Exploring the behavioral patterns and cognitive biases of stock market investors

Maciej Tkacz
Politechnika Gdanska
tkacz.mac@gmail.com

Celina Olszak
University of Economics in Katowice
olszak@ue.katowice.pl

Jozef Zurada
University of Louisville
jozef.zurada@louisville.edu

Pawel Weichbroth
Gdansk University of Technology
pawweic1@pg.edu.pl

Abstract

This study aims to explore behavioral patterns and cognitive biases among stock market investors. By analyzing investor behavior through a stock market simulator, the research seeks to understand the impact of cognitive biases on investment decisions. The methodology encompasses a detailed analysis of transaction data to identify prevalent patterns and biases. Findings suggest that biases such as overconfidence, representativeness heuristic, gambler's fallacy, and herd mentality significantly influence investor behavior.

1. Introduction

Financial markets are a crucial component of the global economy (Von Briel and Recker, 2016), serving as a primary avenue for capital investment and wealth creation. However, investor behavior is not always rational, leading to market inefficiencies and anomalies (Ossareh et al., 2021). This study explores how cognitive biases and behavioral patterns among investors impact market dynamics and individual investment strategies. By understanding these patterns, we can develop tools and techniques to improve investor decision-making (Olszak, 2014). The study leverages a stock market simulator to gather transaction data. Big data tools and technologies can collect and process large volumes of complex datasets efficiently (Olszak and Mach-Król, 2018), making it easier to identify patterns and biases in investor behavior. AI techniques, such as machine learning algorithms, can be applied to the transaction data to identify and predict behavioral patterns and cognitive biases. These techniques can automate the analysis process, uncovering subtle and complex relationships in the data that might be missed by traditional analytical methods. The stock market simulator itself can be seen as an AI tool that generates data for analysis. It simulates real-world scenarios where AI can be used to predict market movements and investor reactions, providing a controlled environment to study the impact of cognitive biases. The use of advanced analytics, driven by big data and AI, to dissect transaction data showcases the innovative use of technology in financial analysis. This can help organizations stay ahead in the competitive market by understanding and anticipating investor behavior.

The rest of the paper is structured as follows. In Section 2 we provide the theoretical background of our study. In Section 3 we introduce the decision model, used in the classification process. In Section 4 we describe the experimental settings. In Section 5 we analyze the results of the simulation performed. In Section 6 we discuss and conclude the study.

2. Theoretical Background

2.1. Behavioral Finance

Behavioral finance emerged in the late 20th century in response to traditional financial theories such as the Efficient Market Hypothesis (EMH) (Fama, 1970), which assumes that markets are rational and prices reflect all available information. The field seeks to understand how psychological factors influence financial decision-making and market behavior. The roots of behavioral finance can be traced back to the work of Herbert Simon, who introduced the concept of "bounded rationality," which suggests that people are not always perfectly rational due to cognitive limitations. Later, the prospect theory introduced by Kahneman and Tversky (2013) further advanced the field by demonstrating that people value gains and losses differently, leading to irrational decisions. This laid the foundation for the study of cognitive biases and simulators in the financial context (Furnham and Boo, 2011; Qianyun and Xiaoyan, 2021; Mohanty et al., 2023; Ruggeri et al., 2023).

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2.2. Cognitive Biases in Investing

Cognitive biases are systematic patterns of deviation from rationality, affecting how individuals process information and make decisions. These biases can lead investors to make irrational choices, contributing to market inefficiencies and anomalies. They refer mainly:

- Overconfidence. Overconfidence is a common cognitive bias where individuals overestimate their skills or knowledge, leading to excessive risk-taking and poor investment choices. In investing, this bias can manifest in over-trading, taking unnecessary risks, or holding onto losing stocks with the expectation of recovery.

- Representativeness Heuristic. Representativeness heuristic involves making decisions based on past events or stereotypes. Investors may overestimate the probability of certain outcomes based on historical patterns, leading to flawed assumptions about future performance. This can result in chasing trends or investing in "hot" stocks without thorough analysis.

- Gambler's Fallacy. The gambler's fallacy is the belief that past events affect future probabilities, such as expecting a different outcome after a series of similar results. In investing, this can lead to poor decisions, as investors might expect a change in trends without considering underlying fundamentals. This bias can drive speculative trading and increase market volatility.

- Anchoring. Anchoring occurs when individuals rely too heavily on an initial piece of information when making decisions. In investing, this bias can lead to anchoring on specific price points, preventing investors from adapting to changing market conditions. This can result in missed opportunities or holding onto losing investments for too long.

- Loss Aversion. Loss aversion is a bias where individuals prefer avoiding losses over acquiring gains. According to prospect theory, the pain of losing is psychologically more significant than the pleasure of gaining, leading to risk-averse behavior. In investing, this can cause investors to hold onto losing stocks or avoid potentially profitable opportunities due to the fear of loss.

- Confirmation Bias. Confirmation bias involves seeking out information that confirms existing beliefs while ignoring contradictory evidence. This bias can lead investors to make decisions based on preconceptions rather than objective analysis, reinforcing flawed investment strategies. It can also contribute to "group-think," where investors follow the crowd without independent analysis.

- Endowment Effect. The endowment effect is a bias where individuals value assets they own more highly than similar assets they do not own. This can lead investors to overvalue their current holdings and resist selling, even when doing so would be financially advantageous. This bias contributes to inefficient portfolio management and reduced diversification.

- Status Quo Bias. Status quo bias is a preference for the current state of affairs, leading individuals to resist change. In investing, this can manifest as reluctance to adjust portfolios, even when market conditions suggest a need for change. This bias can result in missed opportunities and poor investment performance.

To mitigate the effects of overreaction bias, investors can use several strategies:

- Long-Term Perspective: Focusing on long-term fundamentals rather than short-term market fluctuations can reduce the impact of overreaction.

- Diversification: A diversified portfolio is less likely to be affected by sudden market swings.

- Automated Trading Systems: These systems can help reduce emotional reactions to news, providing a more objective approach to investing.

2.3. Behavioral Patterns in Investing

Behavioral patterns in investing refer to observable trends in investor behavior. These patterns are influenced by cognitive biases and can lead to herd behavior, trend-following, or contrarianism. Understanding these patterns helps explain market dynamics and investor sentiment. The most well-known behavioral patterns concern:

- Herd Mentality. Herd mentality, or herd behavior, is a pattern where investors follow the actions of others, often leading to market bubbles and crashes. This behavior is driven by social conformity and the fear of missing out on trends. Herd mentality can cause overreactions to news or market events, contributing to increased volatility.

- Contrarianism. Contrarianism is the opposite of herd mentality, where investors deliberately act against prevailing trends. While this approach can lead to unique investment opportunities, it can also result in missed gains if market trends continue. Contrarian investors often focus on undervalued stocks, seeking opportunities that others might overlook.

- Momentum Investing. Momentum investing involves buying stocks that have been performing well and selling those that have been performing poorly. This strategy assumes that trends will continue, but it can lead to overestimation of future performance and increased risk-taking. Momentum investing can contribute to market bubbles if not carefully managed.

3. Classification Model

The recorded fields of stock purchase and sale transactions can be divided into two subgroups: the first contains values that define basic information about the company and the event itself, and the second contains data calculated by the investor's mobile application. The first group contains the following elements: the number of shares that the investor buys or sells, the date of recording the event (defined numerically as a timestamp), the abbreviated company name, the current stock price at the time of creating the event, the type of transaction, which can take one of two values: *Buy* or *Sell*. The second group of elements in the event model is an element called *Response*. This is a symbol that is mapped to a specific answer to the question *Why is the investor selling or buying these stocks?*, as well as to a cognitive bias or behavioral model. Table 1 shows the mapping between cognitive biases and the corresponding reasons for buying and selling stocks.

The mapped responses reflect certain behaviors that occur, such as cognitive biases. For example, consider *overconfidence*, which is characterized by buying a large amount of stock without diversifying the portfolio, demonstrating strong confidence in the decision-making process and in one's ability to predict stock prices.

Another element is "percent", which represents the percentage difference between the last two stock price samples. The *RSI* (Relative Strength Index) is an indicator that measures the strength of a trend in technical analysis and takes values from 0 to 100 (Chou et al., 2014). It contains a weighting factor, which makes it a weighted moving average. *RSI* is calculated according to the following formula:

$$RSI = 100 - 100/(1 + RS) \tag{1}$$

where:

- $RS = a/b$; a is the average increase in closing prices over 30 days, and b is the average decrease in closing prices over 30 days.

A 30-day period was used for calculations without a specific justification for this choice. This time frame was considered the most optimal and transparent. The next element is the trend, which defines the direction in which stock prices are moving. Here, a 30-day period was also chosen, from which price samples are taken. It can take on two values, *Asc* and *Desc*. In simple terms, this parameter shows the direction the market is heading, indicating investor activity over a short time frame. If supply prevails, we see a downward trend, and if demand prevails, we see an upward trend.

Both the *RSI* and *Williams %R* indicators were implemented. The latter was designed for daily intervals, but it's worth noting that at the time of its invention, computing power was much lower than today. Currently, the *Williams %R* (or just *%R*) indicator is also commonly used for shorter time intervals. Interestingly, it is also a tool for long-term market analysis of stocks, bonds, and commodities (Zhang et al., 2019). The following formula was used to calculate *%R* indicator:

$$\%R = ((P - P_{max30})/(P_{max30} - P_{min30})) * 100 \tag{2}$$

where:

- P is the stock price on any given day, P_{max30} is the maximum stock price among all price samples from the last 30 days, and P_{min30} is the minimum stock price among all price samples from the last 30 days.

A 30-day period was also used for this indicator, from which stock price samples are taken. It takes on values from 0 to 100. An extreme value of 100 means that the current closing price is the lowest of the last 30 days, while a value of 0 means that the current closing price is the highest of the last 30 days. The threshold values for buying and selling stocks are defined as below 80 as indicating an oversold market and above 20 as indicating an overbought market.

An important stage in the exploration is mapping events to appropriate labels. The first type of labeling involves mapping numerical values, such as the Williams %R indicator, to binary values of 0 or 1. For example, if the value of this indicator is -90, it means the market is oversold (this happens for values below 80)

Table 1. Table showing mapped responses with symbols for cognitive errors

Symbol	Cognitive bias	Buy	Sell
NPS_K/S	Overconfidence	I base my strategy on executing a large number of purchase transactions because each of my decisions is usually correct.	Based on my experience, I know I just need to sell these stocks because each of my decisions is usually correct, and I am sure the price will not rise.
HR_K/S	Representativeness Heuristic	I previously bought a company that had similar parameters, such as a trend on the chart. Looking at the similarity of this situation, I am buying shares.	I previously sold a company that had similar parameters, such as a trend on the chart. Looking at the similarity of this situation, I am selling shares.
EDP_K/S	Hot-Hand Fallacy	Most of my currently purchased shares are rising, so these will rise too.	Most of my currently purchased shares are falling, so these will fall too.
EZP_K/S	Gambler's Fallacy		Most of my currently purchased shares are falling, so these will fall too.

Table 2. Table showing mapped responses with symbols for behavioral patterns

Symbol	Behavioral pattern	Buy	Sell
ES_K/S	Herd Behavior	My investment partners have also recently bought these stocks, so I am doing it too.	My investment partners have also recently sold these stocks, so I am doing it too.
Z_K/S	Surprise	The company has surprisingly good financial results, so I am buying.	The company has surprisingly bad financial results, so I am selling.

and in this case, a label of 0 is assigned. For the binary stage of labeling, the following logic was developed to assign binary values of 0 and 1:

```
if item.rsi < 50: rsi = 0
    else:    rsi = 1
if item.williams > 80: williams = 1
    else:    williams = 0
if item.amount < 20: amount = 0
    else:    amount = 1
if item.trend == 'Desc': trend = 0
    else:    trend = 1
```

Based on the above logic, we can observe that four elements from the purchase or sale event are considered in the exploration process, along with their respective threshold values:

- RSI indicator and value 50.
- Williams %R indicator and value 80.
- Number of shares purchased and value 20.
- Trend and value *Desc*.

For the number of shares *amount* as a threshold, an experimental value of 20 was established. This means that if we exceed this value, a similar binary label will be created as in the previously discussed example for the Williams %R indicator.

In simple terms, the meaning of each symbol reflects the investor's answer to buying or selling a particular stock. Thus, the second type of labeling is mapping the symbol of a specific cognitive bias or behavioral model to a specific numerical value from 0 to 5, as shown below in the variable *buyAnswersMap*:

```
buyAnswersMap =
{
    "NPS_K":0,
    "HR_K":1,
    "EDP_K":2,
    "EZP_K":3,
    "ES_K":4,
    "Z_K":5
}
```

With all the necessary assumptions, formulas, and labels in place, we will now discuss the decision tree used to classify transaction data, depicted by Figure 1. In other words, the elaborated decision tree aims to identify and categorize specific cognitive biases and behaviors by running labeled purchase and sale events. It should be emphasized here that we used the ID3 algorithm to build the tree.

Our decision tree consists of a root in the form of the parameter *Answers* (marked in blue), nodes such as the parameters *Amount*, *Trend*, *RSI* and *Williams* (marked in orange), and leaves as cognitive biases and behavioral

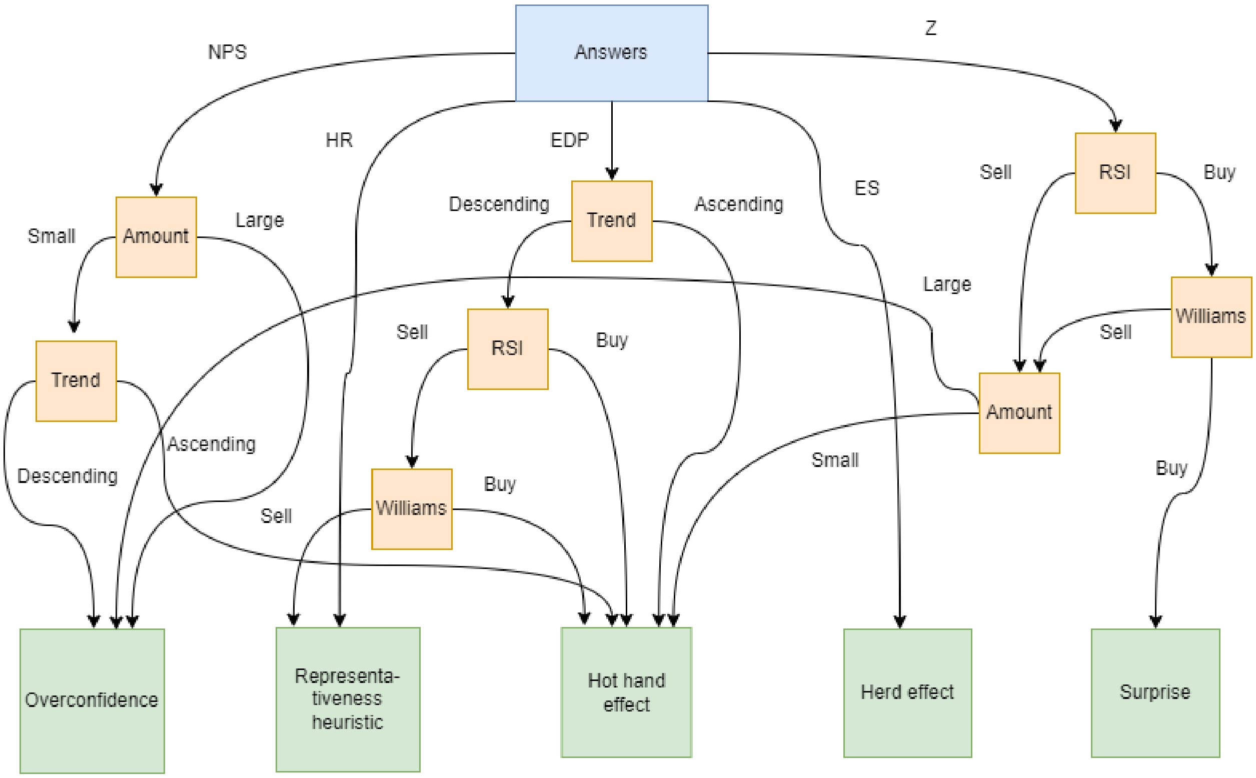

Figure 1. A decision-making process for classifying cognitive biases and behaviors (based on: Fafuła (2010b,a); Korczak and Fafuła (2011))

models, such as *Representativeness Heuristic* (marked in green). On the arrows defining the transition between the root (i.e., the first blue rectangle) and the node (orange rectangles), symbols defining the answer's value are placed to make the chart more readable, as numerical values from 0 to 5 are less intuitive. Considering the next arrows (emanating from the orange rectangles), binary values 0 and 1 are shown as text for readability. These indicate the following binary labels, namely:

- Large $\Rightarrow$ 1, or Small $\Rightarrow$ 0.
- Rising $\Rightarrow$ 1, or Falling $\Rightarrow$ 0.
- Buy $\Rightarrow$ 1, or Sell $\Rightarrow$ 0.

The transitions between the various parameters, or the values of the ID3 algorithm model, were determined based on the assumptions made by the authors of this study. To illustrate how the decision algorithm works in the tree, let's walk through an example from the root to the leaf. According to our classification model we label the data from the event, obtaining the following values:

- Answer $\Rightarrow$ EDP,
- RSI $\Rightarrow$ 0,
- Amount $\Rightarrow$ 0,
- Trend $\Rightarrow$ 1, and Williams $\Rightarrow$ 0.

We start with the answer given by the investor, which is the symbol *EDP*. Therefore (going from the root to the leaf in the decision tree) the next element to consider is *Trend*. It has a binary value of 1, which on the graph means that we turn to the right, since it is *Rising* (binary value 1). The other elements of the event are no longer considered at this stage; we have reached the leaf of the tree, which is *Hot Hand Effect*, reflecting an identified cognitive bias of an investor.

Let's consider another example for the event described below:

- Answer $\Rightarrow$ NPS.
- RSI $\Rightarrow$ 1.
- Amount $\Rightarrow$ 0.
- Trend $\Rightarrow$ 0.
- Williams $\Rightarrow$ 1.

We start with the answer symbol *NPS* and then verify the number of shares, which is small (with a binary value of 0). Next, the trend is falling, so in the end, we arrive at the leaf *Overconfidence* which concludes the journey through the tree.

4. Experimental Setup

We developed a mobile simulator of the stock market system, which allows one to buy and sell shares, as well as provide all the necessary information in this regard (Tkacz et al., 2023). We also implemented scripts responsible for retrieving stock market data from the cloud, as well as a separate set of scripts responsible for retrieving buy and sell events and identifying investors participating in the experiment. The latter are used to explore cognitive biases and behavioral models.

Data set. Historical data from the American NASDAQ stock exchange was used for performing simulations, involving the purchase and sale of shares of individual investors by using our mobile application. The input data for the includes three components: (*i*) key, (*ii*) abbreviated name of the company, and (*iii*) time horizon (in this case it is 2021). A data set was composed of 10 public companies, listed in Table 3.

Table 3. Companies selected for the performance of the experiment

Code	Company	Mkt cap
ADI	Analog Devices	116.36B
COKE	Coca-Cola Bottling Co.	9.20B
CRMT	America's Car-Mart	385.25M
DBX	Dropbox	7.44B
EBAY	eBay	27.23B
HSDT	Helius Medical Technologies	3.57M
NTGR	NETGEAR	401.47M
OZK	Bank OZK	4.73B
PSMT	PriceSmart	2.58B
RCKY	Rocky Brands	289.43M

As one can notice, the companies selected represent different sectors of the economy and have very different market values as of 3 June 2024, based on data from the Google Finance website.

Mobile application. For the purpose of the study, we also developed a mobile application for the Android system. The most important features are ability to authenticate a user by using his/her private Gmail account, visualization of stock market data, recording purchase and sale events, and synchronizing portfolio status. Another component of the application is its timing. Given the historical stock market data, it was necessary to establish from what time frame the investor would be able to purchase shares.

Simulation of buying and selling shares. A market investor first logs in. A local database is created based on the downloaded data. Each new simulation starts with an account balance of $100,000. Two views are available. The first view shows a list of companies with company information, including current share price, company name and percentage change between the last two samples (Figure 2A). Clicking on an item brings up the second view (Figure 2B), depicting detailed information about that stock, including abbreviated company name, current share price in US dollars, latest percentage change between the last two price samples, *RSI* indicator *Williams %R* indicator, current trend (*Rising* or *Falling*) and graph showing the share price distribution in 2021.

Next, an investor can buy shares by clicking on the button at the bottom of this view. An application returns a summary of the selected stock and asks the investor to select a reason for buying this particular stock and to specify the number of shares to buy (Figure 2C). These are necessary conditions for completing the purchase process. Last but not least, the application allows investors to track the value of their portfolio (Figure 2D). In the tab *Portfolio*, the investor has access to the following elements value of the stocks, quantity of currently purchased shares, available funds, profit calculated from the first login to the application, and list of currently owned stocks. An investor can sell owned stocks by Clicking on a particular item redirects to the view for selling stocks.

The process of selling stocks is quite similar to buying stocks. The difference lies in two price fields of *Purchase Price* and *Current Price*, as well as the *Balance* field. The values for *Current Price* and *Balance* are refreshed by a background thread, which is triggered upon re-entering the application and returning from the background. The portfolio status is synchronized with database with each change, so after logging out and back in, the data in the application will not be lost. Here, it should be noted that each answer is mapped to a specific cognitive bias or behavioral model. This means that during the exploration of purchase and sale events, a given answer will influence which cognitive bias or behavioral model is identified by the decision tree (see Figure 1 for details).

5. Results

In order to collect the necessary data, we sent a significant number of invitations to our colleagues through electronic channels (email, social media communicators) asking them to participate in our experiment. However, due to the low or even non-existent stock trading, the relatively low number

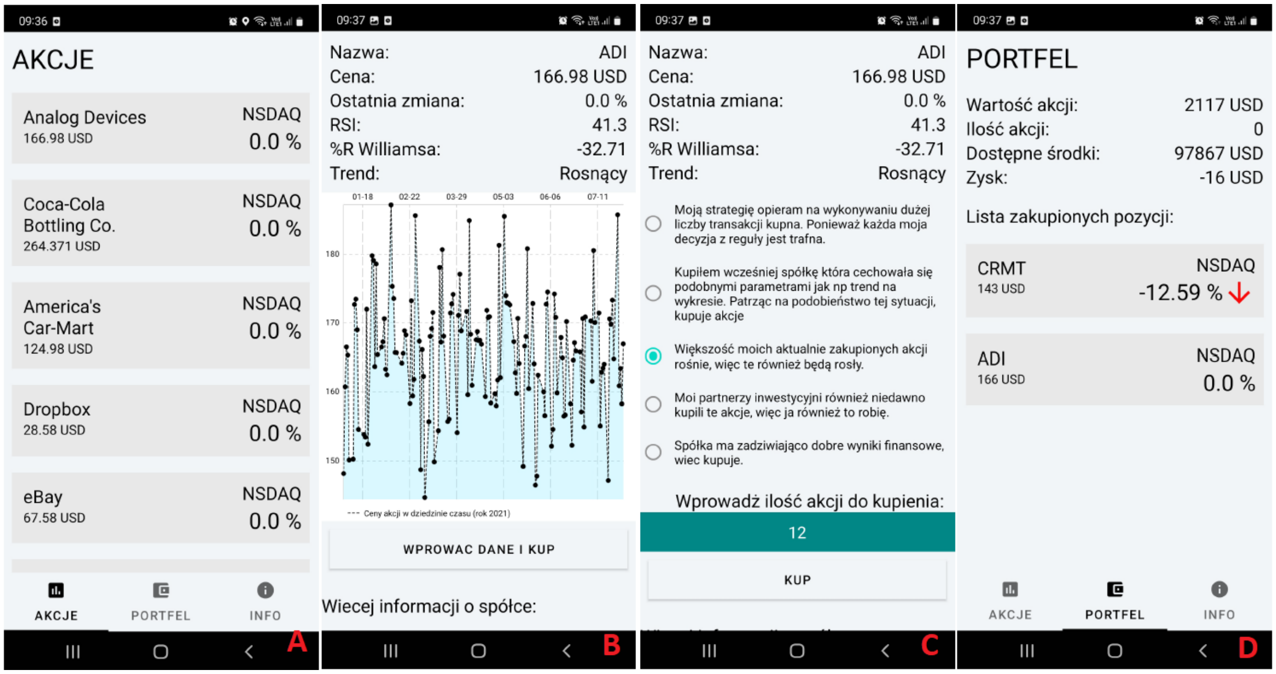

Figure 2. View of the process of buying shares in the Stock Trader mobile app.

of requests was finally accepted. In total, less than 50 investors made at least five transactions.

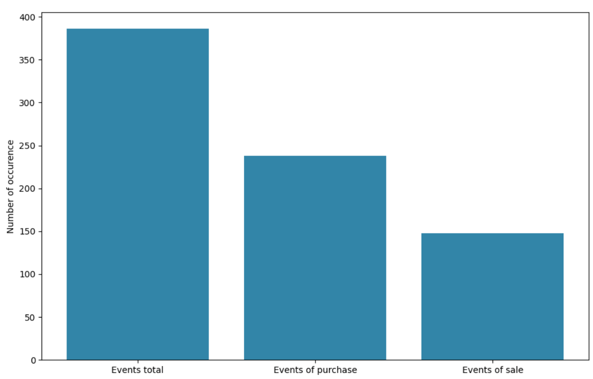

Figure 3. The Total Number of Events

Figure 3 shows the overall activity of the experiment participants. The domain in this case consists of events generated in the mobile application for buying and selling stocks. The total number of events was 385, with 245 for buying and 145 for selling. The investors' activity was expected to be higher, but the application required quite frequent adjustments during the production process, so the time horizon was not long. The chart shows a significant difference between the number of buying and selling transactions. This discrepancy arises from the fact that participants were more inclined to buy stocks without closely monitoring their current prices (motivation is low when not investing real money). Moreover, the experiment did not involve long-term investments, so it is possible that a majority of investors adopted such an investment strategy.

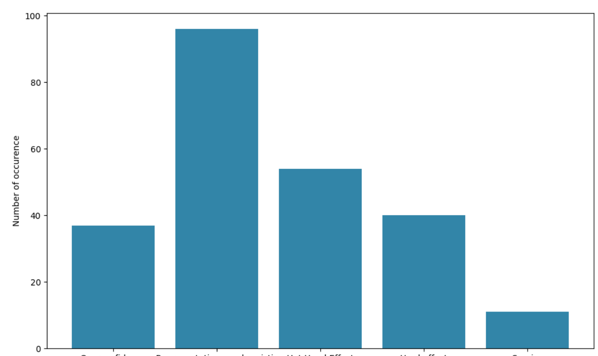

Figure 4. The Number of Specific Cognitive Biases and Behavioral Patterns Among All Participants for Stock Purchases

Figures 4 and 5 summarize the results of the experiment, highlighting the cognitive errors and behavioral patterns detected among all events triggered by investors for both buying (Figure 4) and selling (Figure 5) transactions. Referring specifically to the detected positions, it is evident that the decision tree logic in both cases frequently allowed the exploration of the "representativeness heuristic." This cognitive error is the most prevalent on both charts, which aligns with the theory that investors tend to underestimate the probability of events and draw general conclusions based on historical events.

Another common pattern is the behavioral model ”surprise” which is the least frequent (see Figure 4, and Figure 5). The low value of this element might be due to the lack of knowledge about the history of the individual companies whose stock data was used in the experiment. Without awareness of the companies’ previous financial parameters, investors could not experience the effect of surprise during the experiment. Although the application implemented technical parameters such as the *RSI* indicator, the approach of ”fundamental analysis,” which is prevalent in the investment environment, was not considered in this study. Consequently, there were few stimuli that could cause surprise.

Additionally, apart from analyzing economic and financial data (which is an element of fundamental analysis), the experiment participants did not have direct access (through the application) to information that creates speculative elements in the market, based on events related to the companies’ business activities. For example, situations like changes in a company management or investments in property development significantly impact stock prices and are closely monitored by investors. Unfortunately, the experiment did not include the capability to track such information related to the companies.

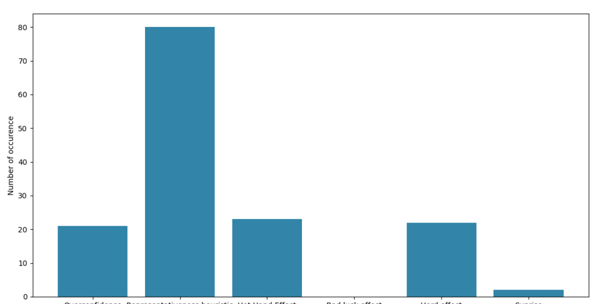

Figure 5. The Number of Specific Cognitive Errors and Behavioral Patterns Among All Participants for Stock Sales

Another important reason why the behavioral model ”surprise” is the least detected by the decision tree logic is the form of responses given by participants during the buying and selling of stocks. Emotions often play an indirect role in decision-making processes in everyone’s life, and it is no different when responding to the question of whether to sell or buy certain stocks. It is possible that the placement of the response option at the end of the list in the mobile application also contributed to the lack of interest from experiment participants (the last position on a list is rarely chosen). To improve the authenticity of the collected events, shuffling the list of responses each time the user accesses the stock purchase view could help avoid the randomness effect in transaction processes.

The lack of behavioral errors for the ”gambler’s fallacy” can be attributed to incorrect assumptions in the process of building the decision tree model for sales events. As previously described, the decision rule selection logic was experimental, so conclusions and tree calibration could only be drawn after the data collection phase. The gambler’s fallacy is a cognitive error that may only appear after a longer time horizon. Here, the tree’s construction is more responsible for its absence on the graph.

Now let’s move on to discuss the subsequent graphs in Figures 6 and 7. They show the detected cognitive errors and behavioral models for the first random user who participated in the experiment, respectively for buying and selling events.

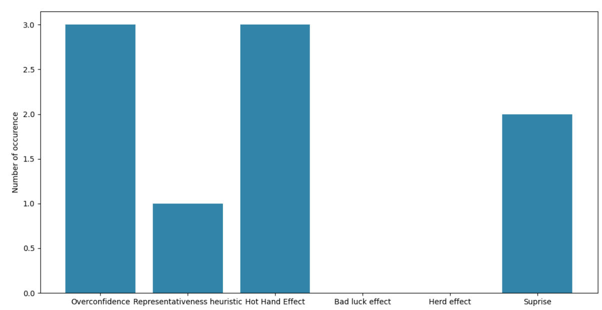

Figure 6. The Number of Detected Cognitive Errors and Behavioral Patterns for the First Random Participant for Stock Purchases

Figures 6 and 7 clearly illustrate the direction and intentions in the investment strategy, as depicted on the charts. ”Overconfidence” and the ”hot-hand fallacy” are decidedly predominant. This indicates that the investor has a strong belief in the quality of their skills and the accuracy of their trading decisions. Both cognitive errors are quite similar, as they share several common elements. These include a high confidence in one’s beliefs, a significant number of purchased stocks, and a substantial profit (not considered in data exploration). The difference between them lies in the impact of the portfolio’s actual performance, such as the real values like profit from stocks, creating the hot-hand effect. Simply put, an investor needs to buy several stocks and sell them at a profit to tangibly see that it yields positive results. Only then can we talk about the hot-hand fallacy. Overconfidence can appear earlier, even at the initial stages of building an investment portfolio. For the random participant considered in the experiment, their own experiences might have triggered their confidence (the experiment likely lasted too short to acquire it otherwise). We can identify the participant's investment approach, which translates into errors reducing the quality of their transactions and provide a diagnosis of why this is happening. The exploration lacks an analysis of the portfolio's value. Graphs where the domain is time and the values are portfolio parameters and buying and selling events would give us a broader view of what the investor did and how they can change their approach to achieve better results in the stock market.

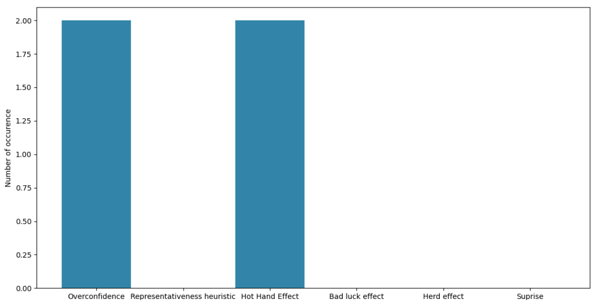

Figure 7. The Number of Detected Cognitive Errors and Behavioral Patterns for the First Random Participant for Stock Sales

Let's move on to the second random participant, who was the subject of cognitive errors and behavioral patterns detection (see Figures 8 and 9). Similar to the first participant, this individual also exhibited confidence and belief in his/her own skills, as both events (buying and selling) showed the cognitive errors of "overconfidence" and the "hot-hand fallacy." The reasons for these occurrences were transparently described in the case of the first participant. However, in addition to the aforementioned approach, the second participant relied on their decision-making process based on how their peers (other investors participating in the experiment or external individuals) invested and historical events related to the company. This is evidenced by the occurrence of the cognitive error "representativeness heuristic" and the behavioral model "herd behavior."

The representativeness heuristic appears in the investment strategy that seeks causes (e.g., changes in stock prices) in similar historical events. Herd behavior involves observing other investors to identify the market direction and applying a similar strategy to one's portfolio. Both elements are somewhat related since the representativeness heuristic can include herd behavior. Summarizing the exploration analysis of the second random experiment participant, it is possible

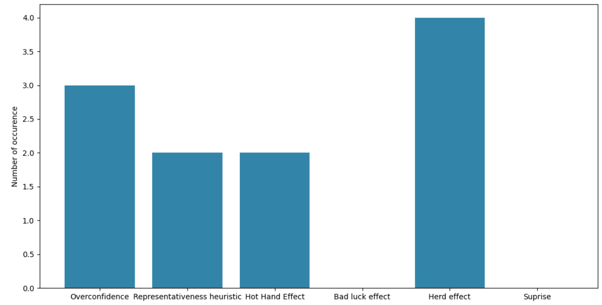

Figure 8. The Number of Detected Cognitive Errors and Behavioral Patterns for the Second Random Participant for Stock Purchases

to identify the strategy the investor followed and draw conclusions. The exploration helps us understand the underlying strategies and cognitive errors, providing insights into how to improve investment approaches.

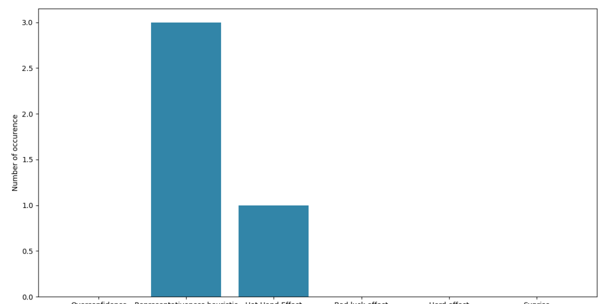

Figure 9. The Number of Detected Cognitive Errors and Behavioral Patterns for the Second Random Participant for Stock Sales

6. Discussion

The above stock market simulator study and the exploration of buying and selling events were not able to fully answer the question, "Is it possible to explore and, based on this, improve an investment strategy using an investor's transaction history?" However, failures teach us when we draw wise conclusions from them. Therefore, it is worth considering further development possibilities. Several elements can be highlighted, hypothetically assuming that the work could be continued:

- Real-time Stock Data: Integrating real-time stock data.
- Portfolio State Recording: Recording the state of the portfolio with each buying and selling event.
- Time-based Portfolio Parameter Graphs: Creating graphs with portfolio parameters over time.

- Decision Tree Testing: Testing the decision tree in the context of preventing cognitive errors or behavioral patterns.

Understanding cognitive biases can help organizations create more sustainable investment strategies by reducing the impact of overconfidence and herd mentality, leading to more stable financial markets and long-term economic sustainability. The insights derived from study can foster collaboration among regulatory bodies, financial institutions, and individual investors, leading to the creation of educational programs and tools that support informed decision-making and market stability. The application of AI and big data in analyzing investor behavior is a novel approach that can lead to the development of new financial products and services. AI-driven advisory tools, for example, can mitigate the impact of cognitive biases on investment decisions by offering personalized advice based on individual behavioral patterns. Organizations can use these findings to enhance risk management practices, predict market trends, and improve risk assessment models. Additionally, the study's insights can inform the design of training programs for investors and financial professionals, promoting better decision-making practices. This collaborative approach to understanding behavioral patterns and cognitive biases through technology ultimately contributes to the sustainable development of financial organizations and more informed, stable financial markets.

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