market Simulator” composed of three types of traders: rational, emotional, and mimetic to explain the causes of stock market crash through the composition of the stock market. In his approach, the author presented emotional agents whose temperaments vary randomly, independently of the market dynamics, which reduced the reliability of the proposed approach. To analyze the behavior of cryptocurrency users, some interesting work has been done by Krafft et al. [45] who conducted online experiments to assess the strength of peer influence on cryptocurrency users. This study provided insight into the causal impact of individual opinion on large cryptocurrency markets.

Aspembitova et al. [46] combined k-means clustering and support vector machines to infer the types of investor behavior in the Bitcoin and Ethereum cryptocurrency markets. They deduced four distinct strategies that are common to both markets: optimists, pessimists, positive traders, and negative traders. They concluded that bitcoin (ethereum) users tend to take a short-term (long-term) view of the market during local events and optimistic (pessimistic) behavior toward the future of the market for large systemic events. The authors proposed basic agent-based models of similar behaviors and did not establish a relationship between price movements and investors' behavior.

Overall, there is limited work to understand the cryptocurrency system with respect to investor behavior [47]. So far, a few research works have been done to understand the behavior of investors in cryptocurrency markets [25, 48]

The investigation of deep learning methods to identify outliers, save historical data, and improve the cryptocurrency prices prediction is of great interest for the behavioral DbrA decision making. Our proposed model is composed of the most relevant forecasting behavior raised by the literature: fundamentalist, chartist, and herding or mimetic. We introduce the sentiment parameter in the emotional agent expectations. We model three types of agents: rational, behavioral, and mimetic to match the financial markets' reality.

3 Approach: deep learning-based agents to simulate cryptocurrency market dynamics

Stock market modeling with heterogeneous behavioral agents offers a relevant solution to describe the market complexity and predict its dynamics, especially during and after the crisis [49, 50].

Specifically, we aim to represent, by different DbrA models, the realistic decision-making strategies of cryptocurrency users and explain the obvious market composition.

The cryptocurrency market is composed of heterogeneous DbrAs whose common goal is to maximize the gain and avoid investment loss in cryptocurrencies. A DbrA predicts cryptocurrency prices by the deep learning model LSTM and acts accordingly on the market by making decisions (or actions) to hold, buy, or sell cryptocurrencies. The DbrA uses the LSTM model to solve the multivariate time series forecast of cryptocurrency prices. The input data represents historical sequences of cryptocurrency prices and associated indices; the output is the predicted value.

We propose three behavioral DbrA models:

- Rational DbrA represents an experienced investor who mainly focuses on the determinants of cryptocurrency price variation such as historical cryptocurrency prices, volatility indexes, and Market-Value -To-Realized-Value ratio (MVRV). It makes predictions of cryptocurrency prices based on the LSTM model and accordingly takes the most appropriate actions [51].
- Chartist DbrA represents an experienced emotional investor who is influenced by crowd psychology in the cryptocurrency market. It predicts cryptocurrency prices using the LSTM model that considers historical cryptocurrency price sequences and the corresponding market sentiments as input. His final decision includes a confidence level in the deep learning model results [52, 53].
- Mimetic DbrA represents a novice investor who decides from LSTM cryptocurrency price forecasts (which process the latest recent cryptocurrency prices as input) and the most frequent actions of other investors in the market [54].

Different agents behave in ways that can influence, along with other factors, the stability of a cryptocurrency market. The challenge for DbrA investors is to take the most appropriate action of buying, selling, or holding based on an accurate LSTM cryptocurrency price prediction. As shown in Fig. 1, the relational, chartist, and mimetic DbrAs collaborate with the environment agent EnvA to collect data for their market price predictions and decision making.

The EnvA provides updates of cryptocurrency market data according to the actions DbrAs and shares them with all market users. After a set of buying and selling actions, the market price is recalculated according to the observed excess demand D and Supply S. The price impact function is given by Eq. (1) [55]:

$$P_t = P_{t-1} + a((D_t) - (S_t)). \tag{1}$$

where

- $\mathbf{1} < \mathbf{a} > \mathbf{0}$: denotes the speed of price adjustment
- D_t: the number of buying actions at date t
- S_t: the number of selling actions at date t

Equation 1 relates the number of buys and sells actions to the change in the cryptocurrency price. Indeed, excessive buying actions contribute to the price increase, while excessive selling actions contribute to its decrease.

3.1 The DbrA models

The "*DbrAs*" collect from the EnvA the historical cryptocurrency prices of the assets for a given period and activate LSTM-based reasoning to predict the closing price of the asset at the current date. They react by buying, selling, and holding based on the decision-making module. The different proposed agent architectures are described as follows.

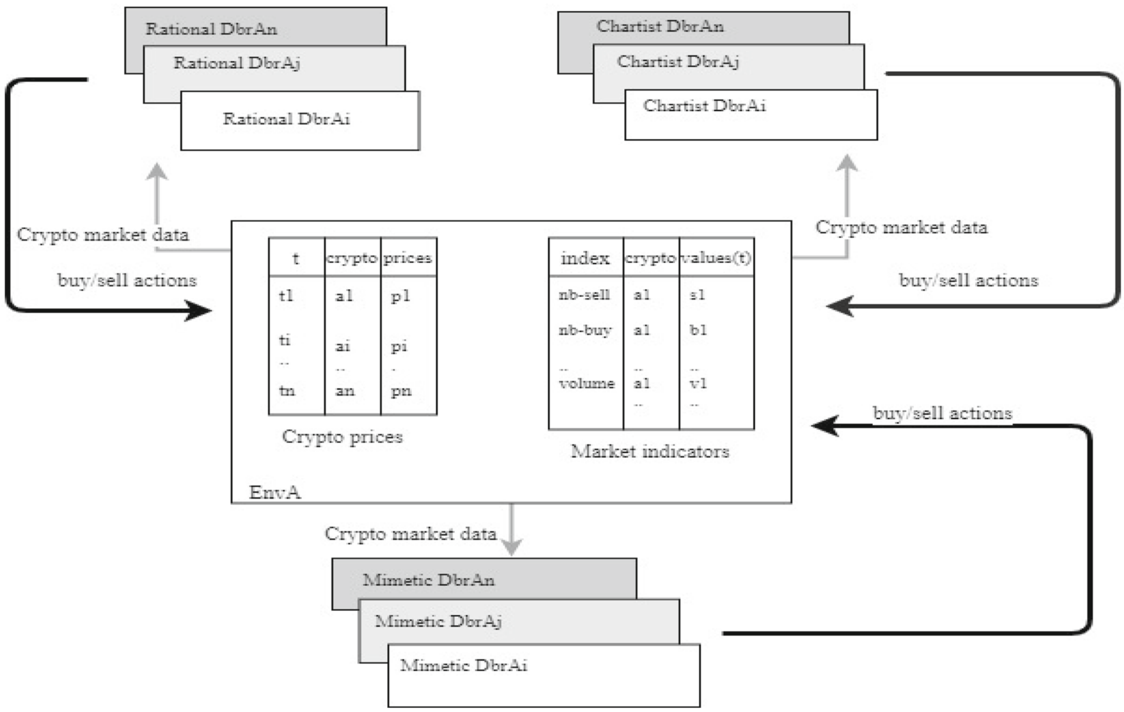


Fig. 1 DbrA-based multi-agent system to simulate the cryptocurrency market

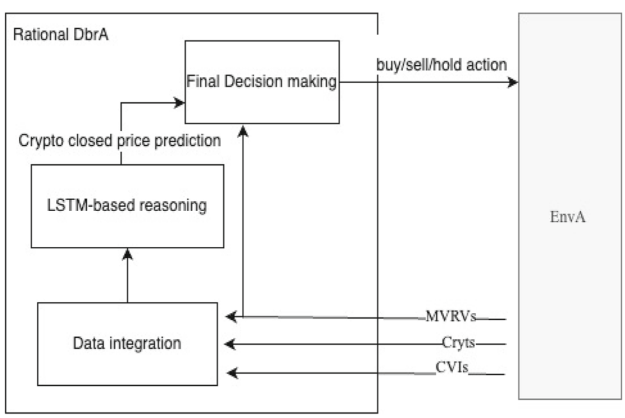


Fig. 2 Rational DbrA model

3.1.1 Rational DbrA model

Rational DbrA assesses the truthful of cryptocurrency prices, the bullish and bearish trend, and the stability of the market via MVRVs ratios and cryptocurrency volatility indices (CVI). He takes rational action that guarantees his long-term gain.

Figure 2 presents the Rational DbrA model where the input data is the n lagged historical cryptocurrency prices Cryts $[\mathrm{Cryt}_t, \mathrm{Cryt}_{t-1}, \ldots, \mathrm{Cryt}_{t-n}]$, the n last CVIs $[\mathrm{CVI}_t, \mathrm{CVI}_{t-1}, \ldots, \mathrm{CVI}_{t-n}]$, and the n last MVRVs $[\mathrm{MVRV}_t, \mathrm{MVRV}_{t-1}, \ldots, \mathrm{MVRV}_{t-n}]$, and the output is the corresponding action $A(t+1)$.

The rational decision making dependent on the LSTM-based cryptocurrency price prediction, the estimated cryptocurrency short trend “e” [defined by Eq. (3)] and the Market-Value-to-Realized-Value (MVRV)[1] ratio. The LSTM-based cryptocurrency price prediction: Our approach involves the LSTM (long short-term memory) model, to accurately predict the cryptocurrency price based on historical cryptocurrency prices, MVRV ratios, and daily volatility (CVI) index. We specifically chose the MVRV ratios and the daily volatility index (CVI) (defined by equation) as essential inputs for the LSTM model due to their strong endorsement in the academic literature as valuable indicators for predicting future cryptocurrency trends and values. These indicators have been referenced in several research papers such as, “Volatility estimation for Bitcoin: A comparison of GARCH models” by Paraskevi Katsiampa [56], “Datestamping the Bitcoin and Ethereum bubbles” by Corbet et al. [57], “Bitcoin Market-Value-to-Realized-Value Ratio” by Murad Mahmudov and David Puell (2018)[2], and “Observing Cryptocurrencies through Robust Anomaly Scores” by Bae and Kim [58].

[1] https://academy.glassnode.com/market/mvrv/mvrv-ratio. [Accessed on 16/07/2023].

[2] https://medium.com/@kenoshaking/bitcoin-market-value-to-realized-value-mvrv-ratio-3ebc914dbaee. [Accessed on 16/07/2023].

The Market-Value-to-Realized-Value (MVRV)[1] ratio compares the market value of a crypto-asset to its realized value, which is the average price at which all coins were last moved. When the MVRV ratio is high, it indicates that the market value is significantly higher than the average cost basis of investors, suggesting a potential overvaluation. Conversely, a low MVRV ratio may indicate an undervalued or attractive buying opportunity. More precisely, we use a range of 2.0 to 3.0 (as proposed in [50] that indicates that an MVRV > 3.7 denotes overvaluation) as a guideline for identifying potential overbought conditions. This means that when the MVRV ratio exceeds 2.0 or approaches 3.0, it suggests that the current market value is significantly higher than the average cost basis of investors, potentially indicating a level of market exuberance. On the other hand, we consider MVRV ratios below 1.0 to be indicative of an undervalued bitcoin market, and thus signal a buying opportunity. The formula of MVRV is defined by Eq. 2.

$$\text{MVRV} = \frac{\text{Market Cap}}{\text{Realized Cap}}. \tag{2}$$

where

- *MarketCap* represents the current market value of a crypto-asset and is widely recognized as a measure of capitalization. It reflects the total value of a cryptocurrency based on its prevailing market price.
- *RealizedCap* refers to the cost basis of the cryptocurrency supply. It evaluates the value of cryptocurrencies by considering the acquisition price of each coin/token.

The ultimate rational decision-making process considers the current cryptocurrency value ($crypt_t$), the estimated LSTM-based cryptocurrency value at $t + 1$ ($\hat{crypt}^{lstm}_{t+1}$), the gap e [59] (defined by Eq. 3), and the MVRV ratio

$$e = (\hat{\text{crypt}}^{\text{lstm}}_{t+1} - \text{crypt}_t)/\text{crypt}_t. \tag{3}$$

The rational final decision to buy, sell, or hold cryptocurrency is governed by the following rules:

1. If MVRV is within the range [2, 3], the decision is to sell the cryptocurrency.
2. If MVRV is within the range (0, 2) and $e > 0$, the decision is to buy the cryptocurrency.
3. If MVRV is within the range (0, 2) and $e < 0$, the decision is to sell the cryptocurrency.
4. Otherwise, the decision is to hold the cryptocurrency.

[1] https://academy.glassnode.com/market/mvrv/mvrv-ratio. [Accessed on 16/ 07/2023].

3.1.2 Chartist DbrA model

Chartist believes that the cryptocurrency price market trend will continue in the short term, and it is impacted by investors' emotional tendency. Therefore, he supervises the greed & fear market sentiment indicator to assess whether the cryptocurrency markets are bullish or bearish. He quantifies sentiment as a score between 0 and 100, with lower scores indicating panic among investors and higher scores denoting greed.

As shown in Fig. 3, to predict the closing Bitcoin prices, he combines the Cryptocurrency Sentiment Indexes (CSIs) and the historical cryptocurrency prices Cryts as the input set of the multivariate LSTM. His final decision depends on the "C" confidence level which marks his confidence degree in the LSTM predictions. Generally, the chartist buys when the predicted price increases with an upward trend and sells when it decreases with a downward trend.

Chartist uses an emotion-based decision-making process based on two key factors: the LSTM expected cryptocurrency closing price, and the Cryptocurrency Sentiment Indexes (CSI) indicator. The process involves integrating the CSI market indicator and the historical prices of cryptocurrencies (Cryts), into a sophisticated multivariate LSTM model. In doing so, chartists acquire the ability to make predictions about future cryptocurrency price movements based on market sentiment and historical crypto-prices. The use of the CSI market indicator, in conjunction with historical prices, enables chartists to assess market sentiment and its potential impact on cryptocurrency performance. The latter quantifies sentiment as a score between 0 and 100, with lower scores indicating panic among investors and higher scores denoting greed. The CSI indicator provides insights into market sentiment and its impact on cryptocurrency performance, enabling chartists to make appropriate prediction of the cryptocurrency's trends. The integration of the CSI indicator into chartists' model is supported by notable research articles such as "Predictive power of investor sentiment for Bitcoin returns: Evidence from the COVID-19 pandemic" by Ahmed Bouteska, Salma Mefteh-Wali, and Trung Dang (published in Technological Forecasting and Social Change, 2022), as well as "Gauging the effect of investor sentiment on the cryptocurrency market: an analysis of bitcoin currency" by Muhammad Mohsin, Sobia Naseem, Larisa Ivascu, Lucian-Ionel Cioca, Muddassar Sarfraz, and Nicolae Stănică (2021). This research underscores the essential role of investor sentiment analysis in understanding a company's performance [60, 61]. The chartist uses the LSTM model's predicted price and the confidence level "C" of the predicted LSTM value to make well-informed decisions. The confidence level "C" regarding the expected LSTM cryptocurrency price is categorized into three values: "Confident," "Fairly Confident," and "Very Confident." The numerical

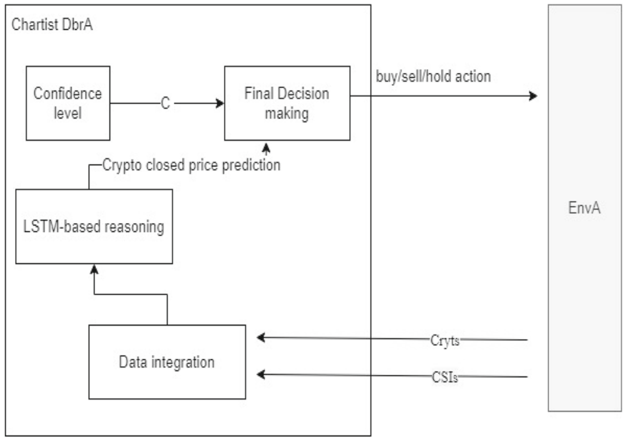


Fig. 3 Chartist DbrA model

value of "C" falls within the range [0.6, 1], where C $\approx$ 0.6 indicates "Confident," C $\approx$ 1 indicates "Very Confident," and any other value corresponds to "Fairly Confident." The ultimate decision depends on the range of values provided by the confidence-weighted cryptocurrency trend estimator δ defined by Eq. (4):

$$\delta = C * e \tag{4}$$

where:

- If $\delta \geq 0.05$
  the cryptocurrency trend is bullish and the decision is buying
- Elseif $\delta \leq -0.05$
  the cryptocurrency trend is bearish and the decision is selling.
- Otherwise the decision is holding

3.1.3 Mimetic DbrA model

He lacks experience in the cryptocurrency market, does not master the determinants of cryptocurrency prices, and considers the recently collected cryptocurrency prices insufficient to make the right decision. He takes into consideration in his final decision the dominant market actions. As illustrated in Fig. 4, the Mimetic DbrA makes a primary decision based on deep reasoning and then looks for the action (buying, selling, observing) most frequently taken by other investors including its own actions. The final action taken by this agent is the one most decided by all agents.

More precisely, mimetic behavior in cryptocurrency trading involves considering the most recent cryptocurrency prices and the decisions made by other traders to arrive at a well-considered final decision. Initially, this decision relies on the estimated cryptocurrency price generated by the LSTM model. This estimation can lead to either buying, selling, or holding cryptocurrency, depending on whether the trend is bullish, bearish, or stagnant, respectively. Afterward, this initial decision is combined with the prevailing action commonly taken by other rational and chartist traders. Ultimately, the final decision is determined by the dominant choice, which considers both the initial decision and the behaviors of other traders in the market.

3.2 LSTM-based reasoning model

By processing lagged cryptocurrency prices and market indices, LSTM-based reasoning cite [62] provides short-term trend forecasting of the cryptocurrency's closing price C_t (see Fig. 5). We adopt the LSTM model due to its effectiveness in solving financial prediction problems based on past observation series. Likewise, it is marked by the ability to save relevant financial data such as capitalized cryptocurrency historical prices and forget outliers.

Figure 5 presents the LSTM structure which is mainly composed of three gates:

- The forget gate removes irrelevant information and determines which information from the previous hidden state h_{t-1} and the current input data x_t should be kept or forgotten. The output value f_t, presented by Eq. 5, is between 0 and 1. The value closest to 0 means forget, and the value closest to 1 means keep.

  $$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f). \tag{5}$$

  where

  - σ: the nonlinear sigmoid functions, $\sigma(x) = \frac{1}{1+e^{-x}}$
  - W_f: weight matrix,
  - t: time step
  - h_{t-1}: previous hidden state
  - x_t: input data, b_f: forget bias.

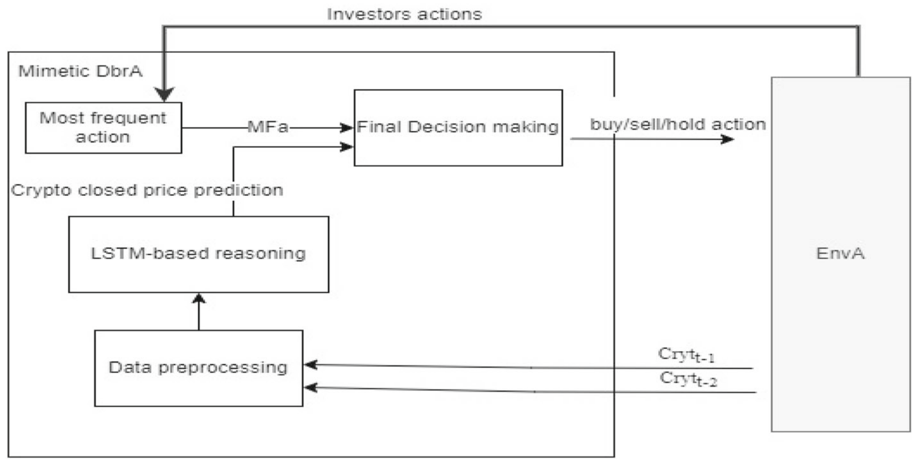
- The input gate adds input data to the cell's hidden state and determines which values will be updated by multiplying the function by the tanh. The output value i_t of this gate at time step t is defined by Eq. (6)

  $$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \otimes \tan(W_c[h_{t-1}, x_t]). \tag{6}$$

  where

  - t: the time step,
  - σ: sigmoid functions,
  - tan: hyperbolic tangent function,
  - W_i, W_c: weight matrices between input and output gate,

Fig. 4 Mimetic DbrA model



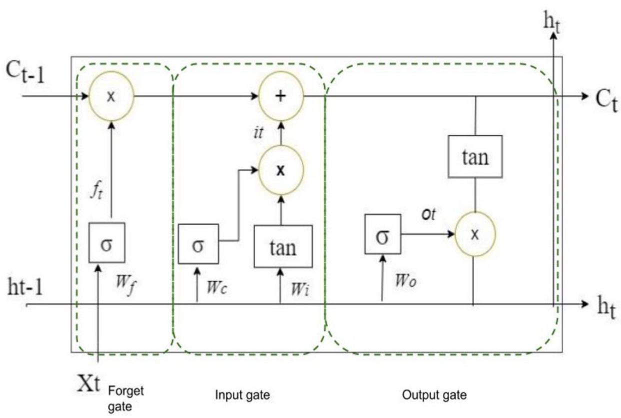


Fig. 5 LSTM structure

- b_i: input bias.

- The output gate provides the relevant information to keep in output. It provides the final state of the cell C_t (predicted data) and the hidden state h_t (stored data) of the network at the next time step (t). The outputs gate h_t and C_t are defined by Eqs. (7) and (8).

$$h_t = o_t \times \tan(C_t). \tag{7}$$

where

- $\tan(C_t) = \frac{2}{1+e^{-2C_t}} - 1$,
- $o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$,
- W_o: Weight matrix
- b_o: Output bias.

$$C_t = \sigma(f_t * C_{t-1} + i_t). \tag{8}$$

4 Experimental study

To assess the rational, chartist, and mimetic DbrAs' behaviors along with their impacts on cryptocurrency price variation, and to explain the cryptocurrency market composition that closely reflects the real market, we conduct microscopic experiments dealing with the individual DbrAs behaviors and macroscopic experiments describing the effect of the DbrAs' crowd behavior on the cryptocurrency market dynamics.

4.1 Individual DbrA behaviors

The different behavioral DbrAs (rational, chartist, and mimetic) could collect data from several resources, prepare the data to be handled by the LSTM-based price prediction, and perform a holding, buying, or selling action in the cryptocurrency market. The actions of the different DbrAs contribute to cryptocurrency market dynamics.

We chose to simulate the DbrAs' behaviors in the Bitcoin-USD market given the investor interest in this currency as a secure [63, 64] safe haven [65], especially during and after the COVID'19 crisis [66].

We conduct three in-depth experiments detailing the different DbrA reasoning: Experiment 1, Experiment 2, and Experiment 3.

4.1.1 Experiment 1: rational DbrA behavior simulation

The rational DbrA collects data from Yahoo Finance cryptocurrency market, and Coinmetrics websites and decides to observe, sell, or buy BTC-USD based on the historical bitcoin prices, the MVRV ratios (see Eq. 5), and the daily Bitcoin Volatility Indexes "BVI" [67–69] (see Eq. 9). In fact, the MVRV index indicates whether the price of BTC is fair or not and allows for a long-term market cycle evaluation: if this index is high, BTC will experience significant growth, otherwise it will fall. The volatility index measures the stability of the market and the amount of BTC price fluctuations over a time frame. A buy action is taken if there is an expected future gain, a sell action if there is an immediate profit or loss aversion, and no action if there is no profit [69].

$$\text{BVI} = \sqrt{\left(\frac{\sum_{t_0}^{t_n}\left(\text{BTC}_{t_0} - \text{BTC}_{t_n}\right)^2}{n}\right)}. \tag{9}$$

where

- BTC_{t_0}: the Bitcoin value at t_0,
- BTC_{t_n}: the Bitcoin value at t_n,
- n: the number of sample.

4.1.2 Chartist DbrA behavior

The DbrA chartist collects historical Bitcoin prices from Yahoo finance, and the "Greed & Fear" Bitcoin Sentiment Indexes "BSI" from the "Bitcoin sentiment—Bull & Bear Index" websites to make the safest and most reassuring decision. A buy action is taken if there is a safe future gain, a sell action if there is an immediate profit or loss aversion, and no action if there is no profit. A chartist is characterized by an emotional "C" character that marks his level of confidence in the bitcoin price prediction by the LTSM process. "C" can take the values "confident," "fairly confident" and "very confident."

4.1.3 Mimetic DbrA behavior

The mimetic DbrA collects recent BTC data from Yahoo-Finance, predicts the next short-term BTC price, and then compares its own decision with those of other DbrAs to make the most dominant hold, buy, or sell action. He considers the major decision of the crowd to be the most appropriate and fair. The mimetic behavior has a very important impact on the dynamics of the cryptocurrency market.

4.1.4 LSTM-based deep reasoning training

LSTM training is based on the Backpropagation algorithm and Real-Time Recurrent Learning [70]. In each training epoch, the weights $W = (W1, \ldots, WL + 1)$ connecting the different layers $L = (1 \ldots L)$ of the network and $b = (b1, \ldots, bL + 1)$ are updated by the backpropagation learning algorithm to minimize the cost function E defined by Eq. 10.

$$E_t = \left(y_t - \hat{y}_t\right). \tag{10}$$

y_t is the desired output and $\hat{y}_t$ the network output at time t. The overall network error is E defined by Eq. 11.

$$E = \frac{1}{2}\sum_{1}^{T} E_t^2. \tag{11}$$

E is used to update the network weight ΔW presented in Eq. 12.

$$\Delta W = \mu \frac{\delta E}{\delta W}, \mu \in [01] \quad (\mu \text{ is the learning rate}) \tag{12}$$

The proposed LSTM model has subsequent layers with 40, 20, and 1 nodes. The last layer of the model is a fully connected neural network with 1 output node. The function activations are sigmoid and tanh functions, and the model was set for 100 and 200 epochs. The model is using early stopping algorithm to gain the best value of validation accuracy and RMSE.

To train the LSTM model, we collect BTC historical daily prices from yahoo finance, and the MVRV and the CVT historical index values from the Coinmetrics website from the period 2019-12-07 to 2022-05-10 (COVID'19 crisis period). We separate the dataset into a training set (60%) and a test set (40%). We fitted the model with the training set and evaluated it with the test set. In the different experiments, we set the number of LSTM training epochs to 100 (the number that gave optimal LSTM training results).

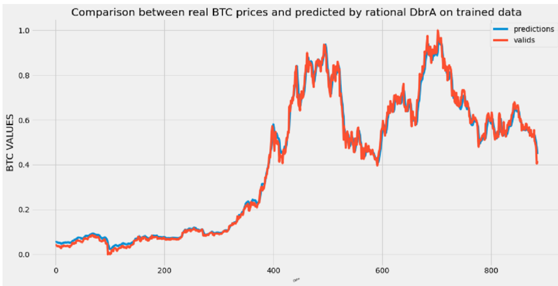
To assess the performance of the LSTM-based model, we conduct a comparative analysis between the LSTM-predicted BTC values and the real market values for trained data and out sampled data.

4.1.5 Results: comparison between Real BTC versus predicted BTC

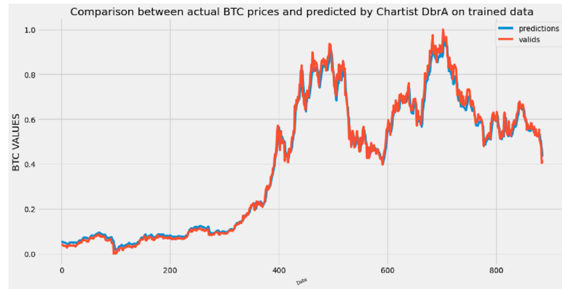
Figure 6 analyzes the real market BTC values against the predicted LSTM values obtained from the three experiments (Experiment 1, Experiment 2, and Experiment 3). In each window in Fig. 6, the blue line shows the predicted BTC values and the orange line shows the real values. As the two lines overlap, it appears that the real BTC values coincide with the predicted values with an R^2 score [71] equal to 0.99 for all three experiments (1, 2, 3). The results prove that the LSTM is well fitted and can accurately predict USD-BTC values for trained data. Table 1 summarizes the prediction error metrics of the proposed models compared to the real bitcoin values on the training data.

We find that the different LSTM-based multivariate models provide low values of RMSE, MAE, and MSE, which proves the forecasting performance of these models.

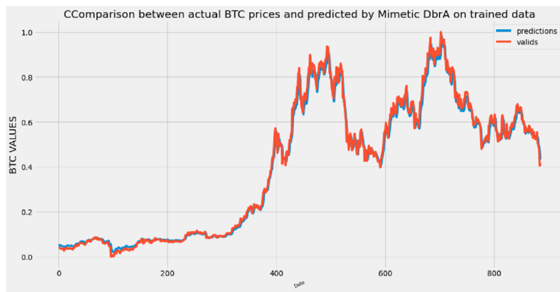
The results presented in Table 1 offer compelling evidence of the remarkable predictive prowess of DbrAs models in



(a) Experiment 1: Rational DbrA behavior



(b) Experiment 2: Chartist DbrA behavior



(c) Experiment 3: Mimetic DbrA behavior

Fig. 6 Experimental results of behavioral DbrAs predictions

Table 1 Errors metrics of DbrAs's predictions on trained data

Experiments	RMSE	MSE	MAE
Experiment 1	0.0241	0.00058	0.0166
Experiment 2	0.0265	0.0007	0.0184
Experiment 3	0.0262	0.0007	0.0201

Table 2 Error metrics of DbrAs's predictions on out-of-sample data

Experiments	RMSE	MSE	MAE
Experiment 1	0.0765	0.0058	0.0541
Experiment 2	0.0957	0.0091	0.0716
Experiment 3	0.0824	0.0068	0.0611

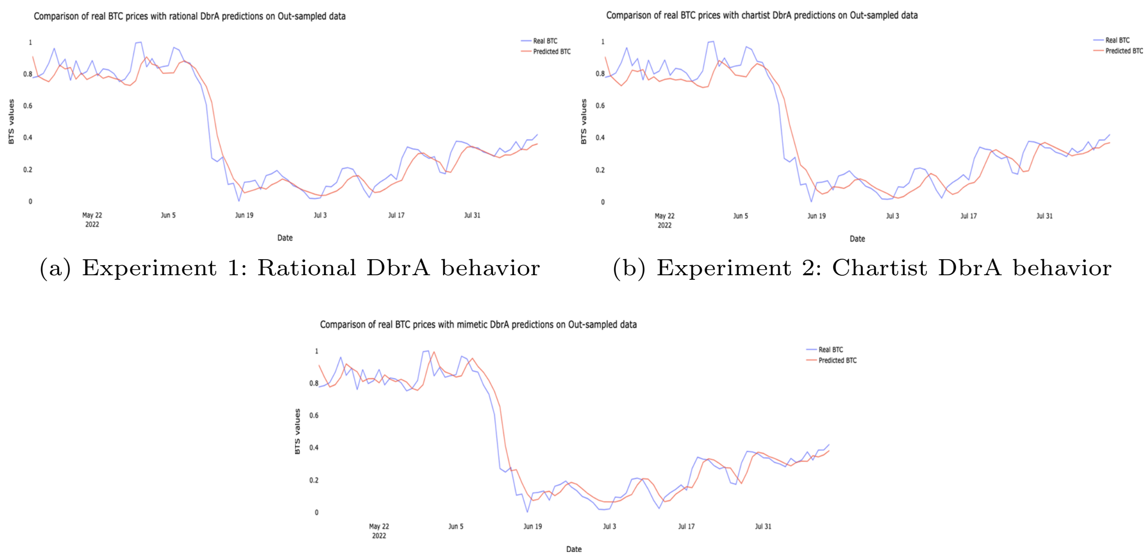
the realm of cryptocurrency price forecasting. This exceptional accuracy can primarily be attributed to the model's reliance on the LSTM model, renowned for its impressive predictive capabilities. By harnessing LSTM, our approach demonstrates a strong capacity to deliver highly accurate price predictions within the dynamic cryptocurrency market. Moreover, the outstanding predictive performance of DbrA can be attributed to the careful selection of input variables integrated into LSTM, including MVRV and CSI ratios. These variables are widely acknowledged for their significant impact on cryptocurrency price variations, rendering them crucial for enhancing the overall predictive accuracy of our model. By incorporating these vital indicators, our DbrA approach gains a significant edge in effectively capturing market trends and fluctuations in the cryptocurrency domain.

4.1.6 Models' validation on out-of-sample data

This phase aims to test the different DbrA models on unobserved (or out-of-sample) data. The goal is to evaluate the already fitted models by calculating the MSE (Mean_Squared_Error), RMSE (Root Mean_Squared_Error), and MAE (Mean Absolute Error) errors [72] between predicted and actual values. We overfit the DbrA models on the new BTC values and the associated indices (MVRV, CVI, SVI) from the period May 11, 2020, to August 12, 2022 (post-COVID-19 crisis), and evaluate the predictive performance of the three models (see Table 2). The out-of-sample data help us to evaluate the generalization error of these models [73]. Figure 7 shows the real BTC values compared to those predicted by the rational, chartist, and mimetic DbrA models for the above period. The R2 score is respectively 0.94225, 0.9096 and 0.933 for Experiment 1, Experiment 2, and Experiment 3.

4.2 Currency price prediction based on the actions of agent-based investorCryptos

We deploy behavioral DbrAs on an artificial bitcoin market to examine the price changes incurred by the different agents' actions, and then study the market price change using the



(a) Experiment 1: Rational DbrA behavior (b) Experiment 2: Chartist DbrA behavior

(c) Experiment 3: Mimetic DbrA behavior

Fig. 7 Experimental results of behavioral DbrAs predictions on out-of-sample data

econometric method (see Eq. 1) presenting the formation of stock market prices as a function of the number of purchases and sales. Our goal is to simulate the real bitcoin stock market and to explain its composition and the main causes that can lead to its growth or failure. The multi-agent system is composed of a set of DbrA investors that observe new BTC prices (out-of-sample) and the related indexes to take adequate actions.

We simulate 4 scenarios with different numbers of rational, chartist, and mimetic DbRAs. Each scenario specifies the dominance of a DbrA type. Table 3 presents the metrics errors of the 4 scenarios defined as follows:

- *Scenario 1* Equal-sized DbrAs
- *Scenario 2* Rational DbrAs are dominant
- *Scenario 3* Chartist DbrAs are dominant
- *Scenario 4* Mimetic DbrAs are dominant

In each scenario, we run 1000 agents distributed in rational, chartist, and mimetic DbrAs for a test period from May 11, 2020, to August 12, 2022. The objective is to evaluate the predicted bitcoin price p_t at each time step t generated by Eq. 1 [55] by comparing it with the real market value and assess the impact of dominant behavior on price variation. As well as to explain the DbrAs distribution that reflects the real structure of the bitcoin market.

4.2.1 Scenarios 1: equal-sized DbrA's simulation in the artificial bitcoin market

The artificial bitcoin market is composed of an equal number of DbrA types. Each type has its own decision strategy to get an estimated gain. In this scenario, the DbrAs are distributed as follows: 33.5% rational, 33.5% chartist, and 33.5% mimetic. Figure 8 shows the price prediction by the DbrAs-based multi-agent system compared with the real one. The red color in the graph shows the actual bitcoin values and the blue shows the DbrAs-based multi-agent price prediction. The blue curve has the same shape as the red one confirming that the multi-agent system based on equal-sized DbrAs has well learned the market trend with an MAE error equal to 0.0560 (see Table 3).

Table 3 Accuracy tests between predict BTC and real BTC for out sampled data

Scenarios	RMSE	MSE	MAE
Scenarios 1	0.0756	0.00571	0.0560
Scenarios 2	0.0746	0.0055	0.0542
Scenarios 3	0.0807	0.0065	0.0621
Scenarios 4	0.1076	0.0115	0.0881

4.2.2 Scenarios 2: rational DbrA are dominant

The distribution of DbrAs is 60% rational, 20% chartist, and 20% mimetic. Figure 9 shows several crossover points and a close alignment between the two curves indicating a small error margin between the predicted and real bitcoin values.

As presented in Table 3, the MAE of this scenario is 0.0542, which means that the dominant rational DbrA has an accurate prediction of the bitcoin price dynamics and controls the bitcoin market.

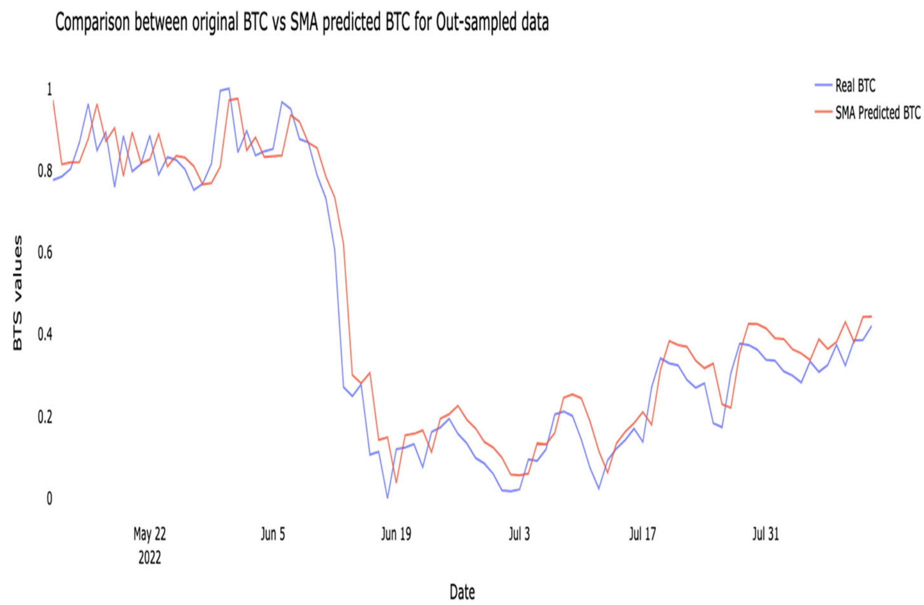


Fig. 8 BTC close price prediction by Multi-Agent-Equal-sized DbrAs VS real BTC values

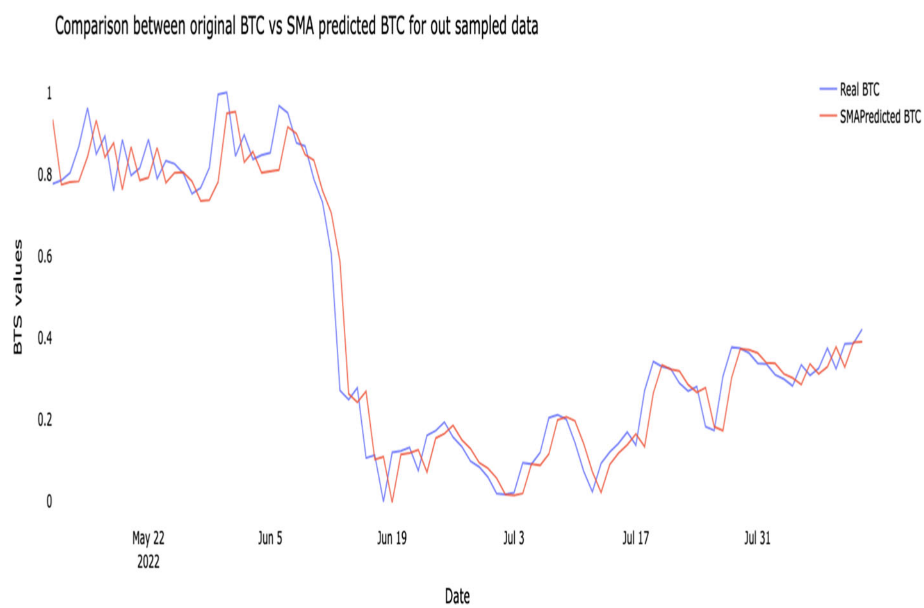


Fig. 9 BTC close price prediction by multi-agent-dominant rational VS real BTC values

4.2.3 Scenarios 3: chartist DbrAs are dominant

The DbrAs distribution is 20% rational, 60% chartist agents, and 20% mimetic agents. Figure 10 shows that the predictions of the multi-agent system dominated by the chartist DbrAs are very close to those of the real values. This means that the dominant chartist correctly predicts the bitcoin trend influenced by market sentiment with an MAE value equal to 0.0621.

4.2.4 Scenarios 4: mimetics DbrAs are dominant

The DbrAs distribution is as follows: 20% rational agents, 20% emotional agents, and 60% mimetic agents. Figure 11 outlines that the prices predicted by the multi-agent system dominated by the chartist DbrAs are far from the actual BTC values with an MAE error equal to 0.0881 (see Table 3).

Comparing the different scenarios, we conclude that the composition of the bitcoin market is closest to reality in the second scenario since it provides the lowest error measures.

We can conclude that the bitcoin market is dominated by rational experts based on a deep-LSTM-learning model who

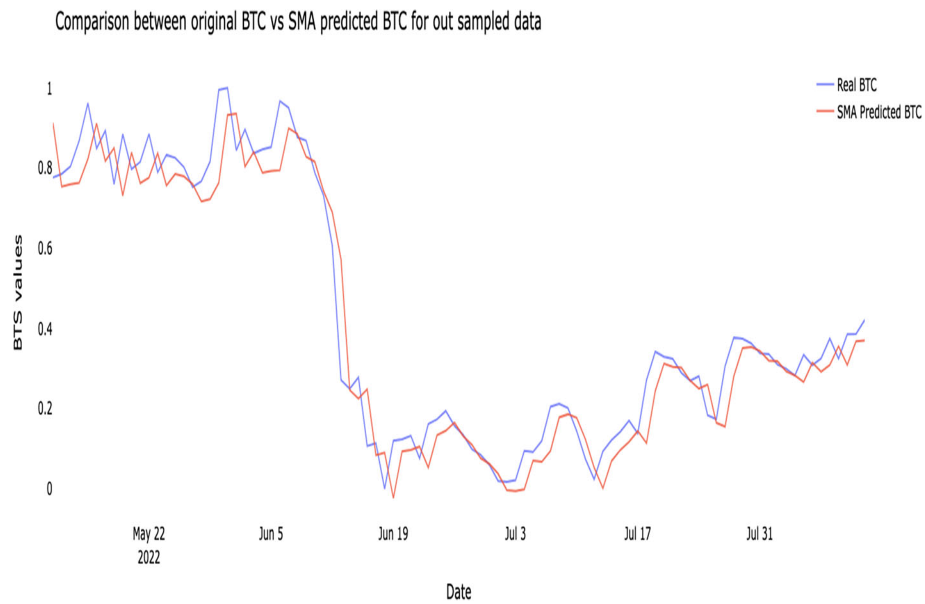


Fig. 10 BTC close price prediction by multi-agent-dominant chartist DbrA VS real BTC values

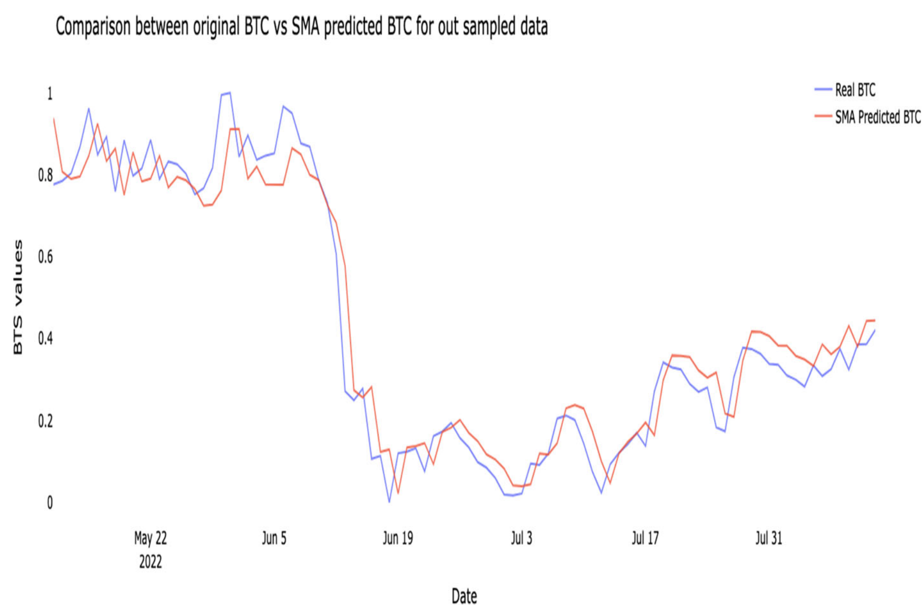


Fig. 11 BTC close price prediction by multi-agent-dominant mimetic DbrA VS real BTC values

can accurately predict the market dynamics and take the most appropriate actions to buy, sell or hold.

5 Discuss

The aforementioned findings substantiated the high prediction accuracy of the proposed LSTM-based DbrAs models. This was achieved by evaluating various metrics, including the mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE), which measured the disparities between the projected and actual values of bitcoin price.

By analyzing the outcomes of our simulations, we gain insight into the structure of the bitcoin market throughout two distinct periods: the COVID-19 period spanning from December 7, 2019, to May 10, 2022, and the post-COVID-19 period from May 11, 2020, to August 12, 2022. Moreover, we determine which of these periods better aligns with the actual market conditions. It becomes evident that the behavior exhibited by rational agents proves most fitting for accurately capturing the dynamics of the real bitcoin market. The above-mentioned findings provide strong evidence supporting the superior prediction accuracy of the proposed LSTM-based DbrAs models. This was demonstrated through the evaluation of several metrics, such as mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE), which quantified the disparities between the predicted and actual values of bitcoin price. The high accuracy of the DbrAs models can be attributed to two key factors. Firstly, the LSTM model itself, with its ability to capture complex temporal dependencies, plays a pivotal role in achieving precise predictions. Secondly, the crucial aspect of the model lies in the thoughtful selection of input variables to the LSTM. These variables aptly represent the state of cryptocurrency variations, ensuring that the model is provided with essential information to make accurate predictions. By incorporating significant indicators like MVRV and CSI ratios, the DbrAs approach gains a competitive edge in capturing the intricate dynamics of the cryptocurrency market.

There are several avenues for enhancing our current research. One such avenue involves integrating additional forms of diverse input data into our analysis. Moreover, we can advance the learning model itself to achieve even more robust and accurate results. Additionally, it is worth exploring the applicability of our proposed model in forecasting other types of cryptocurrencies, thereby broadening its scope and potential impact.

6 Conclusion

In our investigation, we employed the multivariate LSTM approach within the framework of DbrA models to simulate diverse behavioral patterns among investors in the cryptocurrency market. By doing so, we elucidated the influence of investors' decisions on the fluctuation of market prices. Our findings unequivocally demonstrate that the actual market is predominantly steered by rational DbrAs, capable of effectively predicting market dynamics and making optimal decisions. We also proved the advantage of LSTM-based reasoning to effectively predict bitcoin prices in a dynamic and context-sensitive market by including key determinants of the trading environment such as MVRV (Market Value To Realized Value), CVI (Cryptocurrency Volatility Indexes), and CVI (Cryptocurrency Sentiment Indexes) in the learning process. In order to validate the efficacy of the proposed DbrA models, we conducted a thorough comparison between the bitcoin price predictions generated by various individual DbrAs and the observed prices obtained from Yahoo Bitcoin USD (BTC-USD). Our analysis conclusively revealed that the rational DbrA model outperforms other models, exhibiting significantly higher accuracy with a minimal error rate. This serves as compelling evidence of the superior predictive capability and reliability of the rational DbrA model.

In the subsequent phase of our research, we conducted a comprehensive analysis encompassing four distinct scenarios that delineated the behaviors of the DbrA-based multi-agent system. These scenarios were categorized as follows: (1) Equal representation of Rational DbrAs, (2) Dominance of Rational DbrAs, (3) Dominance of Chartist DbrAs, and (4) Dominance of Mimetic DbrAs. We proceeded to compare the price outcomes generated by the DbrAs-based multi-agent system with the observed prices obtained from Yahoo Bitcoin-USD (BTC-USD) spanning the period from May 11, 2020, to August 12, 2022. Through an in-depth examination of error measures, we deduced that the bitcoin market primarily governed by rational DbrAs closely resembles the actual market dynamics, thus indicating its proximity to reality. Taking various perspectives into consideration, our objective is to enhance the rational model by incorporating emotions. This addition aims to more accurately depict the behavior of expert investors in the dynamic cryptocurrency market. Furthermore, we plan to incorporate non-financial data resources, such as social network data and media news trends, to construct a comprehensive decision support system. This system will be designed to adapt decisions in response to contextual events, resulting in a versatile and adaptable model. By incorporating these elements, our aim is to create a generic decision support system that effectively captures the complex interplay of factors in the cryptocurrency market.

Author Contributions The work presented within this paper is attributed to DK, who has made substantial contributions in conceptualizing, executing, and documenting the research findings. DK is acknowledged as the primary author and contributor to this paper.

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Data availability Data is available at Yahoo Finance and Cointmetrics.com websites.

Declarations

Conflict of interest I kindly request the evaluation and potential publication of my manuscript titled "Context-adaptive intelligent agents behaviors: Multivariate LSTM-based decision making on the cryptocurrency market" in the International Journal of Data Science and Analytics, particularly in the "Special Issue on Data Science and AI in Finance." I affirm that this work is original, has not been previously published, and is not currently under review for publication elsewhere. I hereby declare that I have no conflicts of interest to disclose. Any communication regarding this manuscript should be directed to me at dalel.kanzari@issatso.u-sousse.tn. Thank you for considering my submission, and I look forward to your response.

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