Visual Voyage of Stock Market Strategies

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Abstract

Investors rely on judgmental heuristics and comparative analysis for future stock price prediction based on specific components of information in hand. Information components are used as anchors for price estimation. Through an eye-tracking experiment, we aim to understand the perceived significance of various formats of information, particularly focusing on graphical and numerical components, and to explore the influence of complex time-varying patterns in stock price line plots. Results show that graphical components capture higher visual attention. Participants are not always loss-averse and prominently exhibit disposition effects for investment decisions in profitable scenarios. The 52-week high is allotted the highest fixation duration, signifying its perception as a strong reference point. Investment choices were found to be varying based on levels of prior knowledge and experience. The visual gaze analysis provides behavioural insights into complex decision-making processes.

Keywords: Investment decisions; Anchoring bias; Eye-tracking

Introduction

Investments in stock markets require individuals to make decisions under risk and uncertainty. The advent of the internet and the web has allowed for access to huge volumes of data, thus helping investors who base their choices on different types of available information (Bashir et al., 2013). These information pieces act as anchors (Tversky & Kahneman, 1974) for future price prediction. Considering that all human judgments are comparative in nature (Mussweiler, 2003; Kahneman & Miller, 1986), the presented information components are assigned different weights in determining the choice. Exploring the influence of various anchors can provide deeper insights into investors' decision-making process. Eye-tracking acts as an efficient tool to understand the weightage assigned to information components through the analysis of visual attention data (Shavit et al., 2010). This study seeks nuanced insights into the impact of graphical and numerical formats of stock price information that influence investment decisions.

Standard financial theories consider the market and investors efficient and systematic. The Efficient Market Hypothesis (EMH) considers that investors process all the available information for price estimation (Fama, 1970). Expected Utility Theory (EUT) proposes that we make rational choices by thoroughly analysing all the available choices and the associated utility and risk (Schoemaker, 1982). The stock market is an uncertain and dynamic environment. Investor decisions are not always rational and exhibit various biases (Kengatharan & Kengatharan, 2014; Kumar & Goyal, 2015; Madaan & Singh, 2019). Through empirical studies, Kahneman and Tversky (1979) observed investor behaviour inconsistent with EMH and EUT. Individuals apply heuristics and exhibit behavioural biases while making decisions under uncertainty (Tversky & Kahneman, 1974). Anchoring bias occurs when an investor's decision-making for future predictions is influenced by initially exposed information (Ishfaq & Anjum, 2015; Robin & Angelina, 2020).

Stock price graphs are a rich information source and an effective visual tool for comparisons (Mussweiler & Schneller, 2003; Cardoso, Leite & de Aquino, 2016). Behavioural biases significantly influence investment decisions when only textual and tabulated information is provided, whereas the bias is reduced after incorporating graphical information (de Goeij, Hogendoorn & Van, 2014). Graphical information is given more weightage when presented simultaneously with textual information (Lurie & Mason, 2007). Further, Huddart, Lang, and Yetman (2003) found that extreme points in historical price trends play an important role in investment decisions. That is, 52-week highs are considered significant reference points (Clarkson et al., 2020; Della, Grant & Westerholm, 2022; Mussweiler & Schneller, 2003).

Other factors include circumstantial information, the processing of which depends on the investor's experience and investment horizon. (Holm & Rikhardsson, 2008). Investment strategies and the nature of risk-taking change with age and experience (Lodhi, 2014). Miazee, Shareef and Hasan (2014) observed that financial literacy assists preliminary decision-making in order to avoid major losses.

Through empirical studies, Tversky and Kahneman (1992) showed that individuals have varying risk attitudes based on the estimated probability of an event and whether they are incurring a loss or a profit. Individuals exhibit loss aversion (Kahneman, Knetsch & Thaler, 1991) and disposition effect by selling profitable assets and retaining loss-making ones during financial decision-making (Odean, 1998). Loss aversion is the tendency for individuals to be more impacted by potential losses than by equivalent gains, causing them to focus on avoiding losses. Because of Loss aversion, individuals tend to hold on to losing assets. The disposition

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effect refers to investors' tendency to sell winning assets and hold on to losing assets, whereas rational strategy suggests otherwise. This phenomenon can be explained by the fourfold pattern of risk-taking (Kahneman, 2011), which states that individuals are risk-averse in the domain of gain and risk-seeking in the domain of losses.

Techniques to Measure Information Processing

Eye movements of participants provide rich information about the attentional process employed during decision-making and help to understand the underlying cognitive process of decision-making (Acartürk & Habel, 2012). Results of prior studies have shown that eye-tracking can be used as a reliable tool to understand the underlying aspects of information processing and decision-making (Acartürk & Habel, 2012; Wang, Spezio & Camerer, 2010). The mere exposure effect states that looking at a stimulus increases preference in making a choice (Zajonc, 1968; Kunst-Wilson & Zajonc, 1980; Moreland & Zajonc, 1977; Moreland & Zajonc, 1982). It is also observed that the component given greater visual attention significantly influences the decision made (Orquin & Loose, 2013). The visual gaze data indicated that participants base their decisions on the past performance of mutual funds and exhibit the hot hand fallacy, with disclaimers showing no discernible effect (Hüsser & Wirth, 2016). Toma et al. (2023) used eye tracking to understand investor behaviour in boom-bust scenarios.

An alternate metric is the response time to complete a task, though not considered a replacement for the richer eye-tracking data (Harrison & Swarthout, 2019). A study by (Shavit et al., 2010) to examine the overweighing of specific components from the presented portfolio analysed the time spent looking at information components, and it was found that specific components are allotted more attention than others, the focus can be explained by behavioural biases.

Our research study considers visual gaze and attention allotted to graphical and numerical data associated with stocks to understand the decision-making process. The twofold objective of the current study is to identify the information component considered most influential in investment decisions (specifically comparing graphical and numerical data) and to analyse the impact of complex patterns in graphical data on estimating price trends. Though the choices can give an idea about the cumulative impact of the presented information (buying action implies a positive impact, and selling action implies a negative impact), we cannot determine which components are given more attention and are most influential in decision-making. To the best of our knowledge, no prior study has looked at the influence of complex graphical patterns using visual gaze analysis.

Methodology

We conducted an eye-tracking experiment with participants performing a decision-making task on stock investment.

Participants

Seventy-six participants (54 males, 22 females) in the age group 17 to 57 years (Mean = 21.06, Std dev = 6.56) participated in the experiment. The population mainly contained undergraduate and graduate students, with few investment professionals. All the participants had normal or corrected to normal vision. 39 participants reported having a basic understanding, 14 reported good knowledge, whereas 23 participants reported no knowledge of the stock market. 54 participants have never traded, 6 have traded in the past, and 16 are currently trading in the stock market.

Apparatus

A Tobii X-30 eye-tracker (capturing gaze data at a rate of 30 Hz) was used to track the eye movements of the participants while they were performing the task. On a laptop LCD screen, graphical and numerical data for nine different stocks were presented through an in-house developed web application (Link). Participants used a mouse to mark the choice in the decision-making task.

Stimuli

Figure (1a) shows the interface display. The following information is presented (currency in INR) -

Graphical component

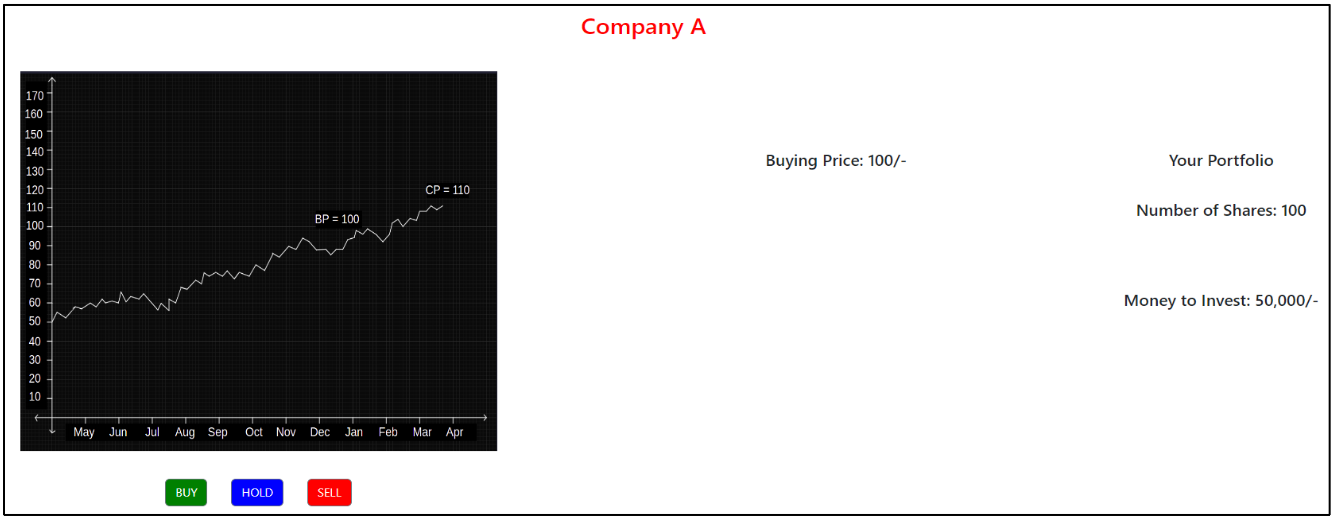
- Depicts stock price trends for a 1-year period.
- Contains Buying and Current price of the stock.
- The two prices indicate the beginning and ending points of the investment period, aiding investors to understand the price fluctuations between them.

Numerical component

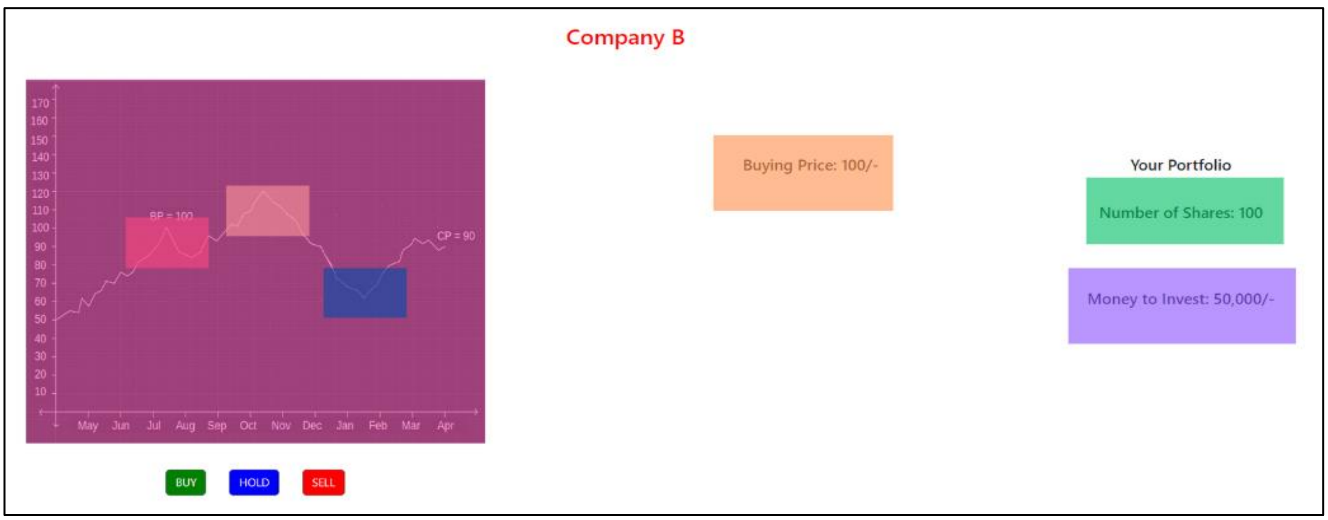
- Buying price of the stock.
- Portfolio section
  - Number of shares: Current shares in the portfolio.
  - Money to invest: Available funds to invest

The numerical information remains consistent for nine stock entries labelled with hypothetical company names (A to I). The plot pattern and occurrence of loss or profit vary across the stocks. The buying price is INR 100, and the current price is INR 110 in case of profit and INR 90 in case of loss. The number of shares currently owned is 100 units, and the amount of money the participant has in hand to invest further is INR 50,000. The amount of loss or profit is INR 1000 for all nine stocks.

Graphical patterns for the tasks were chosen to reflect an unequal number of highs and lows. The highs (H) and lows (L) are permuted to obtain four patterns - HHL, HLH, LLH and LHL. These patterns are considered to examine the difference between the role of visual representation of highs and lows in conveying or predicting the stock price trend. The stock price graphs were randomly generated but controlled to show a price fluctuation between INR 50 and INR 120 over the period of one year.



(a)



(b)

Figure 1: (a) Displays the stock information for company A. In the graph, BP denotes the buying price, and CP denotes the current price. (b) The highlighted areas represent Areas of Interest.

The eye-tracking data were analysed by focusing on four areas of interest (AOIs) - graph, buying price, number of shares and money to invest. Within the graph, the extreme points were considered distinct AOIs. Figure (1b) contains all the areas of interest highlighted on the interface. The Total Fixation Duration (TFD) is compared across AOIs. TFD measures visual attention allotted to the component, which can efficiently explain the role of components in an investment decision (Shavit et al., 2010).

Procedure

Before starting the experiment, each participant performed the 9-point eye-tracker calibration procedure for the eye tracker. A set of instructions on the flow of the experiment were provided. There was no time restriction, and the participant could take the desired time to decide on each stock. A participant required around 8 to 10 minutes to finish the experiment. The participant was instructed to choose from buy, sell, and hold based on the information presented.
The user interface had three distinct press buttons for each decision. A blank white screen with a plus sign (fixation target) at the centre was displayed for 6 seconds between two consecutive graph patterns. The nine stocks were shown in succession, with an additional sample stock at the beginning to familiarise the participant with the display. The data for the sample stock was not included in the analysis.

After completing the task, the participant was asked to complete a questionnaire containing questions from the Domain Specific Risk-Taking (DOSPERT) survey from the social risk and financial risk-related sections (Blais & Weber, 2006). These questions require the participant to rate how likely he or she will perform the activity mentioned in the question on a Likert scale of 1 to 5, where 5 is most likely and 1 is not at all likely. The responses to the questionnaire helped us understand the risk-taking nature of the participants.

Hypothesis: We propose hypotheses based on established psychological theories and prior eye movement analysis. We anticipate visual attention patterns influenced by confirmation bias (Kahneman, 2011) as components supporting decisions are assigned greater importance.

1. Comparing graphical and numerical data, we anticipate investors will allot greater visual attention to the graph as the price trend offers anchoring points that serve as the basis for estimations.
2. In the case of loss - The investors will hold the stock due to loss aversion (Kahneman, 2011). Because of confirmation bias (Kahneman, 2011), the stock price graph's peaks will be more focused.
3. In the case of Profit – The investors tend to be risk-averse, exhibiting the disposition effect (Kahneman, 2011), leading to a greater inclination to sell stocks. We anticipate the recency effect (Kahneman, 2011) to influence decision-making, with investors holding the stock after a recent peak and selling after a recent valley in the graph, with the most recent extreme point receiving higher visual attention.

Table 1: Graph states and corresponding hypothesis. Hypothesis ‘a’ states the expected choice, and hypothesis ‘b’ is the anticipated graphical region with the highest TFD.

Stock	Graph, State	Hypothesis
A	Steady increase, Profit	H1 a: Buy H1 b: Peak
B	HHL, Loss	H2 a: Hold H2 b: Peaks
C	HLH, Profit	H3 a: Hold H3 b: Peaks
D	HHL, Profit	H4 a: Sell H4 b: Valley
E	LLH, Loss	H5 a: Hold H5 b: Peak
F	LHL, Loss	H6 a: Hold H6 b: Peak
G	HLH, Loss	H7 a: Hold H7 b: Peaks
H	LLH, Profit	H8 a: Hold H8 b: Peak
I	LHL, Profit	H9 a: Sell H9 b: Valleys

There exists a strong association between the allocation of visual attention and the significance of visual stimuli components in decision-making (Orquin & Loose, 2013). The process of visual selection tends to favour information components that align with the individual's goals (Rajsic, Wilson, & Pratt, 2014). In our study, we anticipate that participants' behavioural biases (mainly loss aversion, disposition effect and recency effect) will predominantly shape their investment choices, subsequently influencing their visual gaze patterns. Based on these considerations, Table 1 contains details for anticipated behaviour for each stock. The second column denotes the graphical pattern and state associated with each of the nine stocks. H represents a high (peak), and L represents a low (valley) in the graph. The current state denotes whether the investor would have profit or loss if all the stocks were sold at the current price. The third column contains the expected behaviour in each of the cases. Hypothesis ‘a’ proposes the expected investment behaviour. The Expected visual attention is stated in subpart ‘b’ of the hypothesis.

Results

The proportion of TFD allotted was considered a measure of visual attention allocated for an AOI. Since there can be variation in the time taken to make a decision, the proportion of TFD instead of the absolute values will be an efficient indicator of visual attention (Takahashi, Todo & Funaki, 2018). For each stock, entries with TFD values of zero for all AOIs were excluded from the participant data. We applied the Wilcoxon Signed Rank test to compute if there is a statistically significant difference (p-value < 0.05) between visual attention allotted to graphical and numerical components. Kruskal Wallis test was performed to find if there was a statistically significant difference ($p < 0.05$) between the percentage distribution of TFD for the three extreme points in the graph.

Overall Analysis

The results showed that graphical components are attributed greater importance than numerical components in investment decisions (Figure 2). We found a statistically significant difference between the proportion of TFD allotted to graphical and numerical data, where graphical data had a higher mean percentage fixation than numerical data for all the stocks, satisfying the proposed hypothesis.

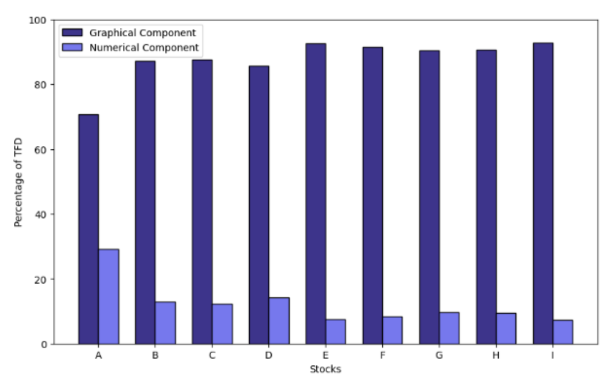


Figure 2: TFD comparison for graphical and numerical components

Figure 3 depicts the choice-wise distribution of participants. In loss scenarios, most investors chose to hold stocks for company B. Company G saw a preference for buying, while companies E and F had investors divided between holding and selling. In profitable situations, the predicted behaviour was observed in companies D and I. Company C witnessed most investors selling, while for Company H, there was a tie between holding and selling decisions.

Role of prior knowledge of the stock market

We divided the dataset into three parts based on an individual's knowledge of the stock market (none, basic and good). The participants' choices indicate that those with basic knowledge demonstrate higher loss aversion and a disposition effect compared to both the no-knowledge and good-knowledge groups. Interestingly, the choices made by the no-knowledge and good-knowledge groups exhibit a striking similarity in distribution. The graphical data is given greater visual attention for all nine stocks in all three groups. Comparing the TFD distribution for the three extreme points in the graph, statistically significant results were obtained for stocks F (p-value = 0.013) and I (p-value = 0.006) for the no knowledge group, stocks B (p-value = 0.005), F (p-value < 0.05), and I (p-value < 0.05) for the basic knowledge group and stock F (p-value = 0.007) for the good knowledge group.

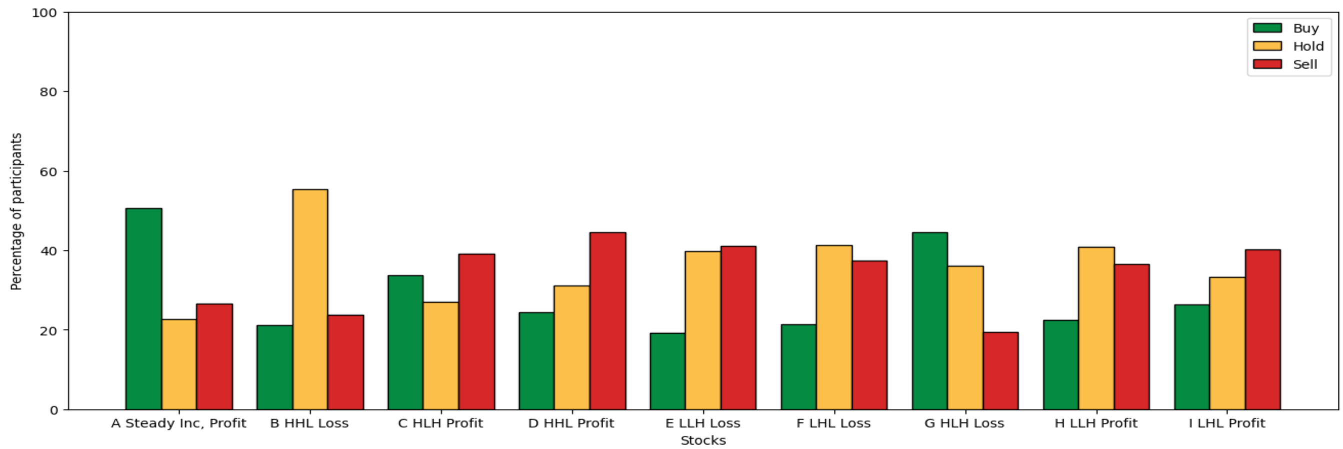


Figure 3: Choice preferences among participants

Comparing the TFD distribution for three extreme points in the graph (Figure 4) for loss, a statistically significant difference in administering the Kruskal Wallis test was found for three of four stocks (B, F and G). For these three stocks, the attention on the peaks was higher than the graph's dips, validating the hypothesis. A statistically significant difference was found for two of the four stocks (C and I) in the profit condition. The rest showed a difference between only one pair of extreme points. between 1st High and the Low for HHL (p-value = 0.036) and 2nd Low and the High for LLH (p-value = 0.039). No recency effect was observed, and peaks were allotted greater visual attention for all four profit conditions.

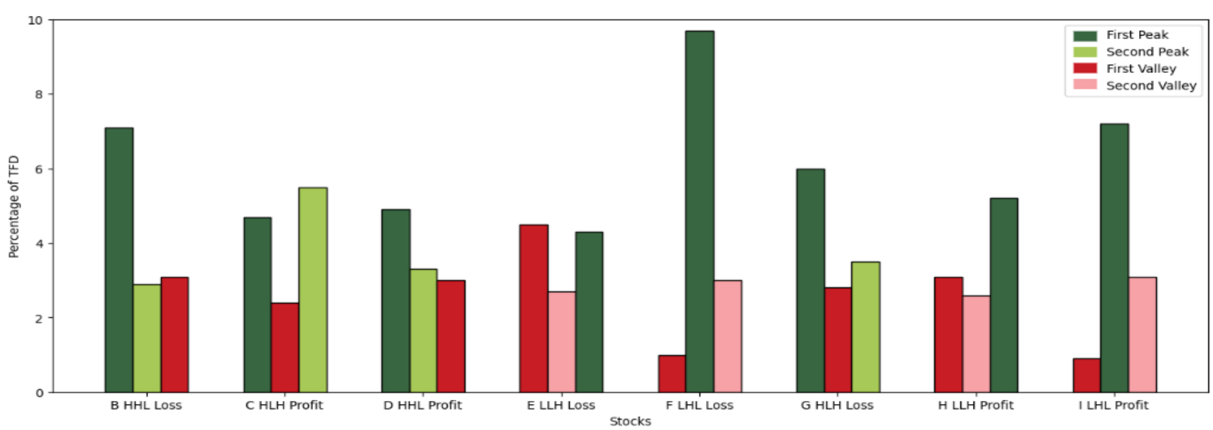


Figure 4: Average distribution of TFD for the three extreme points. Shades of green represent TFD for peaks, and shades of red represent TFD for valleys.

Role of Experience in Stock Market Trading

Segmenting the dataset based on trading experience revealed that both experienced (having traded in the past or currently trading) and amateur participants focus more on graphical information than numerical information. Comparing the choice distribution between the two groups, amateur participants displayed higher loss aversion and a slightly greater disposition effect than their experienced counterparts. A statistically significant difference between TFD for the three extreme points was observed only for stock B (p-value = 0.013), F (p-value < 0.05) and I (p-value < 0.05) for the amateur group, while statistically significant differences were observed for stock C (p-value = 0.015), F (p-value < 0.05), and G (p-value = 0.044) in the experienced group.

Applying the multinomial logistic regression, we did not find a correlation between the risk scores for the DOSPERT survey and the investment decisions.

Discussion

We could spot specific behavioural patterns from the investor strategies used in the investment tasks. Irrespective of the level of prior knowledge and experience, graphical data was given more weightage in decision-making as the past price trend provides an anchor for estimating the future price (Mussweiler & Schneller, 2003). The declining visual attention to numerical components (Figure 2) shows a learning effect.

Prior studies have observed that investors provide greater significance to the 52-week highs and 52-week lows (Guo, 2021; Burghof & Prothmann, 2011; Della, Grant & Westerholm, 2022; George & Hwang, 2004; Huddart, Lang & Yetman, 2009). In our experiment, the peaks (precisely the peak corresponding to the 52-week high) were allotted more visual attention for seven of nine stocks. Extensive buying for stock G (HLH Loss) could be attributed to two peaks in the graph acting as a strong indicator of a positive price trend and the 52-week high being used as a strong reference point (George & Hwang, 2004), data also supported by the eye-tracking gaze analysis. The selling behaviour for E (LLH Loss) and C (HLH Profit) could be due to stock downgrading as the price is approaching a 52-week high (Li, Lin & Lin, 2021).

Contrary to our hypothesis, participants do not consistently exhibit loss aversion, whereas, in the case of profit, the disposition effect was prominently observed. The participants who had reported having a basic knowledge of the stock market exhibited the highest levels of loss aversion and disposition effect compared to the other two groups (no knowledge and good knowledge). Contrary to (Suresh, 2021; Baker et al., 2019), we did not observe a specific correlation between prior knowledge and behavioural biases in investment decisions. Comparing the visual attention allotted to the extreme points, the three groups slightly varied. The statistically significant difference observed for the LHL pattern across all three groups highlights the significance associated with a 52-week high peak (George & Hwang, 2004). Based on the TFD distribution for extreme points, it can be inferred that participants in the good-knowledge group do not assign particular significance to a specific extreme point in terms of visual attention (except for stock F), thereby treating them equally in investment decisions.

In terms of stock trading experience, our findings revealed that experienced participants showed lower levels of loss aversion and a slightly reduced disposition effect compared to novice participants. However, it should be noted that experience alone does not eliminate behavioural biases (Feng & Seasholes, 2005). The visual focus on extreme points displays minor differences between the two experience groups, while stock F stands out as a common factor, where the 52-week high has the highest TFD value, indicating its perceived significance (George & Hwang, 2004).

Psychological research indicates that individual preferences influence information processing (Ditto & Lopez, 1992; Ditto et al., 1998). Investors tend to interpret information in line with their directional preferences (Hales, 2007). When examining the distribution of choices for identical graphical patterns in instances of loss and profit, we observe notable distinctions across all four patterns. Although the TFD distribution shows that peaks are allotted higher visual attention, decisions are also influenced by the current state of the stock. This suggests that the perception of the same information varies depending on whether an immediate or recent loss or profit is associated with the investment.

The dataset can be further expanded by including participants with different levels of trading experience while also examining long-term and short-term traders as distinct groups. We could integrate more stock-related data, including news related to the company, sector-specific performance and historical data for stock market performance.

In summary, we identified diverse decision-making patterns correlated with stock price trends spanning a year. Visual gaze patterns offer deeper insights into decision-making. They expand our comprehension regarding which information components receive greater attention, indicating their heightened significance in investment decisions. While our study focuses solely on decision-making within the stock market context, the findings contribute to understanding the underlying information processing mechanisms in making a choice. They reveal how individuals evaluate and prioritise various components (as inferred by allocated visual attention) during decision-making, particularly in scenarios with an abundance of information, and highlight the influence of behavioural biases on decision-making.

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