HEC MONTRÉAL

Determinants of decision-making when predicting the outcome of charts.

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CERTIFICAT D'APPROBATION ÉTHIQUE

La présente atteste que le projet de recherche décrit ci-dessous a fait l'objet d'une évaluation en matière d'éthique de la recherche avec des êtres humains et qu'il satisfait aux exigences de notre politique en cette matière.

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Sommaire

Cette mémoire explore la prise de décision des individus lorsqu'ils prédisent l'issue de graphiques. Plus précisément, cette étude cherche à observer l'impact des caractéristiques du graphique et des caractéristiques individuelles du participant (croyances, préférences de risque, réactions émotionnelles, connaissances financières) sur la prise de risque et la direction anticipée de la courbe des graphiques dans le futur. Nous avons mené deux expériences distinctes, avec 37 et 264 participants respectivement, et utilisé le même modèle de recherche dans les deux expériences pour observer l'impact de ces variables. Nous avons développé une tâche expérimentale unique appelée *Pattern Task* dans laquelle les participants devaient prédire l'issue d'une série de graphiques, générés de manière aléatoire ou répliquant des tendances graphiques bien connues en analyse technique. En combinant une série de questionnaires et la mesure de la réaction émotionnelle en temps réel tout au long de l'expérience, nous avons pu évaluer l'impact des caractéristiques des graphiques et des caractéristiques individuelles sur la de prise de décision.

Nos résultats indiquent tout d'abord que ni les caractéristiques des graphiques, ni les croyances, ni les préférences en matière de risque, ni les connaissances financières n'ont un impact significatif sur la prise de risque dans la *Pattern Task* lors de la prédiction de l'issue des graphiques dans nos deux expériences. Il s'avère également que la réaction émotionnelle n'agit pas comme une variable médiatrice dans l'explication de la relation entre les caractéristiques des graphiques et la prise de risque pour les deux expériences. Nous obtenons des résultats similaires d'absence de relation pour la direction anticipée des graphiques dans notre deuxième expérience. Les résultats concernant la direction anticipée des graphiques dans notre première expérience, cependant, ne sont pas aussi clairs. Nous constatons d'abord que les réactions émotionnelles n'ont pas d'impact significatif sur la direction anticipée des graphiques dans le futur, que ce soit un impact direct ou en tant que variable médiatrice. Cependant, nous constatons que la tendance générale du graphique a un impact significatif sur la direction anticipée, les résultats indiquant que les participants s'attendent à un renversement de tendance lorsqu'ils analysent les graphiques. Nous constatons également qu'une variabilité plus élevée conduit les participants à anticiper un mouvement à la baisse dans le futur. Les résultats de notre première étude indiquent également que la tolérance au risque financier, la tendance à faire preuve d'apophénie et la connaissance financière moyenne des participants ont tous un impact significatif sur la direction anticipée du graphique dans le futur.

Cette étude contribue à la littérature existante en développant une expérience en laboratoire permettant d'observer le comportement d'individus confrontés à différents types de graphiques. Notre expérience peut donc servir de point de départ pour des recherches plus approfondies sur les comportements de négociation

sur les marchés financiers qui combinent à la fois les facteurs techniques financiers et la personnalité. Avec l'intérêt récent des investisseurs individuels pour les marchés, comprendre le comportement et les préférences des investisseurs est crucial pour les professionnels de la finance dans l'anticipation des mouvements boursiers. Les institutions financières et les négociateurs professionnels pourraient fortement bénéficier de recherches qui les aideraient à mieux comprendre et anticiper les prises de décision des investisseurs individuels lorsque les conditions de marché changent.

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1. Introduction

In recent years, stock markets have seen renewed interest from retail investors across the globe. Easily accessible online brokerage platforms have allowed novice investors to actively participate in financial markets by managing their own portfolios. This phenomenon has become increasingly popular since the beginning of the Covid-19 pandemic. A 2021 newspaper article on WealthSimple, a Canadian based online investment management firm, reveals that the firm increased its clientele by 185% between March 2020 and May 2021, while seeing its assets under management jump from 6.8G$ to 10G$ (Pavic, 2021). This has attracted many inexperienced investors with little or no technical financial knowledge on the financial markets. Data now suggests that individual investors make up close to 20% of the total equity markets trading volume (BNY Mellon, 2021), which marks a drastic increase in the past decade and even in the past two years. Volatility also continues to grip the marketplace with equities being under pressure across the globe since the beginning of 2022. Global markets have been down by more than 20% year to date and volatility, as measured by the VIX Index, has been showing steady nervousness coming from investors.

Multiple studies have already explored the impact of retail investors on financial markets. Most of these studies have been conducted empirically, using historical stock market data on trading patterns and volume. However, very few experiments on retail investor behavior have been done in a laboratory setting. As novice investors become more and more involved in financial markets, it becomes increasingly important for finance professionals to understand their decision-making process and how it can ultimately impact markets. Retail and novice investors once made up a negligible part of trading volume in financial markets, but today, their involvement cannot be overlooked. This phenomenon combined with highly risky and volatile markets makes the case for us to further investigate individual behaviors and more specifically the mechanism behind the decision-making process of individuals when they are confronted with various chart patterns.

We develop a proprietary experimental task in which individuals are presented with a series of graphs, either replicating frequently observed price patterns in stock markets or exhibiting randomly generated patterns and asked to predict their outcome. We are interested in the impact of the chart characteristics, and to whether emotional reaction acts as a mediator variable in explaining the relationship between chart characteristics and both the level of risk taken and the anticipated direction of the graph in the future when predicting the outcome of these graphs. We also seek to analyze the impact of the individual's personal characteristics on the level of risk taken and on the anticipated direction of the graph in the future. The individual's characteristics are measured through a series of questionnaires on risk preference, tendencies to perceive patterns and financial literacy. Emotional reactions are measured through electrodermal activity, heart rate variability and facial expression throughout the experimental task.

Our ultimate goal is therefore to answer the following research question: *What are the determinants of an individual's decision-making process when predicting the outcome of graphs?*

We conducted two separate experiments to better understand the decision-making process of individuals. Our first experiment was conducted in a laboratory setting but done remotely by participants as Covid-19 restrictions remained in effect at the time of data collection. Participants in this first experiment were provided with the appropriate physiological data collection material developed by the Tech3Lab team which enabled us to collect data on emotional reactions remotely. Our second experiment was conducted through the Amazon Mechanical Turk platform and allowed us to test our hypothesis on a larger sample of participants and contrast the results with the first experiment done in a laboratory setting. The second experiment consisted of a shortened version of the first experiment where participants were presented with fewer charts, and where some independent variables were left out. The extension of results to the real world remains challenging and our study presents a number of limitations. However, we propose a new behavioral experiment designed to capture the decision-making process of individuals when they are presented with chart patterns.

This thesis is presented in multiple different sections. Section 2 brings forward existing literature on the efficient market hypothesis, technical analysis, emotional reaction, beliefs, risk preferences and financial literacy. Section 3 presents our Research model and proposed hypothesis for both of our experiments. Section 4 explains our methodology for conducting our study and includes a separate section for both of our experiments. Section 5 covers the results from our analysis and their implications for our model. Section 6 summarises the results by linking them with our study's hypotheses. Section 7 discusses the results, the limitations of our study and concludes by exploring possible avenues for subsequent studies on our subject.

2. Literature Review

2.1: Efficient market hypothesis

2.1.1. Definition

Efficient market hypothesis theory states that all known information on a security is already reflected in the security's price on stock markets. In that sense, an investor would not be able to take advantage of any type of mispricing situations to beat the general market and passive investing would be the best form of investing possible (Fama, 1970). The theory was developed by Eugene Fama throughout the 1960s and has since been reviewed, studied and applied in thousands of studies across the finance field. To this day, EMH still acts as the basic assumption and base case in financial studies or financial modelling.

2.1.2. Forms of Efficiency

As Fama (1970) explains, the efficient market hypothesis can take on different forms, each with different intensities and in which the ability to generate excess returns may be possible. Markets can take on the weak form of efficiency, where past information is included in a security's market price and therefore technical analysis or pattern traders can't generate above market returns, but fundamental analysts may be able to find undervalued securities based on their fundamentals. Markets can also take on the semi-strong form of efficiency in which all public information is included in a security's price, meaning that the use of fundamental or technical analysis can't help in generating excess returns. Only people possessing insider information on specific securities would be able to achieve above market returns. Finally, the market can take on the strong form of efficiency in which all information, public and private, is included in the price of a security and therefore no one can generate excess return.

Multiple studies have tested the presence of the three different forms of efficiency throughout the years and have come to different conclusions depending on the study's parameters. Mobarek and Keasy (2000) test the presence of weak-form efficiency in emerging markets, more specifically in the Dhaka stock market of Bangladesh, and conclude that weak-form efficiency is not present in that particular setting. Similar results are found in Eastern European equity markets where markets were found to be inefficient which could in turn allow investors to generate abnormal returns using technical analysis (Guidi et al., 2011). Indian markets have also been shown not to exhibit weak form efficiency, but rather exhibit day of the week effect, giving investors the opportunity to generate abnormal returns based on the timing of their trades (Poshakwale, 1996). By observing returns following dividend or earnings announcements in Malaysia, Hussin et al. (2010) test for the presence of semi-strong market efficiency on the Malaysian stock exchange. Results show signs of semi-strong form efficiency on these markets as prices appear to efficiently adjust to dividend and earnings information. Khan and Ikram (2010) also test the presence of semi-strong form efficiency on Indian markets. They find that Foreign Institutional Investors have a significant impact on Indian stock markets which in turn leads them to conclude that these markets are semi-strong efficient. Through the presence of monopolistic insiders, Chau and Vayanos (2008) observe the presence of strong-form efficiency on markets. They find that markets can be close to strong-form efficient, but that insider profits don't converge to zero over time.

2.1.3. Validity of EMH

Over the years, many other studies have had contradicting conclusions with regards to the validity of the efficient market hypothesis in various markets and conditions. Malkiel (2003) analyzes various studies that critique efficient market hypothesis theory and concludes that EMH is still a valid theory without however implying markets are perfectly efficient. In fact, he suggests that temporary mispricing is possible, but that they are short-lived and overall, markets tend to be efficient in pricing securities. Some studies have also proposed variations to the efficient market hypothesis that allow for a better predictability of returns in financial markets when considering external factors. Titan (2015) argues that due to the constantly evolving and changing nature of financial markets, combined with the difficulty related to testing EMH, new theoretical models should be developed to better forecast returns. Many studies have also criticized the efficient market hypothesis theory by exploring various market anomalies that contradict the theory and its logic. For starters, the rise of behavioural theories and emphasis on the investor's behaviour over the years has forced scholars to reassess the validity of theories based on investor rationality. Over the past decades, various bubbles and market anomalies have proven to be a sign of irrationality and thus expanded academic vision beyond purely quantitative models. This rational basis on which EMH is based is therefore one of the theory's major drawbacks in a modern world. (Singh et al., 2021)

EMH can be considered as a strong base hypothesis for financial markets, but many external factors which may affect investor rationality can directly or indirectly affect market efficiency, making the theory imperfect. With the growing popularity of self-brokerage accounts and the growing presence of retail investors in financial markets, the idea that investors might not be totally rational cannot be overlooked. We look further and explore various technical or psychological factors which could potentially affect decision-making to see if these factors can cause some risky or irrational behaviours. Factors that we explore in the upcoming sections include technical pattern analysis, emotional reaction, beliefs, and financial literacy.

2.2: Technical Analysis and Retail Investors

2.2.1. Definition

Technical analysis is a method that is studied and applied by many stock market enthusiasts and finance professionals. Although this theory has evolved over the past 50 years, its main objective has mostly remained the same. Allen and Taylor (1992) defined technical analysis as a method used to forecast future asset prices by visually examining past price movements, and by using a set of quantitative indicators. As they note, this technique does not take into consideration the underlying company's fundamentals, such as revenues, earnings and capital structure. In other words, technical analysts observe historical variations and the stock price and try to predict future price trajectories with this information. It is also important to highlight the subjective nature of technical analysis. As Lo, Mamaysky and Wang (2000) point out, geometric shapes and patterns are observed differently by each person. There are, however, well-known and identifiable chart patterns that are studied in technical analysis theory. These patterns include but are not limited to: head and shoulder patterns, double downs, ascending or descending triangles, pennants, and wedges. These patterns will be discussed in later sections of this study.

2.2.2. Individual Investors

As mentioned earlier, novice investors have recently started to take a keen interest in financial markets. When presented with data on the underlying companies or the market in a stock market simulation, beginner or novice investors have been known to focus their attention on irrelevant information rather than on relevant fundamental metrics when compared to finance professionals (Glanger, 2018). One example of irrelevant information in this financial context is the stock's price chart. Kroll et al. (1988) find in their experimental tests that subjects tend to find patterns when observing return data. De Bondt (1993) finds that amateur traders use these chart patterns and expect prices to continue in their past trends. They tend to rely on this information even though past prices do not necessarily have an impact on future prices. Other studies find that participants in his study tend to believe that stocks will reverse their trend, prompting them to buy stocks after a low and sell them after a high. Andreassen (1988) These contradicting conclusions illustrate the subjective nature of chart pattern analysis, especially in stock market activities. Achelis (2000), states that prices move in trends, and that the reversal of these trends occurs when participants change their expectations. Other studies also show that individuals tend to exhibit confirmation bias when trading, meaning that traders who receive new information and trade on the basis that information tend to bias their decision-making process with their original view. This in turn will create some price patterns in markets, which can subsequently be identified as popular technical analysis patterns (Friesen, Weller and Dunham, 2009). It is therefore important to understand that stock market trends can be created by the very people who attempt to profit on them.

Individual investors have also been known to trade more actively than institutional investors, often to the detriment of their portfolio's performance. Barber and Odean (2000) discuss the fact that households trade their stocks very actively, turning over more than 75% over their portfolio every year, and that their trading activity is linked to overconfidence. Through a sample of Dutch discount brokerage clients, Hoffman and Shefrin (2014) find similar results in which individual investors who use technical analysis to make decisions trade frequently and exhibit lower returns on their investments. This once again illustrates the importance of understanding how individuals react to chart patterns.

Ebert and Hilpert (2019) explore traders' preference for positive skewness when making investment decisions which in turn helps explain the popularity of technical analysis despite the lack of evidence of its success and strength of its foundation. They discuss the fact that this preference could potentially explain investors' tendency to rely on unrelated patterns when making decisions, ignoring the efficient market hypothesis. Nevertheless, the arrival of individual investors to markets combined with accessible technical tools only increases the relevance of investigating the effects of technical analysis in finance.

2.2.3. Link With Investor Behaviour

Vasiliou & al (2008) draws a line between technical analysis and behavioural finance, combining subjects' rational and irrational behaviours in their decision-making process. Although the goal of technical analysis is to rely on historical data to predict future price trajectories by using rigid tools, traders are in fact irrational beings with emotions that affect their decision-making. It is therefore important to understand the general population's behaviour when confronted with these charts and the subsequent decision-making process. Achelis (2000) also mentions the fact that humans are involved in trading activities brings a lot of unpredictability to markets. Personal experiences, personality and behaviour influence decision-making when it comes to investment decisions. Other studies have also shown that the way in which traders regulate their emotions has a material impact on how they behave and perform in a trading situation (Fenton-O'Creevy et al., 2010). Although traders might be able to regulate these emotions, individual investors with no advanced financial knowledge to fall back on might not be able to regulate that easily.

2.2.4. Volatility in Financial Markets

Studies have also examined the effects of volatility in financial markets. Messis and Zapranis (2014) study the relationship between, which essentially represents investors all moving in the same direction on markets, and volatility. They find the presence of a linear relationship between herding and volatility measures, meaning that stocks exhibiting a larger level of herding generally present a higher level of volatility. They therefore position herding as a risk factor to consider when assessing market risk.

Other studies have also studied the impact of retail investors directly on market volatility, making volatility a consequence of retail investing. Brandt et al. (2009) study the idiosyncratic risk puzzle and whether it is the consequence of a time trend or speculative episodes. They find that idiosyncratic volatility is higher for low price stocks and that the high level of risk was only significant when for low-priced stocks with a high level of retail trading. This suggests that the presence of retail investors in financial markets can create volatility in certain cases. The negative relationship between volatility and returns is also analyzed in other studies. (Han & Kumar,2008) They find that retail investors prefer stocks with high idiosyncratic risks when it comes to holding and actively trading in major part because these stocks offer greater opportunities. This once again solidifies the importance of retail investing in explaining volatility and returns in stock markets.

Using a daily sentiment composite index, Rupande et al. (2019) observe the impact of investor sentiment on return volatility in the Johannesburg Stock Exchange. They find that investor sentiment has a significant impact on volatility, stressing the importance of adding a proxy for sentiment in widely used and popular pricing models such as CAPM in order to better understand risk and volatility. Qadan (2019) uses Fama and French's 5-factor model to explore the effects of investor sentiment on the relationship between returns and idiosyncratic volatility. The results show that appetite for risk has a significant impact on financial decision-making in the form of picking riskier stocks, which in turn positively impacts the expected return and idiosyncratic volatility relationship. Studies have also observed the behaviour of Forex traders on markets with regards to success and failure periods in their trading. Ben-David et al. (2018) find that retail traders on Forex markets tend to increase their risk-taking behaviour as measured by larger trading amounts and that this behaviour was found to continue even after periods of losses.

Retail investors have also been categorized as noise traders in other studies as their activity on stock markets has been shown to generate volatility. Retail investors can, however, not be identified as only noise traders, but to a certain extent, they tend to react and make decisions with respect to market movements (Foucault et al., 2011). In accordance with most noise trading models, Kumar and Lee (2006) find that retail trading tends to explain the return movements, especially for stocks with a high retail presence. This further strengthens

the theory that individual investors tend to move together when buying or selling stocks on financial markets. Idiosyncratic volatility as measured by the variance of residuals in an asset-pricing model has been shown to be positively and significantly related to mispricing in securities in financial markets. This reflects the increasingly important role of noise traders on markets (Aabo et al., 2017). Considering that retail investors have been characterized as noise traders, we must be aware of their increased participation in financial markets and ultimately their impact on asset prices and volatility of returns. Noise trading is closely linked to investor sentiments as people tend to follow trends and the general market movements when noise trading. A positive relationship between investor sentiment and stock returns has been as well as a negative relationship between investor sentiment and return volatility on stock markets have been observed in previous studies. Irrational sentiment has also been found to significantly affect volatility (Verma & Verma, 2007).
Other studies study the impact of the investor type on volatility in stock markets and find that retail (individual) investors do not necessarily increase volatility on stock markets. In fact, Che (2018) finds that foreign investors create the most volatility due to the frequency of their trades, short investment horizon and momentum bias while retail investors trade very little and have a longer investment horizon which in turn helps reduce the volatility of returns on financial markets.

To sum up, technical analysis, chart analysis and subsequent trading behaviours are interesting topics to explore. With self-brokerage platforms becoming more and more popular and individual investors becoming an important part of financial markets, we must further analyze individuals' behaviour when making financial decisions. Individuals have been known to react to stock market price trends and cause reversal in these trends when trading. Observing participants' decision-making process when confronted with various charts or levels of volatility can help us better understand if this factor significantly explains individuals' decision-making process which in turn can allow us to better understand behaviours on financial markets.

2.3. Emotional Reaction

2.3.1. SOR Theory

SOR theory (Stimulus—Organism—Response) is a psychological theory that helps better understand how an organism responds to a stimulus, or in other words, the reasons behind a person's behaviour. A person is presented with a stimulus (S), reacts to that stimulus (O) and then produces a response (R). The "o" therefore relates to the person's behavioural response. The reaction or internal reaction to the presented stimulus could be either unconscious or conscious for the subject and leads to a certain level of emotion that is displayed by the subject. SOR theory has been used by many researchers to better understand a person's decision-making process when faced with a stimulus.

SOR theory has been previously used to examine the retail environment, more specifically to measure the role of hedonic motivation in impulse buying behaviour. The positive emotional responses of consumers, measured by pleasure, arousal and dominance, were classified as the organism in the framework and used to mediate the relationship between the retail environment and the consumer's buying behaviour (Chang et al., 2011). Other researchers have also used the SOR theory in the context of online shopping. Joginapelly and Sheng (2012) use the SOR theory to examine the effects of atmospheric website cues on users' purchasing intention. The user's emotional response, measured by valence and arousal represented the organism part of the framework for the study. Their study has shown that atmospheric cues in websites positively affect users' emotional responses and in return leads to higher intentions of purchasing on these websites. SOR theory has also been used to examine how the social commerce marketing mix can influence a customer's value perception, and ultimately influence customer loyalty. (Wu and Li, 2018) In this study, customer value, which represents the organism part of the SOR framework, acts as a mediator in explaining the relationship between social commerce marketing mix and customer loyalty. Rick and Loewenstein (2007) develop the distinction between immediate emotions, relating to internal or external events or stimuli and emotional states, which represent a person's overall state of emotions. Teubner et al. (2015) further develop this concept in an auction event approach by analyzing participants' immediate emotional responses as measured by skin conductance when you place a bid in an auction and are waiting for a response.

The SOR framework is rarely used in a financial decision-making context, making it interesting for us to further explore this theory while extending its use to finance and more specifically chart pattern analysis. Does the graph or the underlying trend (stimulus), influence the person's reaction (organism) and ultimately shape the decision-making process with regards to that graph. Chart analysis constitutes a large part of technical analysis theory, which therefore leads us to believe that it could be interesting to pursue a study that combines these two.

2.3.2. Mediator Variables

Mediator variables are variables that help explain the link between a dependent and an independent variable. In other words, the mediator variable acts as an intermediary between the independent and the dependent variable. Baron and Kenny (1986) are important actors in the mediator variable landscape. They propose a series of regressions that can help test the hypothesis that a variable acts as a mediator. First, we must see if the independent variable predicts the dependent variable. Second, the relationship between the independent variable and the mediator must be explored. Third, we test the relationship between the independent variable and the mediator with the dependent variable. The first two regressions must show a significant relationship and the mediator variable significantly impacts the dependent variable in the third regression. We can then observe if we are in the presence of complete mediation or partial mediation depending on the relationship between the independent and dependent variable once the mediator is controlled.

We can highlight an important link between SOR theory and mediator variables when analyzing people's behaviour. In SOR theory, the individual is presented with a stimulus (S), reacts to the stimulus (O) and then responds (R). This process can be explored by using the mediation analysis process in which the independent variable represents the stimulus, the mediator variable represents the organism that reacts to this stimulus and the dependent variable represents the response.

2.3.3. Emotions in auctions

Many studies explore the role of emotions in an auction context. These financial markets are in fact mostly characterized as large-scale auctions between investors, where securities are priced according to their supply and demand. Adam et al. (2015) find that competition between participants is a key driver in higher bids as arousal increases in high time pressure auctions. Adam et al. (2019) also find that arousal does indeed increase bidding in an auction setting, but that the arousal can be brought on by external sources, in other words, not only the auction's characteristics. This study also shows that participants are not necessarily aware of the effects of that arousal on their decision-making. Astor et al. (2003) use skin conductance response as well as heart rate variability to measure the participant's emotional reaction in an auction setting. They find that heart rate decreases more when participants lose an auction rather than when they win one. They also find that skin conductance response is higher when participants win an auction rather than when they lose one and increases in intensity as the money at stake increases. Adam et al. (2016) also explore the impact of affective images on decision-making (bidding) in an auction experiment. They find that participants who are presented with images inducing competitive emotions before placing bids tend to place lower bids than participants who are presented with pictures inducing community emotions. These results suggest that the nature of the stimuli that is presented to people affects their subsequent decision-making.

2.3.4. Risk/Decision-making and Emotions

Many studies have analyzed the impact of a person's emotions or mood on their risk-taking tendency, whether in a financial context or not. Kugler et al. (2010) examined the effect of anger in fear on individuals' risk-taking behaviour in a series of tasks based either on randomization or on another person's behaviour. They find that for risks based on randomization uncertainty, fear yields risk averse behaviours while anger yields riskier behaviour and the opposite for people-based uncertainty, therefore highlighting that the person's risk-taking tendencies depend on the type of uncertainty that they face. Studies have also explored the relationship between testosterone and cortisol levels with risk taking in financial settings. Coates and Herbert (2007) explored these relationships on traders in London and found that cortisol levels increased when risk levels increased, with risk being measured by the variance of the traders' returns as well as the volatility of overall markets. They also found that the traders' morning testosterone levels helped predict the traders' future profitability throughout the day. This ultimately means that the trader's decision-making can be influenced by his physiological reactions.

Various tools can be used to measure people's emotional reactions. These tools can be useful to use in a laboratory setting to measure participants' reactions to various stimuli and subsequently the impact on decision-making. Electrodermal activity, heart rate variability, valence and phasic are well-known and widely used measures of psycho-physiological reactions which have been covered in literature with regards to decision-making and risk-taking behaviour.

Studer and Clark (2011) study the role of emotions in a decision-making context under risk by developing a gambling task with various risky options. They found that EDA increased as the size of the bed increased, while the participant's heart rate decreased when they were faced with lower chances of winning. Overall, their study illustrated that arousal impacts decision-making in a risk-related context. Studies in other fields, such as construction work, observe the usefulness of EDA in assessing workers' perceived risk when undertaking risky tasks in their workplace. Short-term changes in EDA were found to have been significantly different between high risk and low-risk tasks and high-risk tasks were found to significantly affect workers' electrodermal responses (Choi, Jebelli & Lee, 2019). In a study designed to contrast the assessment of subjective versus objective risk in finance-related decision-making, Holper, Wolf and Tobler (2014) use EDA as a measure of objective risk and functional near-infrared spectroscopy as a measure of subjective risk. They find that EDA increases in response to high risk, regardless of participants' risk attitudes, which further strengthens the power of EDA as a measure of objective risk processing.

Fenton-O'Creevy et al. (2012) explore the impact of emotions in decision-making, specifically in the financial world. Their study finds that high frequency heart rate variability is inversely related to market volatility, suggesting that traders have more difficulty with regulating their emotional reactions in those periods. On the other hand, high frequency heart rate variability was found to have been positively related to trader experience, suggesting that experience helps traders better regulate their emotions. The role of high frequency heart rate variability (HF-HRV) as a modulator between anxiety and risk aversion has also been observed in Ramirez, Ortega and Reyes Del Paso's (2015) study. Through various tests such as the Balloon Analog Risk Task, they found that HF-HRV was negatively associated with risk aversion, arguing that higher HR-HRV seems to act in a protective manner for individuals suffering from strong anxiety.

Valence has also been used as an emotional proxy when analyzing risk decision-making in various settings. Hogarth et al. (2011) find that simple valence measures help better understand everyday risk perceptions. Jones et al. (2014) observe the relationship between valence and risk perception through the viewing of clips containing emotions images which require hazard perception. They find that images which exhibit either positive or negative valence tend to lead to a reduced sensitivity to potential hazards when compared to images with neutral valence. In consumer behaviour studies, valence has also been used to explain the decision-making process when purchasing goods online (Hao et al., 2010). Valence and risk have also been used to better understand decision-making in adolescents (Wolf et al., 2013). Results show that both valence and risk influence decision-making for adolescents between the ages of 11 and 16, but that the impact of valence on decision-making diminished as the participants age. Wang and Liao (2021) study the impact of valence and arousal as mediator variables in explaining safety attention for Chinese workers. They find that valence and arousal positively affect safety attention and that they both help mediate safety attention and personal characteristics.

2.4—Beliefs

Beliefs are known to be at the core of people's personalities and attitudes. Over time, many studies have explored the impact of various types of beliefs on individuals' decision-making and risk tolerance. What interests us is the impact of beliefs in a financial context. Some other interesting studies have been found to build a bridge between beliefs with financial decision-making and risk aversion. Shu, Sulaeman and Yeung (2012) study the impact of local religious beliefs on risk-taking behaviour in mutual funds. They find that mutual funds located in high-Catholic/low-Protestant areas take more speculative risks on average, as measured by fund volatility. They also explore the effects of these religious beliefs on a series of portfolio risk characteristics such as turnover, interim trading and tournament risk-taking. Kumar, Page & Spalt (2011) study the impact of religion on gambling attitudes in financial decision-making and financial risk taking. They find that investors in highly Catholic regions in comparison with highly Protestant regions tend to hold riskier, lottery-type stocks while also being more inclined to participate in employee stock option plans. This suggests that beliefs, such as religion, have an impact on individuals' financial risk propensity and decision-making.

Although religious beliefs can be interesting to observe, we believe other types of beliefs, which have not yet been analyzed in a financial context, might be worth exploring. Namely, we believe a person's tendency to perceive patterns in unrelated situations and a belief in the possibility to predict the future might be interesting to explore and link to a person's decision-making process. Those two concepts are referred to as apophenia and precognition and will be discussed in the following section.

2.4.1. Patternicity

Shermer (2008) defines patternicity as the tendency to find meaningful patterns in meaningless noise. The human brain is programmed to connect dots and make links between different things that we see in our everyday life. These patterns can be anything from seeing animals in clouds or faces in food. Shermer discusses the fact that scientists consider patternicity as a type I error in which people believe they see something real when it is in fact not. In his book The Believing Brain (2012), Shermer discusses the fact that patternicity is essential for animals and helps them navigate and survive. The brain's instinct is to detect these patterns and make sense of them as a form of security and protection. Other studies have also explored the fact that the human brain systematically seeks to explain causality and association between events in an attempt to predict and control the environment in which the person is living (Beitman, 2009). Ultimately, the fact that the human brain is programmed to make meaningful connections creates some situations in which unmeaningful connections are made and believed.

Another important element to discuss is the difference between causation and correlation. Foster and Kokko (2009) test Shermer's theory in a study designed to measure the mechanism behind assigning causality between two events. They find that people are unable to accurately assign causal probabilities to all events in their lives, which in turn forces them to make inaccurate causality links between certain events. As Shermer (2008) points out, the human brain is unable to differentiate true and false patterns, which may sometimes lead to bizarre decision-making when confronted with unexplainable situations.

2.4.2. Apophenia/Pareidolia

The definition for the concept of apophenia is quite similar to Shermer's definition of patternicity. Apophenia is defined as "the tendency to perceive a connection or meaningful pattern between unrelated or random things (such as objects or ideas). (Merriam-Webster) Apophenia is a phenomenon that is widely studied in the context of schizophrenia as individuals suffering from this mental condition have a tendency to perceive patterns in unrelated events. Fyfe et al. (2008) put participants through a series of tasks to measure their tendency to perceive patterns. They find that for certain tasks, participants prone to schizophrenia and delusion tend to perceive a larger number of associations in random events.

Apophenia can also be extended to non-medical contexts, for example in management or scientific research. Goldfarb and King (2015) use an alternative version of apophenia, namely "scientific apophenia", to explore the extent to which scientists try to find meaning in unrelated data. They define it as "the assigning of inferential meaning when limited statistical power should have prevented such a conclusion or when the data are actually random", which highlights the broad applications of the concept across various fields. Apophenia can be extended to any context in which patterns can be detected and in which performance can be affected by these patterns. The effect of apophenia on performance in multiple choice exams has also been previously examined (Paul et al. 2014). The students tend to perform poorly when the randomness in answers becomes less apparent. In other words, as patterns arise in correct answers, participants tend to become less accurate in their responses as they become "distracted" by these patterns.

Pareidolia is a form of apophenia that is defined as "the tendency to perceive a specific, often meaningful image in a random or ambiguous visual pattern". People that exhibit pareidolia have a tendency to see faces or objects in random settings, such as in the clouds or in paintings, for example. Many studies have explored Pareidolia in different contexts, but little to no studies have explored the phenomena in a financial context. Uchiyama et al. (2012) explore Pareidolia by creating the Pareidolia Test which they present to participants that suffer from dementia with Lewy bodies and Alzheimer's. Participants were presented with a series of partially blurred images containing various objects or animals and asked to describe what they saw in these pictures. They were then able to see if certain participants suffer from some visual hallucinations. Facial pattern recognition was also observed with car fronts. Specific features of a car's front end, such as headlights, have been found to attract people's attention more, which is in turn interpreted as the human's tendency to perceive faces or facial patterns (Windhager et al., 2010). This once again highlights people's tendency to perceive patterns and attempt to make connections between unrelated things.

We believe that observing patternicity, apophenia and pareidolia in the context of finance and more specifically technical analysis can be interesting. As discussed previously, technical analysis involves a great deal of chart pattern analysis, especially for amateurs, which are becoming important participants in financial markets. Stock market participants' decision-making when analyzing graphs could potentially be influenced by their tendency to perceive patterns in random stimuli. Our goal will be to create an experiment in which these concepts can be combined and where we can observe the participant's behaviour when exposed to various chart patterns.

2.4.3. Precognition

Precognition is defined as "clairvoyance relating to an event or state not yet experienced" (Merriam-Webster). Precognition is an important topic to discuss, even beyond the concept of being able to predict the future. It is rather a person's belief in precognition that can be interesting to observe and how this belief affects the person's decision-making in various settings.

Tobacyk & Milford (1983) developed an interesting 25-item instrument designed to measure people's paranormal beliefs by classifying beliefs in 7 different dimensions. This questionnaire was revisited by Tobacyk (2004) and modified to create the improved Revised Paranormal Belief Scale. This 26-item questionnaire once again measures beliefs through 7 dimensions: Superstition, Witchcraft, Psi, Traditional Religious Beliefs, Extraordinary Life Forms, Spiritualism and finally, Precognition. Belief in precognition is measured with the help of four questions in which the participant self-assesses his beliefs in astrology and the horoscope to accurately predict the future, as well as the ability of psychics and certain other people to inexplicably explain the future. These scales can then be used in various studies which seek to measure beliefs in precognition and observe its impact on other variables.

In their study, Greenaway et al. (2013) observe the impact of participants' belief in precognition on their perceived ability to control their own future. They find that people tend to believe more in precognition whenever they are put in a situation where they lack control, suggesting that these beliefs act, to a certain extent, as a defence mechanism to the lack of control. Precognition was also found to be linked to the illusion of control in other studies (Rudski, 2004). The illusion of control seems to be positively related to precognition, meaning that in situations of uncertainty, people who believe that the future can be predicted will have an illusion that they can control the outcomes of situations. They also explain this situation with precognition being a sort of coping mechanism in creating certainty in an otherwise uncertain environment.

We believe that observing the belief in precognition can be interesting. Beliefs in precognition in the context of finance could potentially influence a person's illusion of control and therefore impact their decision-making process or their risk-taking tendencies. Our goal will therefore be to include this concept in our study and assess its impact on risk taking.

2.5—Financial Literacy

Financial literacy has long been studied, more specifically in a context of decision-making for non-finance professionals. Individual investors may react differently on financial markets or when making strategic decisions to meet their long or short-term financial goals whether they possess some strong financial knowledge or not. This change in behaviour relative to the level of financial literacy can have a significant impact on individuals' long-term well-being. Many studies have also assessed the impact of financial knowledge, along with a series of other variables, on risk tolerance, which is of great interest for our study. Risk tolerance is one of the main drivers of an individual's financial choices, asset allocation and investment decisions.

Grable (2000) explores the impact of financial of various socioeconomic variables and financial knowledge on everyday risk-taking behaviour and individuals. One of the findings of this study is that participants who possess higher levels of financial knowledge tend to have a higher risk tolerance than participants exhibiting lower levels of financial knowledge. The impact of sociodemographic characteristics and financial knowledge as measured by investment, tax, retirement, wealth, and insurance planning, was also observed in India (Reddy & Mahapatra, 2017). Financial knowledge was found to have a positive and significant impact on risk tolerance, which ultimately translates into higher risks being taken when making informed financial decisions. Mishra (2018) also studies the impact of self-assessed financial literacy, risk tolerance and investment awareness individuals' stock market decisions. Results show that households with a higher level of self-assessed financial literacy along with higher risk tolerance tend to participate more in stock markets as opposed to households with low self-assessed literacy and risk tolerance which tend to shy away from such markets. Similar conclusions were drawn in Pakistan to assess the impact of financial literacy and experience in explaining risk-taking behaviour on financial markets (Awais et al., 2016). Results show that financial literacy helps individuals analyze complex financial information in an efficient manner which in turn allows them to take higher financial risk. These findings are like those found by Bashir et al. (2013) a few years earlier, also in Pakistan. Individuals who are willing to take more risks tend to have better knowledge of financial markets and financial instruments. Risk aversion has also been found to have been significantly affected by the individual's financial literacy in Italy (Bajo et al., 2015). Participants in the study who possess higher levels of financial literacy tend to exhibit higher risk tolerance than participants that exhibit higher levels of financial literacy. Hermansson and Jonsson (2021) come to a similar conclusion with their findings by showing that financial interest and financial literacy has a significant impact on risk tolerance. Swedish banking data showed that participants exhibiting a higher level of financial literacy and higher financial interest tend to have a higher risk tolerance. Aren and Zengin (2016) find that both risk perceptions and financial literacy are significant considerations in explaining individuals' investment decisions. Investors who possess low levels of financial literacy tend to prefer less risky investments such as deposits and foreign currency while investors who possess high levels of financial literacy tend to prefer riskier investments and create portfolios and invest in equities.

Other studies have also observed the role of financial literacy when explaining the gender differences in financial risk taking. By contrasting perceived and actual financial literacy, Bannier and Neubert (2016) find that standard investments are strongly related to perceived and actual financial literacy for men and actual literacy only for women. They also find that sophisticated investment decisions were more strongly related to perceived literacy for women than for men. Ultimately, this study highlights the fact that financial literacy was found to play a significant role in explaining financial risk taking. Other studies have observed the impact of financial literacy and if it plays the role of a moderator in explaining the relationship between financial risk tolerance and sociodemographic characteristics (Shusha, 2017). Results show that financial literacy acts as a moderator when explaining Egyptian individuals' risk propensity when making financial decisions.

Other studies also distinguish between actual financial knowledge and perceived financial confidence and observe their impact on financial decision-making Asaad (2015). Results indicate that individuals that exhibit overconfidence in their financial literacy while also possessing low actual financial knowledge tend to exhibit riskier financial behaviours. This highlights the importance of considering self-assessed financial knowledge when analyzing the source of risky investment decisions. Lucarelli and Brighetti (2010) assess the impact of both unbiased risk tolerance, as measured by psycho-physiological reactions, as well as biased risk tolerance, as measured through psychometric questionnaires, on individuals' financial decisions. They find participants tend to make risky financial decisions in accordance with their self-assessed risk tolerance while acting in almost opposite contrast to their feeling of risk.

Without drawing a direct link with risk preferences in financial markets, other studies have studied the impact of financial literacy on financial planning. Using data from France, Arrondel et al. (2013) find that individuals who exhibit better financial literacy are more likely to prepare clearer financial plans for their future. The same findings were also found in China where participants who presented higher financial literacy scores were more likely to both plan for their retirement and use financial markets to reach their objectives (Chen et al., 2018).

2.6. Conclusion

Many financial models and theories still used to this day assume that markets are efficient and investors rational. Throughout the years, many studies have shown some irregularities in investor behaviour that have deviated from the traditional rationality beliefs. The recent keen interest in self-brokerage platforms has led to the increased presence of retail novice investors, further impacting investing trends in global markets.

Several factors including technical and chart pattern analysis, emotions, apophenia tendencies, precognition beliefs and financial literacy have the potential of shaping a person's decision-making process and risk tendencies in all aspects of life, including in a financial context. These factors can be further explored in an experiment to see if investor behaviour can be better anticipated.

3. Research Model

The goal of our study is to explore various factors that can affect the risk preferences and the decision-making process of individuals when confronted with various chart patterns. We seek to create an experiment in which participants are asked to predict the outcome of various charts, but in which participants are also unaware that chart patterns are taken from stock markets to ensure that the observed behaviours are as unbiased as possible.

We seek to study the impact of chart characteristics, emotional reactions, beliefs, risk preferences and financial literacy on risk taking or on the expected direction of the graph in the future (rise, fall, remain at the same level). If the factors do not affect the level of risk taken when anticipating the outcome of graphs, it is possible that they will affect the direction in which participants believe the trend will take on in the future. We first start by looking at if the chart itself guides the risk preferences and then move on to see if other external variables affect the decision-making process.

We separate participants into two different groups where one group is presented with randomly generated charts while the other group is presented with manually created patterns which can be identified as well-known chart patterns in technical analysis. Although we do control for this group difference and also for the learning effect throughout the experiment, we do not have any hypothesis that directly touches this subject.

The base case for all four of our hypotheses is that these factors do not ultimately have an impact on the individual's risk preferences or on the anticipated direction of the chart. Following the efficient market hypothesis as a guideline, we believe that no trend should come out of the analysis due to each individual's rationality and that the decision-making in our study's main task should follow a random distribution. Because predicting the future is not possible, we believe that the answers we get from our task will be random and therefore base our hypotheses off this idea.

3.1 Chart characteristics

We define the various chart characteristics by grouping the chart patterns in different categories. These categories include overall chart trends, partial chart trends and volatility. When looking at price charts for various stocks, one can see visually if the overall trend is ascending, descending or relatively stable, but most importantly, one can make an investment decision with regards to these trends. While certain studies argue that retail investors tend to follow trends when investing (De Bondt, 1993), others have found that investors tend to bet against trends and ultimately cause their reversal (Andreassen, 1988 & Achelis (2000). Without looking at the company's entire historical price chart, technical analysts will look at specific sections of price charts and base their decision-making process on these perceptible patterns. Return volatility can also cause some erratic behaviour on stock markets, so observing the impact of large variations in a chart on a person's decision-making process and risk preference is valuable (Kumar and Lee, 2006). With our first hypothesis, we first want to test if the underlying characteristics of the charts have an impact on the participant's decision-making process and risk preference when predicting the outcome of these graphs.

Hypothesis 1a: ***Chart characteristics, as measured by the chart's general, first half and second half trends, as well as the chart's volatility, do not impact the individual's risk preferences when predicting the outcome of graphs.***

Hypothesis 1b: ***Chart characteristics, as measured by the chart's general, first half and second half trends, as well as the chart's volatility, do not impact the anticipated direction of the graph's outcome.***

3.2 Emotional reactions

Emotional reactions have been known to influence decision-making and risk taking in individuals. Many studies, especially in the User-Experience field have used measured physiological reactions as well as perceived reactions and observed the impact of these variables on decision-making. As seen in section 2.3 of this thesis, multiple physiological measures have been used as proxies for emotions in those studies, including valence, arousal, EDA, HRV and phasic.

Without directly assessing the impact of emotions on a decision or action, many studies have used the mediator concept to explore the relationship between emotions and decision-making (Baron & Kenny, 1986). We use this concept to explore this relationship ourselves in this study. Since very few studies in a laboratory setting have explored the link between emotions and technical analysis or pattern recognition, we decided to test this in our study. For our second hypothesis, we introduce emotional reactions in the mediation framework and test to see if emotions act as a mediator variable in explaining the relationship between chart characteristics and risk taken when predicting the outcome of those graphs.

Hypothesis 2a: ***Emotional reactions, as measured by valence, phasic, EDA and HRV do not act as a mediator in explaining an individual's risk preferences when predicting the outcome of graphs.***

Hypothesis 2b: ***Emotional reactions, as measured by valence, phasic, EDA and HRV do not act as a mediator in explaining an individual's anticipated direction of the graph's outcome.***

3.3 Risk taking tendencies and Beliefs

Multiple studies have observed the impact of beliefs and general risk preferences on decision-making in other aspects of an individual's life. For example, individuals with higher risk tolerances oftentimes tend to take more risks in financial situations. Individuals with higher financial risk tolerance also tend to translate these preferences into riskier investments such as risky stocks (Qadan, 2019). Beliefs in precognition also tend to influence a person's illusion of control about the situations that they go through, which could ultimately impact the decision-making (Rudski, 2004). Individuals who experience important levels of apophenia tend to see patterns in unrelated things, leading them to make conclusions about events with no inherent causality (Uchiyama et al., 2012).

After having observed the impact of both chart characteristics and emotions on risk taking tendencies when predicting the outcome of graphs, we seek to test the impact of beliefs on the individual's decision-making process to see if personality traits have a significant impact. For our third hypothesis, we test the impact of lottery preferences, financial risk tolerance, apophenia and beliefs in precognition on the individual's risk-taking behaviour when predicting the outcome of graphs.

Hypothesis 3a: ***Beliefs and individual risk preferences, as measured by lottery preferences, financial risk tolerance, apophenia tendencies and beliefs in precognition, do not impact the individual's risk preferences when predicting the outcome of graphs.***

Hypothesis 3b: ***Beliefs and individual risk preferences, as measured by lottery preferences, financial risk tolerance, apophenia tendencies and beliefs in precognition, do not impact the anticipated direction of the graph's outcome.***

3.4 Financial Knowledge

Financial knowledge has been known to impact decision-making and more importantly risk tolerance in a financial setting. Multiple studies have found that higher financial knowledge logically translates into higher risks being taken by investors (Grable, 2000 & others). Although we do not frame our study as a stock market simulation, the charts that are shown to participants can be closely linked to well-known technical analysis patterns that are studied in finance. Ultimately, our goal is to observe different factors that could affect risk preferences when individuals are exposed to charts and asked to predict their outcome.

After having observed the impact of chart characteristics, emotions and beliefs/risk tolerance on an individual's risk-taking behaviour when predicting the outcome of graphs, we now seek to test the pact of financial knowledge on this same dependent variable for our fourth hypothesis. We use the participant's self-assessed financial literacy and their knowledge of the GameStop events that took place in early 2021 as proxies for financial knowledge to test this relationship.

Hypothesis 4a: ***Financial knowledge, as measured by self-assessed financial literacy and knowledge surrounding the GameStop events, does not impact the individual's risk preferences when predicting the outcome of graphs.***

Hypothesis 4b: ***Financial knowledge, as measured by self-assessed financial literacy and knowledge surrounding the GameStop events, do not impact the anticipated direction of the graph's outcome.***

3.5 Secondary Study

To test our hypothesis on a larger sample of participants, we conducted a second study that took the form of an online questionnaire (details in section 4). Our research model remains the same for this second study as it consists of a shortened version of our initial research with a few variables being left out. Although the research question remains the same, our four hypotheses are slightly changed to reflect our study's new parameters.

Hypothesis 5a): ***Chart characteristics, as measured by the chart's general, first half and second half trends, as well as the chart's volatility, do not impact the individual's risk preferences when predicting the outcome of graphs.***

Hypothesis 5b): ***Chart characteristics, as measured by the chart's general, first half and second half trends, as well as the chart's volatility, do not impact the anticipated direction of the graph's outcome.***

Hypothesis 6a): ***Emotional reactions, as measured by perceived pleasure and arousal, do not act as a mediator in explaining an individual's risk preferences when predicting the outcome of graphs.***

Hypothesis 6b): ***Emotional reactions, as measured by perceived pleasure and arousal, do not act as a mediator in explaining an individual's anticipated direction of the graph's outcome.***

Hypothesis 7a): ***Beliefs, as measured by apophenia tendencies and beliefs in precognition, do not impact the individual's risk preferences when predicting the outcome of graphs.***

Hypothesis 7b): ***Beliefs, as measured by apophenia tendencies and beliefs in precognition, do not impact the anticipated direction of the graph's outcome.***

Hypothesis 8a): ***Financial knowledge, as measured by self-assessed financial literacy, does not impact the individual's risk preferences when predicting the outcome of graphs.***

Hypothesis 8b): ***Financial knowledge, as measured by self-assessed financial literacy, does not impact the anticipated direction of the graph's outcome.***

4 - Methodology

As mentioned in section 3, in order to increase the statistical significance of our analysis, we conducted two separate experiments. This allows us to test our model with more participants. First, we conducted an experiment in a laboratory setting using the Tech3Lab resources. Second, we conducted a remote questionnaire that was administered through the Amazon Mechanical Turk platform. Although the overall model remains the same for both experiments, data for both experiments was collected differently. Details on both experiments are presented below.

4.1. Experiment 1—*BluePanel*

4.1.1. Introduction and Participants

The first phase of our study, the *BluePanel* experiment, took place over a six-week period. To test hypothesis 1 through 4, we conducted a laboratory experiment with participants that were recruited in two panels composed of 18 and 24 participants respectively. Due to the Covid-19 pandemic and sanitary restrictions, we created an experiment which participants could undertake from home while still being able to collect physiological data (Giroux et al., 2021). The entirety of the project was approved by HEC's Research Ethics Board (Certificate No. 2021–4367).

Participants were recruited through a special panel created by the Tech3Lab and composed of 18 and 24 participants respectively. Each panel was made up of participants recruited for a one-month period in which they took part in different experiments each week. Two different panels took part in our experiment in order to collect data on a relevant number of participants (N>30). Because of technical difficulties and withdrawals, 37 participants ultimately took part in the study. Participants that were excluded from the study due to lack of availability to conduct the experiments or technical difficulties related to the physiological data collection material and internet connection for remote-based experiments. Of the 37 participants, 21 were male and 16 were female with ages ranging from 19 to 55+ years old (average 27.05 and standard deviation 8.07). Participants were compensated $50 for participating in the experiment. To create a more realistic experiment, additional compensation in the form of a draw was added.

Participants were told at the beginning of the *Pattern Task* that they each started with 10 coupons for a draw between all participants in the study. For each graph outcome that the participants predicted correctly, participants received an additional 10 coupons for the draw (Details on the *Pattern Task* can be found in further sections). The maximum number of coupons participants could obtain in this task, excluding the 10 free coupons, was 100 coupons. Participants then moved on to the next part of the study: the lottery choice. Participants had to choose one of five heads or tails lotteries with different payoffs and play that lottery (Details on the Lottery task can be found in later sections). After choosing the lottery, participants moved on to the next page to see if they had landed on heads or tails and how many tickets they had won or lost. For technical simplicity, all participants won the maximum number of coupons for the lottery they had chosen. It was therefore impossible for participants to lose any coupons. After the end of the data collection period, results for each participant were compiled, verified, and drawn randomly. The winner of the draw received a $100 amazon gift card in addition to the basic compensation.

To ensure data quality, several exclusion criteria were enforced to participants wishing to be part of the panels. These criteria were strict considering that the study would be conducted remotely:

- Be over 18 years old
- Not have a pacemaker
- Have access to a computer (Windows for material preparation, not necessary for the experiment)
- Have access to residential Wi-Fi on that computer with a bandwidth of more than 5 Mbps (from which the password and network name are known and can be modified if necessary)
- Preferable to have a 2.4 GHz Wi-fi (5Ghz works in certain cases, but not all).
- Have a functional webcam and microphone with the computer
- Have access to an isolated and well light area with a stable table or desk from which to take part in the experiment

4.1.2. Measures

The bulk of the experiment was completed through a Qualtrics questionnaire. Participants were guided through the various sections by a moderator. The main task of our experiment was the *Pattern Task* which will be discussed in section X. To create the stimuli for the *Pattern Task*, we used an internally developed program called "Cobalt Capture" (Courtemanche et al., 2022). The program allowed us to present videos and create multiple choice questions while also allowing us to extract time codes for each of the participant's actions, which we were then able to pair with the participant's Bluebox (Courtemanche et al., 2022). We were therefore able to accurately record the participant's physiological reaction throughout the *Pattern Task* and use it later in the analysis. To access this program, participants were asked to click on a link in the Qualtrics questionnaire. This link led to a second web page where participants were able to perform the *Pattern Task*.

Once the task was completed, participants returned to the Qualtrics questionnaire to complete the remainder of the experiment.

A series of physiological reaction measures were measured using different data collection instruments. Facial expression was recorded by using the participant's webcam and the Lookback platform. Both EDA and EKG were measured using the COBALT Bluebox device, which consists of a 3D printed case that collects biosignals and allows us to conduct studies remotely while also being able to gather valuable physiological data. (Courtemance et al., 2022.) Electrodes were placed in the participant's palm (EDA) and on the participant's upper torso and ribs (EKG) in order to collect the data (see details in Annex 1).

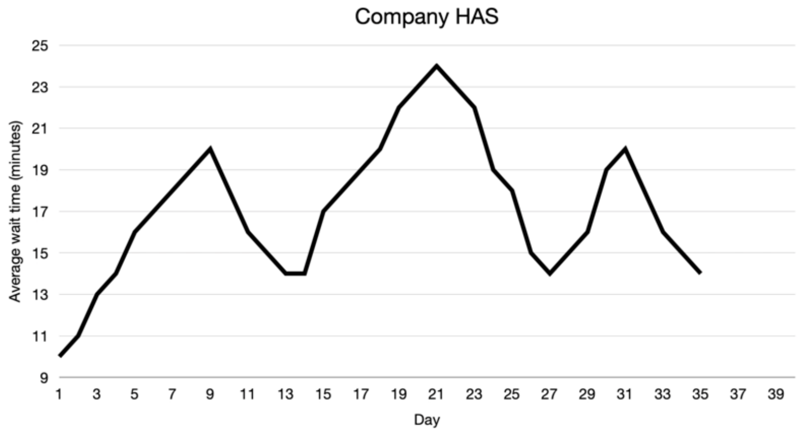
The entirety of the questionnaires was also translated from English to French using the double translation method to ensure optimal and equivalent experiments in both languages.

4.1.3. Experimental Design and Stimulus

To measure the participants' reactions and risk preferences with regards to chart patterns, we developed an experimental task called the *Pattern Task*. In this task, each participant is presented with 10 graphs with a 35-day evolution and are asked to predict the outcome of the graph over the next 5 days. Participants were randomly split into two groups prior to the start of the experiment. 18 participants were randomly assigned to the treatment group while 19 were assigned to the control group.

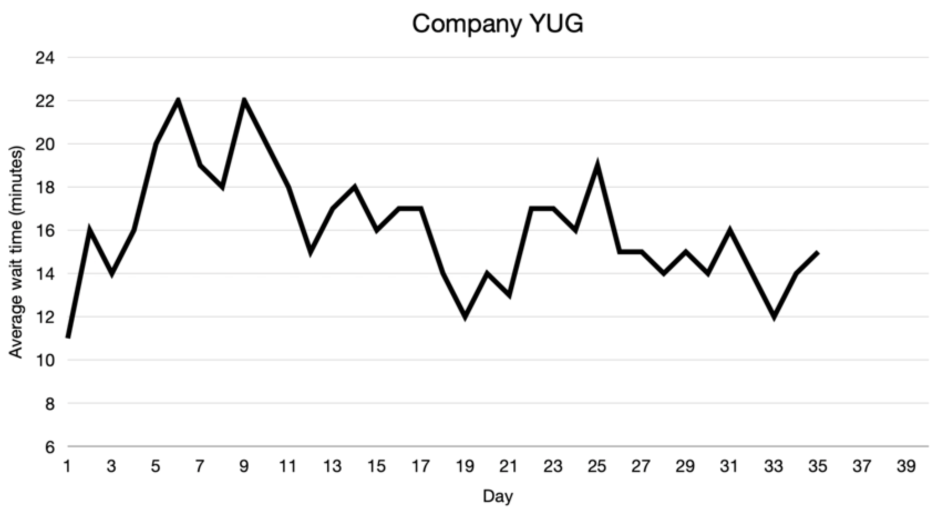
The first group, which represents the Technical condition, was presented with 10 chart patterns replicating well-known chart patterns frequently observed on financial markets, and analyzed in technical analysis theory. They also differ from the charts that we generate randomly by showing a perceivable trend and/or an identifiable pattern. [See Figure 1 below and details in Annex 2]. The first 35 days of the chart were manually created to replicate the desired patterns. The five following days, which represent the graph's outcome, were simulated randomly (see details on random simulation in Annex 3).

Figure 1 – Technical Pattern Example



The second group, which represents the Random condition, was presented with randomly generated graphs. The full 40-day chart was randomly generated to avoid any clearly identifiable technical analysis pattern (see example in figure 2 below and details in Annex 3).

Figure 2 – Random Pattern Example



For both groups, the outcome of the graph over the final 5 days is randomly generated, so the actual chart pattern has no impact on the outcome, even if the participants try to predict based on the observed pattern.

In order to remove the financial bias associated with pattern recognition and the stock market, we do not mention to the participant that these graphs represent potential stock market patterns. We frame these graphs as the average daily wait time to speak to an agent when a call is placed to the company's customer service department. We tell participants that they will see charts of the average daily wait time over a 35-day period for 10 different companies and they must predict the outcome over the next 5 days. Participants are given 5 choices to predict the outcome of the graph in 5 days. In 5 days:

a) The average daily wait time will have increased by more than 4 minutes
b) The average daily wait time will have increased by 1 to 4 minutes
c) The average daily wait time will have remained at the same level
d) The average daily wait time will have decreased by 1 to 4 minutes
e) The average daily wait time will have decreased by more than 4 minutes

Answers to this question translate into the Risk and Direction variables that will be used later in our analysis. This framing allows us to measure the participant's risk preferences with regards to the patterns while also eliminating the financial bias. If a participant chooses either answer a) or e), he believes that there will be large variations in one particular Direction in the graph over a short period of time, which means they are taking a higher risk for this particular graph. Participants also predict the Direction by stating that the wait time will either increase, decrease or remain at the same level over the next 5 days.

The charts are presented in the form of videos where the participants see the evolution of the wait time starting from the 1st day and ending on the 35th day. Once the participants predict the outcome, they are then shown a second video with the actual outcome of the chart over the following 5 days. Participants are therefore aware of their performance throughout the task and are rewarded accordingly. The additional compensation related to this task are discussed in section 4.1.1.

4.1.4. Experiment Protocol

Due to the Covid-19 pandemic and sanitary restrictions, the study was conducted entirely from the participants' homes. Prior to receiving the data collection material, participants were contacted by Tech3Lab research assistants to make sure all participation criteria were met. The physiological data collection material provided by the Tech3Lab was then delivered to participants at their homes, with enough supplies for them to participate in multiple studies over a 4-week period. The experiment was divided into four different parts: preparation, calibration task, *Pattern Task* and questionnaires. The entire experiment lasted approximately 90 minutes.

To conduct the experiment in an identical manner for all participants, participants were assisted by a moderator through a videoconference by using the Lookback platform. Moderators followed a standardized protocol containing verbal instructions to help the participant set up the physiological data collection material and guide the participant through the various tasks.

Participants were asked for their verbal consent for their participation in the study and given general instructions on the experiment. Then, the moderator helped the participant setup the physiological data. The moderator made sure that the participant's face was well centred and well light to ensure facial expression data could be properly measured and that the EDA/EKG sensors were properly installed. The moderator then tested the Bluebox connection with the participant to ensure data could be relayed to the research team. To make sure that the material had been set up properly and that they produced data was of adequate quality, the moderator visualized the participant's physiological data in real time before the start of the experiment.

The socio-demographic questionnaire had already been filled out by the participants in the days preceding the experiment. Therefore, participants directly moved on to the calibration task which was not part of the experiment. Participants were shown a series of 10 videos displaying either positive, negative, or neutral situations. At the end of each video, participants were asked to use a scale to self-assess their levels of arousal and pleasure while viewing the videos. Between each video, participants were presented with videos showing a series changing images with cubes of various colours on each image and were asked to count the number of white cubes they saw appearing throughout the entire duration of the video.

Participants then moved on to the first official task of the experiment: The *Pattern Task* (discussed in section 4.1.3). Participants were presented with a short description of the task and an explanation of its performance-based compensation. Participants also had the opportunity to ask questions about the task to validate their understanding of the instructions. We decided to do the patterns task first to remove any potential bias in the answers. We wanted to make sure participants did not associate the chart patterns with finance.

The participants then moved on to the questionnaires, starting with a choice of 5 lotteries with different payoffs. This was inspired by Eckel and Grossman's task in which five lotteries to choose from. The lotteries each had a 50/50 probability of a low or high payoff. The 5 choices get progressively riskier but offer a higher expected payoff. Participants were asked to choose the lottery they wished to play out of the five possible lotteries. The lottery choice allows us to measure the participant's individual risk preferences, so that the higher the chosen lottery, the higher the participant's risk preferences. Instead of offering monetary payoffs, we offered a coupon payoff, which creates a link with the *Pattern Task*'s performance-based compensation. After choosing, participants were shown a screen that mentioned they had won their bet and that they would receive these additional coupons as compensation. The additional compensation related to these tasks are discussed in section 1.4.

Next, participants were presented with a series of 10 black and white images in random order, designed to measure their level of apophenia. The task was inspired by Uchiyama et al.'s pareidolia test that was previously discussed. For each image, participants were asked to rate on a scale of 1 to 7 the extent to which they saw 4 different objects in the ten images. Only one object was present in each image. To evaluate the participant's tendency to perceive patterns in unrelated images, we summed for each of the three unobserved objects for each image. The higher the participants' score, the more the participant presented signs of visual hallucinations. [See details in Annex 4]

Participants were then asked to answer a series of questions on finance which first measured their financial risk tolerance by using the Grable and Lytton risk tolerance scale. This 13-item scale measures the participant's risk tolerance through a series of scenarios. Each possible answer is assigned a score. The score for each of the 13 answers is summed up to represent the participant's overall financial risk tolerance. A higher score therefore represents higher risk tolerance.

Participants were then asked to self-assess their level of financial literacy. Ultimately, we created a series of financial knowledge questions based on the GameStop situation that took place in January 2021. Participants were once again asked to self-assess their level of knowledge, but this time regarding the GameStop situation. They were also asked to identify the level at which regulators should intervene in such a situation. Finally, participants were to assess the likelihood that such a situation would happen again in the future and the likelihood of them buying shares of a company in the future if such a situation were to happen again.

The last questions in the questionnaire section were on precognition. To measure the participant's belief in prediction of the future, we use the "precognition" section of the Revised Paranormal Belief Scale (Tobacyk, 2004). This 4-point task measures a participant's belief in the horoscope, astrology, and psychics. This task allows us to better understand the participant's belief in precognition with a higher score corresponding to higher beliefs. After completing the different tasks, participants were thanked for their participation and given details regarding compensation. The entire questionnaire can be found in Annex 5.

4.1.5. Variable operationalization

This section presents the variable operationalization. The table below includes the relevant research variables that will be used in our analysis. This included the variables in the *Pattern Task*, the emotional reaction variables as well at the variables from other questionnaires used to measure the individual's preferences, beliefs and financial literacy.

Table 1 - Research Variables - *BluePanel*

Variable	***Measure***	***Description***
Participant ID	Unique participant ID between 1 and 44.	Unique ID for each participant from the 2 panels.
Pattern ID Initial	Numerical ID for each pattern. (1 to 20)	Numerical ID for each of the 20 patterns that the participants see. Patterns 1 to 10 represent created patterns while patterns 11 to 20 represent randomly generated patterns.
View Order	Viewing order for each of the patterns by the participant. (1 to 20)	Viewing order for each of the patterns by the participant. Each participant will see 10 graphs, in random order. This variable represents the order in which participants see each graph. View Orders 1 to 10 are for participants who will see the created patterns and 11 to 20 is for participants who will see the randomly generated patterns. Allows us to capture both the View Order effect and the nature of the graph.
Risk	Categorical variable with values 0 to 2. 2 = Increased/decreased by more than 4 minutes 1 = Increased/Decreased by 1 to 4 minutes 0 = Remained at the same level	Represents the answer to: “In your opinion, the average wait time on the 40th day (compared to the 35th day) will have”: Allows us to measure the level of risk taken by the participant in this task.
Direction	Categorical variable with values 1 to 3. 3 = Increased by 1 to 4 or more than 4 minutes 2 = Remained at the same level 1 = Decreased by 1 to 4 or more than 4 minutes	Represents the answer to: “In your opinion, the average wait time on the 40th day (compared to the 35th day) will have”: Allows us to analyze in which direction (ascending/descending/neutral) the participants believe the wait time will go over the next 5 days.
General Trend	Categorical variable with values 1.2 or 3. 1 = Ascending, 2 = Descending, 3 = Neutral	Identifies the graph’s general trend (start to finish) as measured by the overall slope of the graph. The graph tendency can either be ascending, descending or neutral.
Half	Categorical variable with values 1.2 or 3. 1 = Ascending, 2 = Descending, 3 = Neutral	Identifies the trend for the first half (first 20 days) of the graph as measured by the overall slope. The trend can either be ascending, descending or neutral.
Half_0	Categorical variable with values 1,2,3. 1 = Ascending, 2 = Descending, 3 = Neutral	Identifies the trend for the second half (last 20 days) of the graph as measured by the overall slope. The trend can either be ascending, descending or neutral.
Variability	Continuous variable which represents the standard deviation of values for the first 35 days of each graph.	This variable measures the standard deviation of values for the first 35 days on each graph and therefore allows us to measure the volatility of each graph.
Emotional Reaction	Measured through a series of continuous variables that act as a proxy for the intensity of emotion: EDA Valence Ratio HRV Phasic	Measures both the average and standard deviation of EDA, Valence, Ratio and Phasic. EDA: Measures the electrodermal activity for each trial of the *Pattern Task*. Valence: Measures the valence for each trial of the *Pattern Task*. Ratio HRV: Measures the heart-rate variation for each trial of the *Pattern Task*. Phasic: Measures Phasic EDA for each trial.

Lottery	Categorical variable. Participants choose one of 5 available lotteries. Lottery 1 to Lottery 5.	Adaptation of the Eckel and Grossman task. Allows us to measure risk preferences. Participants must choose one of 5 lotteries to play. This variable represents the lottery they choose. The higher the number, the riskier the lottery.
Apophenia	Discrete variable that represents the sum of answers to the questions for the 10 images. Question: On a scale of 1 to 7, to what extent do you agree with the following statements:	Adaptation of Uchiyama et al.'s pareidolia test. Allows us to measure the participant's level of apophenia (visual hallucinations). Participants are shown 10 different images and must determine to which extent (on a scale of 1 to 7) they see various elements (4 elements per picture) in these images. 3 elements are not the specific item in the picture. This variable represents the sum of the 3 unrelated elements for each picture. Minimum score of 30, maximum score of 210.
Financial Risk Tolerance	Discrete variable that represents the sum of all answers to the 13 questions. Each answer is assigned a numeric value.	Grable and Lytton risk tolerance scale. Allows us to measure financial risk tolerance. Participants must answer 13 questions to assess their financial risk tolerance. Each possible response to the 13 questions is converted to a numeral scale. This variable represents the total score on this 13-question test. The higher the score, the higher the risk taken. Minimum score of 13, maximum score of 44.
Precognition	Discrete variable that represents the sum of all the answers to the questions for the 4 statements. Question: On a scale of 1 to 7, to what extent do you agree with the following 4 statements?	Adaptation of Tobacyk's Revised Paranormal Belief Scale. Allows us to measure the participant's level of belief in precognition. 4 questions are asked to measure the participant's tendency to believe in astrology, psychics and predicting the future. They must answer on a scale of 1 to 7 to what extent they agree with each of the 4 statements. Minimum of 4, maximum of 28.
GameStop Familiar	Discrete variable measured by a 1 to 7 scale.	Allows us to measure to what extent participants are familiar with the GamStop events that took place in early 2021.
GameStop Shares	Binary variable with values 0 or 1. 0 = owns shares of GameStop 1 = does not own shares of GameStop	This variable allows us to identify if the participants own shares of GameStop or not.
GameStop Regulators	Discrete variable measured by a 1 to 7 scale	This variable allows us to measure to what extent participants think regulators should intervene when a situation like GameStop occurs in financial markets.
GameStop Happen Future	Discrete variable measured by a 1 to 7 scale	This variable allows us to measure to what extent participants think such a situation is likely to happen again in the future.
GameStop Buy Future	Discrete variable measured by a 1 to 7 scale	This variable allows us to measure to what extent participants would buy shares if such a situation happened in the future.
Financial Literacy	Discrete variable measured by a 1 to 7 scale	Allows us to measure each participant's self-assessed level of financial literacy. The higher the number, the higher the participant believes his level of financial literacy to be.
Average Financial Literacy	Discrete variable measured by a 1 to 7 scale	Combines the Financial Literacy, GameStop Familiar and GameStop Regulators questions through an Average Financial Literacy measure to be used in the analysis.

Table 2 - Sociodemographic Control Variables - *Mturk*

We also include a separate table with sociodemographic data to assess the composition of our panels in the next section.

Variable	***Measure***	***Description***
Accounts	Categorical variable: 1 = Cash account, 2 = Savings account, 3 = Registered Retirement Savings Plan (RRSP) account, 4 =Tax-Free Savings account (TFSA), 5 = margin account, 6 = Other	Variable that can take on multiple values and identifies all the different bank or trading accounts that the participant possesses.
Number accounts	1 to 6	Variable that represents the sum of accounts that participants previously mentioned.
Employment	Categorical variable: 1 = Student, 2 = Part-time worker, 3 = full-time worker, 4 = retired, 5 = unemployed, 6 = other	Variable that represents the participant's employment status.
Sex	Binary variable: 1 = male, 2 = female	Binary variable representing the participant's sex at birth.
Gender	Categorical variable: 1 = male, 2 = female, 3 = non-binary	Categorical variable representing the participant's gender.
Age	Scale from 0 to 55+	Variable representing the participant's age.
Education	Ordinal variable representing the participant's level of education. 1=primary or earlier, 2=high school, 3=college, 4=undergrad, 5=graduate, 6=postgrad	ordinal variable that represents the participant's level of education.
Marital Status	Categorical variable: 1=married, 2=common-law partner, 3=widow, 4=separated, 5=divorced, 6=single	Variable that represents the participant's marital status.
Annual Income	Ordinal variable: 1=less than \$20,000, 2=between \$20,000 and \$39,999, 3=between \$40,000 and \$59,999, 4=between \$60,000 and \$79,999, 5=more than \$80,000	Variable that represents the participant's annual income in Canadian dollars.
Place Residency	Binary variable: 1=Canada, 2=other country	Variable that identifies the participant's country of residence.
Other Country	Text entry.	If participants select the option of "other country", they must identify which country they are talking about.
Residence Country	Binary variable: 1=individual resides in country of birth, 2=individual resides outside of country of birth	Variable to identify if a participant resides in his country of birth.

4.1.6. Analysis strategy

To test our research model hypothesis, we performed regressions on Stata 17 after having combined data from Qualtrics, the UX Stimuli (*Pattern Task*), the Bluebox (physio data) and Socio-demographic questionnaires. The data was also codified and prepared for the analysis prior to performing these regressions.

Globally, we want to see which factors contribute to the intention of taking risks when participants are exposed to various chart patterns. The participant's answers in the *Pattern Task* will therefore be used as the dependent variable in our analysis. As described above, we categorize the participant's answers in two different ways by creating three different variables. First, to analyze the participant's risk preferences in the pattern task, we group the answers according to the intensity of the variation (no variation/low variation/high variation). An increasing intensity means participants believe there will be a large variation in one direction and therefore represents higher risk taken in the task. Second, we group the answers according to the anticipated Direction of the graph in the following days (descending, neutral, ascending). We will look at four different families of factors that could potentially explain the level of risk taken and the anticipated Direction in the *Pattern Task*, namely the chart characteristics, emotional reaction, beliefs, and individual risk preferences, as well as financial literacy.

We first want to observe the chart characteristics and assess their impact on the risk preferences of participants in the patterns task. We characterize charts according to their general trends, first and second half trends, and also look at each chart's standard deviations as a measure of volatility. We therefore regress these variables on both Risk and Direction using a fixed effects ordered probit model due to the categorical ordinal nature of our dependent variables. This will allow us to test the hypotheses 1a) and 1b). Second, we want to observe the impact of emotional reaction on the participant's decision-making process. More specifically, we want to test if the emotional reaction acts as a mediator variable in explaining the participant's risk preferences in the *Pattern Task*. We measure a series of physiological features for each participant, namely EDA, Valence, Heart-rate variability and Phasic and observe the mean and variance of the features each time a participant sees a graph. We will use Baron and Kenny's (1986) model to test the mediation hypothesis 2a) and 2b). Third, we want to observe the impact of a person's beliefs or risk-taking behaviour on their decision-making process. We use four variables mentioned above to characterize the participant's beliefs, and individual risk preferences: Lottery, Financial Risk Tolerance, Apophenia and Precognition. We will use a fixed effect ordered probit model to assess the impact of these four variables on Risk and Direction and test hypotheses 3a) and 3b). Fourth, we seek to observe the impact of a person's financial knowledge on their risk preference and anticipated direction in the *Pattern Task*. We use the participants' self-assessed financial knowledge as well as a combination of questions on GameStop to measure their financial knowledge. We used a fixed effects ordered probit model to assess the impact of these variables on Risk and Direction and to therefore to test hypotheses 4a) and 4b).

4.2. Experiment 2—*Mturk*

4.2.1. Introduction and Participants

To collect additional data and strengthen the statistical power of our analysis, we conducted a second experiment on Amazon Mechanical Turk over a two-week period. This allowed us to test hypothesis 5 through 8. This second experiment consisted of a shortened version of the laboratory experiment where only certain key variables were kept. The goal was to create a similar experiment that would take participants 10 minutes to complete. To test our hypothesis, we collected data from 300 participants on the online platform. Participants navigated through the questionnaire by themselves while following the instructions, without the aid of a moderator. This second experiment focused on the participant's perceived emotional reaction rather than actual measured reaction since we did not send the physiological data collection material to participants.

Participants were recruited through the Amazon Mechanical Turk platform in four batches. A total of 300 participants were recruited to participate in this study. Ultimately, due to failed attention checks and certain participants having not watched the videos before predicting the outcome of the graph, a grand total of 264 participants (N=264) were kept for the analysis. Participants were compensated $1 for completing the short questionnaire with no additional performance-based compensation. Out of the 300 participants, only 5 were not compensated for having failed an official attention check. All but one of the 264 participants were from the U.S. with 160 participants being male and 86 being females with ages ranging from 21 to 73 years old (average 37.72 and standard deviation 10.83).

To ensure a certain level of data quality, several exclusion criteria were enforced to *Mturk* participants wishing to be part of study. These are standard criteria for *Mturk* remote study participation:

- Be a registered *Mturk* participant with a unique *Mturk* identification code
- Be from either Canada or the USA
- Minimum hit approval rate of 95%
- Participants cannot participate in the study more than once

4.2.2. Measures

The experiment was conducted entirely through a Qualtrics questionnaire. The *Pattern Task* was once again the centre piece of the experiment and will be discussed in section 4.2.3. The Stimuli, which took the form of videos, was presented directly through Qualtrics questionnaire rather than through the Cobalt Capture program. No physiological data collection material was used as only self-assessed emotional reaction was used in our model. The entirety of the questionnaires was translated from English to French using the double translation method to ensure optimal and equivalent experiments in both languages.

4.2.3. Experimental Design and Stimuli

Participants were randomly split into three groups upon the start of the experiment. The first group represents the Technical condition and includes participants who saw only patterns replicating well know chart patterns frequently observed on financial markets. The second group represents the Random condition and includes participants who saw only randomly generated graphs. The third group represents the Mixed condition and includes participants who saw a mixture of both types of graphs. The main task for the experiment was a shortened version of the *Pattern Task*. Upon the start of the experiment, participants were randomly presented with 2 chart patterns (instead of 10 for the first study) and asked to predict the outcome over the following 5 days. The 20 graphs presented were the same as in the first study. One difference with the *Pattern Task* in the first study was that participants were not shown the actual outcome of the graph and therefore did not know if they had predicted correctly. To ensure data quality, participants were asked to identify through a multiple choice question the day in the graph on which the curve stops in the video. This allowed us to remove from the analysis any participant who did not watch the videos. Instead of measuring physiological reactions to the various graphs, participants were asked to identify their perceived levels of both arousal and pleasure by using scales.

4.2.4. Experiment Protocol

The experiment was conducted entirely from home without the assistance of moderators. All questions were included into one Qualtrics questionnaire with specific instructions for each section. A standardized attention check asking participants to simply put a slider on a specific number was therefore added to the questionnaire to ensure data quality. A failed attention check resulted in immediate termination of the questionnaire, which meant the end of the participation in the study.

Participants were first asked to complete the *Pattern Task*. They were shown 2 videos with graphs and asked to predict the outcome over the 5 following days. Participants were also asked to self-assess their emotional reaction to the different graphs, namely their level of arousal and pleasure. Participants were then presented with 5 images in order to measure their level of apophenia in contrast to the 10 images in the first study. 5 out of the 10 images from the initial study were chosen to reduce the duration of the experiment. Participants then answered the financial literacy question that was kept from the first study. Having not completed a socio-demographic questionnaire previously like participants in the first study had, we added these questions in the next section. Ultimately, participants completed the same 4-point questionnaire on their beliefs in prediction of the future as in the first study.

Some questionnaires from the first study were also removed from the second study to reduce the overall duration. The lottery choice as well as the 13 item Garble & Lytton questionnaire on financial risk tolerance were not included. Questions on the GameStop situation were also removed. Ultimately, the second experiment was a trimmed-down version of the laboratory study. The entire questionnaire can be found in Annex 6.

4.2.5. Variables operationalization

This section presents the variable operationalization. The table below includes the relevant research variables that will be used in our analysis. This included the variables in the shortened *Pattern Task*, the self-assessed emotional reaction variables as well as the beliefs and financial risk tolerance data.

Table 3 - Research Variables - *Mturk*

Variable	***Measure***	***Description***
Participant	Represents the participant ID based on their *Mturk* participant ID (alphabetical order).	1 to 246
Pattern ID Initial	Numerical ID for each pattern. (1 to 20)	Numerical ID for each of the 20 initial patterns that the participants see. Patterns 1 to 10 represent created patterns while patterns 11 to 20 represent randomly generated patterns.
Condition	Categorical variable with values 1.2 or 3. 1 = saw 2 manually created graphs, 2 = 2 randomly generated graphs, 3 = one of each	Variable that represents if participants saw 2 manually created graphs, 2 randomly generated graphs or one of each. Separates the participants in three different conditions.
View Order	Binary variables with values 0 or 1. 0= Pattern seen first 1 = Pattern seen second	Viewing order of the patterns by the participant. Each participant will see 2 graphs, in random order. This variable represents the order in which the participant sees each graph.

General Trend	Categorical variable with values 1.2 or 3. 1 = Ascending, 2 = Descending, 3 = Neutral	Identifies the graph's general trend (start to finish) as measured by the overall slope of the graph. The graph tendency can either be ascending, descending or neutral.
Half	Categorical variable with values 1.2 or 3. 1 = Ascending, 2 = Descending, 3 = Neutral	Identifies the trend for the first half (first 20 days) of the graph as measured by the overall slope. The trend can either be ascending, descending or neutral.
Half_0	Categorical variable with values 1.2 or 3. 1 = Ascending, 2 = Descending, 3 = Neutral	Identifies the trend for the second half (last 20 days) of the graph as measured by the overall slope. The trend can either be ascending, descending or neutral.
Variability	Continuous variable which represents the standard deviation of values for the first 35 days of each graph.	This variable measures the standard deviation of values for the first 35 days on each graph and therefore allows us to measure the volatility of each graph.
Risk	Categorical variable with values 0 to 2. 2 = Increased/decreased by more than 4 minutes 1 = Increased/Decreased by 1 to 4 minutes 0 = Remained at the same level	Represents the answer to: "In your opinion, the average wait time on the 40th day (compared to the 35th day) will have": Allows us to measure the level of risk taken by the participant in this task.
Direction	Categorical variable with values 1 to 3. 3 = Increased by 1 to 4 or more than 4 minutes 2 = Remained at the same level 1 = Decreased by 1 to 4 or more than 4 minutes	Represents the answer to: "In your opinion, the average wait time on the 40th day (compared to the 35th day) will have": Allows us to analyze in which direction (ascending/descending/neutral) the participants believe the wait time will go over the next 5 days.
Arousal	Discrete variable that can take values 0 to 100.	Variable that helps measure the intensity of the emotion felt when viewing the video. The scale goes from calm (0) to excited (100).
Pleasure	Discrete variable that can take values 0 to 100.	Pleasure represents the nature of the emotion felt when viewing the video. The scale goes from sad (0) to happy (100).
Apophenia	Discrete variable that represents the sum of answers to the questions for the 10 images. Question: On a scale of 1 to 7, to what extent do you agree with the following statements:	Adaptation of Uchiyama et al.'s pareidolia test. Allows us to measure the participant's level of apophenia (visual hallucinations). Participants are shown 5 different images and must determine to which extent (on a scale of 1 to 7) they see various elements (4 elements per picture) in these images. 3 elements are not the specific item in the picture. This variable represents the sum of the 3 unrelated elements for each picture. Minimum score of 30, maximum score of 210.
Precognition	Discrete variable that represents the sum of all the answers to the questions for the 4 statements. Question: On a scale of 1 to 7, to what extent do you agree with the following 4 statements?	Adaptation of Tobacyk's Revised Paranormal Belief Scale. Allows us to measure the participant's level of belief in precognition. 4 questions are asked to measure the participant's tendency to believe in astrology, psychics and predicting the future. They must answer on a scale of 1 to 7 to what extent they agree with each of the 4 statements. Minimum of 4, maximum of 28.
Financial Literacy	Discrete variable measured by a 1 to 7 scale	Allows us to measure each participant's self-assessed level of financial literacy. The higher the number, the higher the participant believes his level of financial literacy to be.

Table 4 - Sociodemographic Control Variables - *Mturk*

We include a separate table with sociodemographic data to assess the composition of *Mturk* samples in the next section.

Variable	***Measure***	***Description***
Gender	Categorical variable: 1 = male, 2 = female, 3 = non-binary	Categorical variable representing the participant's gender.
Age	Scale from 0 to 80	Variable representing the participant's age.
Education	Ordinal variable that represents the participant's level of education. 1=Some high school or less, 2=High school diploma or less, 3=Some college but no degree, 4=Associates or technical degree, 5=Bachelor's degree, 6=Graduate or professional degree	Variable that represents the participant's level of education.
Marital_Status	Categorical variable: 1=Never been married, 2=Living with a partner, 3=Married, 4=Divorced/Separated, 5=Widowed	Variable that represents the participant's marital status.
Country	Categorical variable: 1= USA, 2= Canada, 3 = Other	Variable that identifies the country in which the participant currently resides.
Annual Income USD	Ordinal variable: 1=less than $20,000, 2=between $20,000 and $39,999, 3=between $40,000 and $59,999, 4=between $60,000 and $79,999, 5=more than $80,000	Variable that represents the participant's annual income in USD. Participants must answer this question if they said that they currently live in the US or elsewhere.
Annual Income CAD	Ordinal variable: 1=less than $20,000, 2=between $20,000 and $39,999, 3=between $40,000 and $59,999, 4=between $60,000 and $79,999, 5=more than $80,000	Variable that represents the participant's annual income in USD. Participants must answer this question if they said that they currently live in Canada.

4.2.6 Analysis strategy

Hypothesis testing was also performed by using Stata 17 for this second experiment. No data merging was necessary as all data was collected through one single Qualtrics questionnaire. The data was again codified and prepared for the analysis prior to performing the regressions. The model used was similar to the one in the first study, but with fewer variables.

Overall, the goal of this second study is like the *BluePanel* study. We seek to identify which factors contribute to the intention of taking risks when participants are exposed to various chart patterns. We once again categorize participants' answers in three different ways by using the same two variables as in the first experiment (Risk and Direction). These variables are used as the dependent variables in our analysis. We still look at the same four different families of factors (chart characteristics, physiological data, beliefs and risk-taking tendencies, financial knowledge). The only difference is that fewer variables are used and therefore the analysis is shortened.

First, we once again analyze chart characteristics and assess their impact on the participant's decision-making in the patterns task. The charts are characterized by the exact same variables as in the first study. We use a fixed effects ordered probit model to test hypotheses 5a) and 5b). Second, we again observe the impact of emotional reaction on the participant's risk preferences, but this time, we measure the participant's self-assessed arousal and pleasure as proxies for the emotional reaction since the participant's lived reaction could not be measured. We once again treat these variables as mediators in explaining the participant's risk preferences in the *Pattern Task* and use Baron and Kenny's (1986) model to test hypotheses 6a) and 6b). Third, we look at the impact of the person's beliefs on risk-taking behaviour. We keep only the Precognition and Apophenia variables for this analysis and discard the Lottery and Financial Risk Tolerance variables that were present in the first study. We once again use a fixed effects ordered probit model to test the related hypothesis 7a) and 7b). Fourth and last, we once again observe the impact of the participant's financial knowledge on Risk and Direction. However, we only keep the self-assessed variable and discard GameStop variables for this second study. We use a fixed effects ordered probit model to test hypotheses 8a) and 8b).

5. Results

5.1: Sociodemographic Data

We first start by observing our participant's sociodemographic data to better understand our studies sample. Without directly incorporating sociodemographic data in our analysis, we still find it relevant to get a general idea of our panels' characteristics.

Table 5—Sociodemographic data— *BluePanel*

	Technical	Random	All participants
Number	19	19	38
Sex—Male	11	10	21
Sex—Female	7	9	16
Gender—Male	11	9	20
Gender—Female	7	9	16
Gender—Non binary	0	1	1
Age - 18 to 24	5	10	15
Age - 25 to 31	12	6	18
Age - 32 to 38	1	0	1
Age - 39 to 45	0	1	1
Age - 46 to 52	0	0	0
Age - 53 +	0	2	2
Education—Primary or earlier	0	0	0
Education—high school	0	0	0
Education—College	1	6	7
Education—Undergrad	10	9	19
Education—Graduate	7	4	11
Education—Postgraduate	0	0	0
Married	0	1	1
Common-law partner	6	1	7
Widow	0	1	1
Separated	0	1	1

Divorced	0	0	0
Single	10	13	23
Never married	2	2	4
Income—Less than $20,000	9	12	21
Income—Between $20,000 and 39,999	1	3	4
Income—Between $40,000 and 59,999	4	3	7
Income—Between $60,000 and 79,999	4	0	4
Income—More than $80,000	0	1	1
Place of residency—Canada	17	19	36
Place of residency—Other country	1	0	1
Other country—USA	1	0	1
Resides in country of birth	11	13	24
Resides outside country of birth	7	6	13
Student	9	9	18
Part-Time Worker	0	4	4
Full-Time Worker	9	4	13
Retired	0	1	1
Unemployed	0	0	0
Other	1	1	2
Number accounts - 1	1	4	5
Number accounts - 2	9	5	14
Number accounts - 3	2	7	9
Number accounts - 4	4	1	5
Number accounts - 5	1	1	2
Number accounts - 6	2	1	3

Our combined panel is composed of 38 participants. One participant did not complete the socio-demographic questionnaire as participants were asked to complete it on their own, without moderator supervision. We therefore only have sociodemographic data on only 37 of the 38 participants in the study. Participants were evenly split into 2 groups: treatments and control. A randomization code was used to assign participants in each group to remove any potential bias. The treatment group consisted of participants that were presented with well-known technical analysis patterns that were manually created while the control group was presented with randomly generated charts.

Of the 37 participants who completed the socio-demographic questionnaire, 21 were male and 16 were female and both were mostly evenly spread between the two conditions. Only one person identifies a non-binary, which means that the gender variable is almost identical to the sex variable. As for the age, 89% of our participants (33/37) were between 18 and 31 years old while 81% (30/37) of our panel had an undergraduate level of education or higher. Following that logic, 22 of the 37 participants identified as full-time students or part-time workers, which is also validated by the fact that 25 participants identified their annual revenue as being between 0 and $40,000 dollars while only 5 participants identified their revenue as being over $60,000. As for marital status, 23 participants identified as single while one participant identified as married and 7 identified as common-law partners. Of the 37 participants, 24 currently reside in their country of birth. As for self-assessed financial literacy, results mostly follow a normal distribution with the median answer of "4" on the scale having the largest number of participants (11) and few participants choosing 1 and 7 (2 for each). 51% of participants possessed 1 or two bank/trading accounts, most often a checking and savings account which makes sense considering the average younger age and "student" nature of our panel.

Table 6 - Sociodemographic data—*Mturk*

	Technical	Random	Mixed	All participants
Number	68	56	122	246
Gender—Male	42	31	87	160
Gender—Female	26	25	35	86
Gender—Non-Binary	0	0	0	0
Age - 20 to 29	13	13	29	55
Age - 30 to 39	34	22	50	106
Age - 40 to 49	11	8	29	48
Age - 50 to 59	7	8	9	24
Age - 60 to 69	2	5	4	11
Age - 70 +	1	0	1	2
Education—Some high school or less	4	3	4	11
Education—high school diploma or less	3	4	6	13

Education—Some college but no degree	7	4	17	28
Education—Associates or technical degree	44	36	72	152
Education—Bachelor's degree	10	9	23	42
Education—Graduate or professional degree	0	0	0	0
Never been married	16	11	31	58
Living with a partner	5	3	10	18
Married	43	38	77	158
Divorced/separated	3	3	3	9
Widowed	1	0	1	2
Income—Less than $20,000	8	7	11	26
Income—Between $20,000 and 39,999	15	9	26	50
Income—Between $40,000 and 59,999	19	16	42	77
Income—Between $60,000 and 79,999	19	18	24	61
Income—More than $80,000	7	4	16	27
Place of residency—USA	68	56	121	245
Place of residency—Canada	0	0	1	1

As mentioned previously in the Methodology section, 300 participants were recruited for the second part of our study. Out of these 300 participants, 54 were removed for not having properly completed the online questionnaire. Ultimately, answers from 246 participants were kept for the analysis to ensure a certain level of data quality. Using Qualtrics functionalities, all participants were randomly shown 2 out of the 20 available graphs, which means that some participants saw both a manually created graph as well as a randomly generated graph. Were therefore categorized participants in three different groups: Manually created patterns, randomly generated graphs and mixed. The group with mixed graph was the largest with 122 participants while the manually created and random groups were composed of 68 and 56 patterns, respectively.

Of the 264 participants who completed the questionnaire, 160 were male and 86 were female while no one identified as non-binary. Unlike with the Tech3Lab panel, the participants were more normally spread across different age groups. 55 out of the 246 participants belonged to the 20–29 year-old age group while 106 and 48 participants belonged to the 30–39 and 40–49 year-old group respectively. Participants were, however, more concentrated on the education level with 62% of the group (152/246) stated that they possessed a technical or associates degree while only 42 participants stated that they possessed an undergraduate degree, which largely differs from our laboratory panel. Income was normally distributed between all income categories with 77 participants belonging to the median category of $40,000 to $59,999. As for the financial literacy self-assessment question, 69% (169/246) of participants possess a level of financial literacy of 5 or higher on a scale of 1 to 7. All but one participant that participated in the study resided in the United States.

5.2: Chart Characteristics— *BluePanel*

We started by looking at the impact of chart characteristics on both the level of Risk and the Direction taken when predicting the outcome of graphs. As mentioned previously, participants were shown a series of graphs that were either randomly generated or manually created to reflect well known technical analysis patterns studies in finance. Details on these chart patterns can be found in Annex 2. Charts were grouped into different categories that reflected common characteristics. First off, graphs were grouped into three categories, ascending, descending and neutral, based on their General Trend. This first variable represents the overall slope that a graph displays once it is first shown to participants. We then distinguish between the slope trend in the first and second halves of each graph to see if participants will give more importance to one of these two variables. It is important to understand that the first and second half trend can differ from the graph's general trend. Each graph's standard deviation of wait time was also measured as a proxy for volatility. These General Trend, First Half Trend, Second Half Trend and Standard Deviation variables were therefore the main inputs in our model for our first hypothesis.

All twenty graphs that were presented to participants were grouped into three general trend categories according to their slope: ascending, descending and neutral. Seven out of the 20 graphs were identified as being ascending, 7 as being descending and six as neutral. The twenty graphs were also grouped into trend categories with respect to the trend in the first half (first 20 days). The tree trend categories remained the same: ascending, descending and neutral. Four out of the twenty graphs were identified as having an ascending first half trend, while seven had a descending trend and 9 a neutral trend. Graphs were also grouped into the three same categories with regards to their second half trend. Six of the graphs presented an ascending second half trend, six presented a descending second half trend and 8 a neutral second half trend. Each of the 20 graphs exhibited a unique standard deviation of wait time. The higher the graph's standard deviation, the higher the variability of the wait time over the course of the first 35 days (initial chart presented to participants from which they are asked to predict the outcome). Standard deviations ranged from 2.39 minutes to 5.11 minutes with the overall average standard deviation coming in at 3.43 minutes.

5.2.1: Chart Characteristics—Risk

The chart characteristic data is analyzed using a fixed effects ordered probit model, due to the panel nature of our data (repeated measures), with robust standard errors since our dependent variable, the level of Risk taken when predicting the outcome of the graph, is a categorical ordinal variable. We also compare our results by using a simple ordered probit and clustering for each participant's ID to see if results varied from one method to the other. The results given were the same for both methods (same level of significance for each variable). The General Trend, First Half Trend and Second Half Trend variables were converted to binary variables and included in the regression due to their categorical nature. The Standard Deviation variable was kept as is due to its numeric continuous nature. The View Order variable was also included in the analysis. Both the nature of the graph that each participant saw (randomly generated graphs or mimicking a well-known technical analysis pattern) and the view order of each graph in the *Pattern Task* were attributed randomly. We therefore introduce View Order (1 to 10 for participants who saw manually created graphs and 11 to 20 for participants who saw randomly generated graphs) as a control variable which captures both the learning effect derived from the view order and the difference in nature of the graphs.
Below is the regression we used for our model:

Risk = $\beta1$ View Order + $\beta2$ Descending General Trend + $\beta3$ Neutral General Trend + $\beta4$ Ascending First Half Trend + $\beta5$ Descending First Half Trend + $\beta6$ Ascending Second Half Trend + $\beta7$ Descending Second Half Trend + $\beta8$ Variability + e **(1)**

As seen in table 7, none of the coefficients for the independent variables were significant for the first regression. The Variability variable is, however, right on the verge of being significant with a p-value of 0.052 (coef. = 0.2139 and standard error = 0.11). If this coefficient were to be significant, this would indicate that a higher Variability yields increased predicted probability of a higher level of Risk when predicting the outcome of graphs. Overall, our findings for our first regression are in line with our hypothesis 1a) which suggests that chart characteristics do not impact the participant's Risk preferences when predicting the outcome of graphs in the *Pattern Task*. Although the level of Risk seems inclined to be influenced by the variability of the graph, our analysis does not allow us to conclude that this variable or any other chart characteristic has a significant impact on the decision-making process of the participants. As seen in previous literature, a relationship exists between volatility and risk in financial markets. However, research has shown that retail investors are the ones who create volatility in markets rather than being the ones who react to volatility by taking risks (Han & Kumar,2008, Brandt et al., 2009). This is in line with our hypothesis that volatility does not influence risk-taking.

Table 7 – Chart Characteristics - *BluePanel*

Risk / Direction	H1a_Risk (1)	H1b_Direction (2)
View Order	-0.0094	-0.0197 **
	(0.0122)	(0.0096)
Descending General Trend	-0.0906	0.7472 **
	(0.2385)	(0.3282)
Neutral General Trend	0.1346	1.1588 ****
	(0.2057)	(0.2635)
Ascending First Half Trend	-0.2824	0.7453 **
	(0.2067)	(0.3356)
Descending First Half Trend	-0.2165 *	0.2641 *
	(0.1299)	(0.1539)
Ascending Second Half Trend	-0.2498	0.0799
	(0.1977)	(0.2523)
Descending Second Half Trend	-0.1301	0.1375
	(0.1574)	(0.1744)
Variability	0.2139 *	-0.4819 ****
	(0.1100)	(0.1438)
cut1		
_cons	-0.6583	-1.3080 ***
	(0.4441)	(0.4627)
cut2		
_cons	1.0051 **	-0.8747 *
	(0.4382)	(0.4785)
sigma2_u		
_cons	0.0082	6.81E-34
	(0.0352)	(0.0000)
N	377	377
N_clust	38	38
p	0.0555	0.0000
chi2	15.1915	56.9019

Notes: We conduct two separate regressions (regressions 1 and 2), one for each of our two independent variables (Risk and Direction). These regressions are perfomed to test hypothesis 1a) and 1b) in our study. We use fixed effects ordered probit regressions with robust standard errors due to the categorical ordinal nature of our independent variables and the panel nature of our data. Separate regressions were ran with regular oprobit models to compare results. For both regressions, we regress the independent variables on seven variables used as a proxy for Chart Characteristics (Descending General Trend, Neutral General Trend, Ascending First Half Trend, Descending First Half Trend, Ascending Second Half Trend, Descending Second Half Trend, Variability) and one control variable to account for the condition and the view order of each graph in the *Pattern Task* (View Order). The General Trend variables are binary variables to identify the graph's General Trend. The first half trends are binary variables to indentify the graph's first half trend. The second half trends are binary variables to indentify the graph's second half trend. Omited variables were chosen on the basis of correlation with other variables in the model. The Variability variables represents the variability of the pattern over the 35 day tome horizon. We also show the cuts for each our ordered probit model and other relevant statistics. The number of observations (N) was of 377, which represents multiple trial data collected for 38 different participants (N_clust). Levels of signficance of each of the variables with regards to their p-values in the regressions are identified by the * symbol: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001. The data in parentheses represents the coefficient's standard errors in the regressions. The regressions were done on Stata 17. Regression 1 : xtoprobit Risk ViewOrderFinal dGenTrendDSC dGenTrendNEU dHalfASC dHalfDSC dHalf_0ASC dHalf_0DSC Std_dev, vce(robust). Regression 2 : xtoprobit Direction ViewOrderFinal dGenTrendDSC dGenTrendNEU dHalfASC dHalfDSC dHalf_0ASC dHalf_0DSC Std_dev, vce(robust).

5.2.2: Chart Characteristics—Direction

For this other hypothesis, we once again used a fixed effects ordered probit model with robust standard errors which we then compared with a simple ordered probit with clustered standard errors. The significance of coefficients remains the same for both regressions. Although the dependent variable changes in this second model, it remains a categorical ordinal variable. The independent variables remain the exact same as above.

Below is the regression we used for our model:

Direction = β1 View Order + β2 Descending General Trend + β3 Neutral General Trend + β4 Ascending First Half Trend + β5 Descending First Half Trend + β6 Ascending Second Half Trend + β7 Descending First Half Trend + β8 Variability + e **(2)**

As seen in table 7, we see that several independent variables have a significant impact on the anticipated Direction of the wait time when predicting the outcome of charts. First off, we find that a learning effect is present in our model. The coefficient for the View Order variable comes out as significant (Coef. = -0.0197 and standard error = 0.0096). This indicated that as the participants progress through the task, the probability of anticipating an increase in wait time decreases. The Descending General Trend coefficient (coef. = 0.7472 and standard error = 0.3282) and Neutral General Trend coefficient (coef. = 1.1588 and standard error = 0.2635) are also significant. The probability of believing that the chart will take on a specific Direction is therefore significantly impacted by the chart's general trend. The significance of these coefficients must be taken in relation with the omitted binary variable Ascending General Trend. When looking at the tabulation of answers, we can see a clear pattern of trend reversion. Participants exposed to an ascending pattern tend to believe that the wait time will decrease in the future and participants exposed to a descending pattern have a tendency to believe that the wait time will increase in the future. Our results show that this difference in answers is significant at a 5% level. These results tie in well with existing literature stating that individuals believe stock trends will reverse (Andreassen, 1988) and that reversal in occur when individuals change their expectations on these stocks (Achelis, 2000). The Ascending First Half Trend coefficient was also significant in our model (coef. = 0.7453 and standard error = 0.3356) and is exposed to a similar conclusion. The coefficient for our Variability variable also came out as significant in explaining the anticipated Direction of the wait time (coef. = -0.4819 and standard error = 0.1438. This implies that as the variability of the chart increases, participants have a higher predicted probability of thinking that the wait time will decrease in the future. High volatility therefore seems to lead to an anticipated decrease, which can be somewhat tied to financial market behaviour of participants. These results are, however, difficult to tie to existing literature. These results contradict hypothesis 1b) which states that chart characteristics do not have a significant influence on the anticipated Direction of the wait time when predicting the outcome of graphs.

5.2.3: Chart Characteristics—Conclusion

We first observed the relationship between chart characteristics and both the level of Risk taken and the anticipated Direction of charts in the future. We first found that none of the chart characteristics in our model exerted an influence on the level of Risk, which supports the hypothesis 1a). However, we also found that several chart characteristics did exert a significant impact on the anticipated Direction, which does not support the hypothesis 1b). Our results show the presence of trend reversal, in that participants exposed to a certain trend will tend to believe that the trend will reverse in the future. This is consistent with behaviour found in stock markets (Ansreassen, 1988). We also found that graphs exhibiting strong variability will lead to an increased probability of an anticipated decrease in wait time, which logically is difficult to interpret.

5.3: Emotional Reactions - *BluePanel*

We then assessed the impact of emotional reactions to see if the measured reactions act as a mediator variable in explaining the relationship between chart characteristics and the level of Risk taken or the anticipated Direction when completing the *Pattern Task*. Physiological data was measured via EKG, EDA and Facial Expression instruments. Inputs for this second model were therefore both the variables from our first hypothesis model (chart characteristics) and a series of physiological reaction variables: EDA, Valence, Ratio HRV and Phasic. These four variables are used as proxies for the participant's emotional reactions when viewing the patterns, which in turn enables us to assess the impact of these reactions on decision-making.

Physiological data was measured throughout the experiment. We focus here on the measured physiological data during the *Pattern Task*, which corresponds to the moment where participants are presented with a series of charts and asked to predict their outcome. As mentioned earlier, each participant was presented with a series of 10 charts. EDA, Valence, Ratio HRV and Phasic were therefore measured for each trial, from start to finish, meaning that they were measured from the time the participant started viewing the simulated pattern to the moment the pattern ended. We then looked at both the mean and standard deviation of each of the variables above for each trial to see if the change in measures have an impact on decision-making. Here are the descriptive statistics we found for each of our 8 variables:

	EDA_Mean	EDA_StdDev	Valence_Mean	Valence_StdDev	ratio_hrv_Mean	ratio_hrv_StdDev	phasic_Mean	phasic_StdDev
Average	2.7811	-0.1220	0.3237	0.1964	0.0332	0.0113	0.0037	0.0277
Std Dev	-1.6606	-0.1039	-0.0308	-0.4914	-0.1064	-0.0142	-0.0029	-0.1225

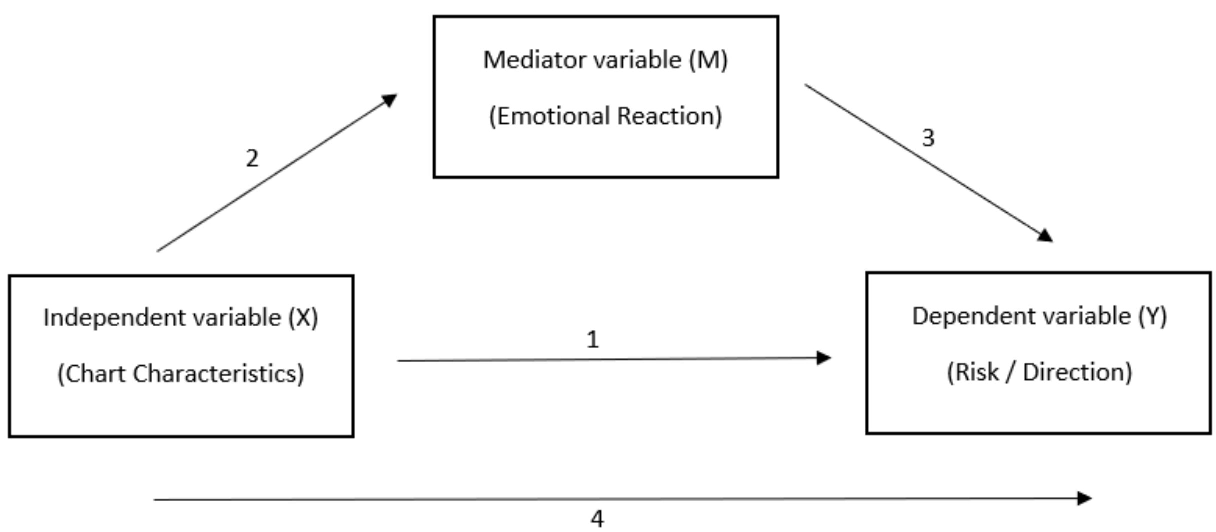
5.3.1: Physiological Data - Analysis

To be included in our model, some of the variables above had to be transformed due to either their small nature or their non-normal distribution. For these variables, we generated the log transformation and multiplied the data by either 10,000 or 100,000. All variables were coded as numeric continuous variables in our model.

We constructed our model for our second hypothesis around SOR theory and mediation analysis. The participant is presented with a graph (stimulus), reacts to this graph (organism) and then takes a decision with regards to this stimulus (response). On this basis, we analyzed the role of emotional reaction as a mediator in explaining the relationship between chart characteristics and the level of Risk taken or the anticipated Direction of the graph.

Using Baron and Kenny's (1986) theory to identify mediator variables, we develop an analysis model for our second hypothesis. The analysis is broken down into four different steps. Each step must be validated in order for a variable to be qualified as a mediator.

Figure 3 – Mediation Analysis - *BluePanel*



First, we must assess the significance of the direct relationship between the independent variable X and dependent variable Y. Second, we must assess the significance of the direct relationship between the independent variable X and the mediator variable M to see if the independent variable predicts the mediator variable. Third, we must assess the significance of the relationship between the mediator variable M and the dependent variable Y to see if the mediator predicts the dependent variable. Fourth, we must assess the indirect impact of the overall relationship by regressing both the independent X and mediator variable M on the dependent variable. All four regressions must yield significant coefficients in order for the studies variable to be declared a mediator.

In our case, we must therefore first assess the impact of chart characteristics (independent variable) on the level of Risk taken or the anticipated Direction when predicting the outcome of the charts in the *Pattern Task* (dependent variable). This relationship has already been analyzed in sections 5.2.2 and 5.2.3 through our model for hypothesis 1. We have determined that none of the chart characteristics have a significant impact on the level of Risk taken in the *Pattern Task*, but that some characteristics do have an impact on the anticipated Direction of the graph. Namely, the Descending Genera Trend, Neutral General Trend, Ascending First Half Trend and Variability had a significant impact on the anticipated Direction of the wait time in the future. We therefore validate this first step in the Baron and Kenny process and move on to the second step.

The second step in the process consists of observing the relationship between the emotional reactions, which act as a mediator variable in our model, and the level of Risk and anticipated Direction of the graph. We therefore regressed each of the 8 physiological variables independently on both the Risk and Direction variables to assess their level of significance. As our dependent variables in this model are of categorical ordinal nature (Risk and Direction), we used a fixed effect ordered probit model with robust standard errors. We compared our findings with those yielded by a regular ordered probit model with clustered standard errors and found similar results. We included the View Order control variable in all of our regressions.
Below are the regressions we used to test our hypothesis:

Risk = β1 View Order + β2 lEDA_Mean +e **(3)**

Direction = β1 View Order + β2 lEDA_Mean +e **(4)**

Risk = β1 View Order + β2 lcmEDA_StdDev +e **(5)**

Direction = β1 View Order + β2 lcmEDA_StdDev +e **(6)**

Risk = β1 View Order + β2 lcmValence_Mean +e **(7)**

Direction = β1 View Order + β2 lcmValence_Mean +e **(8)**

Risk = β1 View Order + β2 lcmValence_StdDev +e **(9)**

Direction = β1 View Order + β2 lcmValence_StdDev +e **(10)**

Risk = β1 View Order + β2 ratio_hrv_Mean +e **(11)**

Direction = β1 View Order + β2 ratio_hrv_Mean +e **(12)**

Risk = β1 View Order + β2 ldmratio_hrv_StdDev +e **(13)**

Direction = β1 View Order + β2 ldmratio_hrv_StdDev +e **(14)**

Risk = β1 View Order + β2 lcmphasic_Mean +e **(15)**

Direction = β1 View Order + β2 lcmphasic_Mean +e **(16)**

Risk = β1 View Order + β2 lcmphasic_StdDev +e **(17)**

Direction = β1 View Order + β2 lcmphasic_StdDev +e **(18)**

8 – Emotional Reaction (EDA) - *BluePanel*

Risk / Direction	H2a_Risk (3)	H2b_Direction (4)	H2a_Risk (5)	H2b_Direction (6)
ViewOrderFinal	-0.0039	0.0128	-0.0003	0.0149
	(0.0142)	(0.0096)	(0.0136)	(0.0093)
lEDA_Mean	0.1295	-0.0136		
	(0.2050)	(0.1580)		
lcmEDA_StdDev			0.049	0.0188
			(0.0337)	(0.0286)
cut1				
_cons	-0.9071 **	-0.3374	-0.7407 ***	-0.1859
	(0.3611)	(0.2110)	(0.2817)	(0.1877)
cut2				
_cons	0.6559 *	0.0578	0.8278 ***	0.2095
	(0.3499)	(0.2039)	(0.2698)	(0.1844)
sigma2_u				
_cons	0.000	0.000	0.000	0.000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
N	198	198	198	198
N_clust	21	21	21	21
p	0.6676	0.4094	0.3266	0.2222
chi2	0.8081	1.7862	2.2383	3.0083

Notes: We conduct four separate regressions (regressions 3, 4, 5 and 6) to assess the impact of EDA on both Risk and anticipated Direction in the *Pattern Task* . These regressions are performed to test hypothesis 2a) and 2b). We use fixed effects ordered probit regressions with robust standard errors due to the categorical ordinal nature of our independent variables and the panel nature of our data. Separate regressions were ran with regular oprobit models to compare results. We seek to measure the direct impact of the emotional reaction variables on both Risk and Direction to test our mediation model. For the regressions, we regress the independent variables on lEDA_Mean and lcmEDA_StdDev and one control variable to account for the condition and the view order of each graph in the Pattern Task (ViewOrderFinal). lEDA_Mean represents the participant's average measured EDA when viewing each pattern. It was transformed lognormally in our model. lcmEDA_StdDev represents the participant's standard deviation of measured EDA when viewing each pattern. It was transformed lognormally and multiplied by 100,000 in our model. We therefore use 2 different metrics of EDA to test our hypothesis. We also show the cuts for each our ordered probit model and other relevant statistics. The number of observations (N) was of 198, which represents multiple trial data collected for 21 different participants (N_clust). Due to data quality, not all participants presented usable data for our analysis. Levels of signficance of each of the variables with regards to their p-values in the regressions are identified by the * symbol: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001. The data in parentheses represents the coefficient's standard errors in the regressions. The regressions were done on Stata 17. Regression 3: xtoprobit Risk ViewOrderFinal lEDA_Mean, vce(robust). Regression 4 : xtoprobit Direction ViewOrderFinal lEDA_Mean, vce(robust). Regression 5 : xtoprobit Risk ViewOrderFinal lcmEDA_StdDev, vce(robust). Regression 6 : xtoprobit Direction ViewOrderFinal lcmEDA_StdDev, vce(robust).

Table 9 – Emotional Reaction (Valence) - *BluePanel*

	H2a_Risk (7)	H2b_Direction (8)	H2a_Risk (9)	H2b_Direction (10)
ViewOrderFinal	-0.2299 **	-0.0442	-0.0168	0.0123
	(0.0937)	(0.0615)	(0.0117)	(0.0086)
lcmValence_Mean	-0.3715	0.8552		
	(0.3316)	(0.8267)		
lcmValence_StdDev			0.068	-0.1009
			0.0556	0.0568
cut1				
_cons	-6.4253 *	6.0431	-0.9086 **	-0.91
	(3.6223)	(7.0426)	(0.4348)	(0.3972)
cut2				
_cons	-4.4071	6.7289	0.7596 *	-0.5774
	(3.3944)	(7.6264)	(0.3992)	(0.3946)
sigma2_u				
_cons	0.000	0.000	0.000	0.000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
N	11	11	213	213
N_clust	3	3	22	22
p	0.0000	0.0000	0.0474	0.0438
chi2	483.2316	266.1440	6.0984	6.2582

Notes: We conduct four separate regressions (regressions 7, 8, 9 and 10) to assess the impact of EDA on both Risk and anticipated Direction in the *Pattern Task*. These regressions are performed to test hypothesis 2a) and 2b). We use fixed effects ordered probit regressions with robust standard errors due to the categorical ordinal nature of our independent variables and the panel nature of our data. Separate regressions were ran with regular oprobit models to compare results. We seek to measure the direct impact of the emotional reaction variables on both Risk and Direction to test our mediation model. For the regressions, we regress the independent variables on lcmValence_Mean and lcmValence_StdDev and one control variable to account for the condition and the view order of each graph in the Pattern Task (ViewOrderFinal). lcmValence_Mean represents the participant's average measured Valence when viewing each pattern. It was transformed lognormally and multiplied by 100,000 in our model. lcmValence_StdDev represents the participant's standard deviation of measured Valence when viewing each pattern. It was transformed lognormally and multiplied by 100,000 in our model. We therefore use 2 different metrics of Valence to test our hypothesis. We also show the cuts for each our ordered probit model and other relevant statistics. The number of observations (N) was of 11 for regressions 7 and 8 and 213 for regressions 9 and 10, which represents multiple trial data collected for 3 and 22 different participants (N_clust). Due to data quality, not all participants presented usable data for our analysis.. Levels of signficance of each of the variables with regards to their p-values in the regressions are identified by the * symbol: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001. The data in parentheses represents the coefficient's standard errors in the regressions. The regressions were done on Stata 17. Regression 7 : xtoprobit Answer_numeric ViewOrderFinal lcmValence_Mean, vce(robust). Regression 8 : xtoprobit Answer_order_3 ViewOrderFinal lcmValence_Mean, vce(robust). Regression 9 : xtoprobit Answer_numeric ViewOrderFinal lcmValence_StdDev, vce(robust). Regression 10: xtoprobit Answer_order_all ViewOrderFinal lcmValence_StdDev, vce(robust).

Table 10 – Emotional Reaction (HRV) - *BluePanel*

	H2a_Risk (7)	H2b_Direction (8)	H2a_Risk (9)	H2b_Direction (10)
ViewOrderFinal	-0.2299 **	-0.0442	-0.0168	0.0123
	(0.0937)	(0.0615)	(0.0117)	(0.0086)
lcmValence_Mean	-0.3715	0.8552		
	(0.3316)	(0.8267)		
lcmValence_StdDev			0.068	-0.1009
			0.0556	0.0568
cut1				
_cons	-6.4253 *	6.0431	-0.9086 **	-0.91
	(3.6223)	(7.0426)	(0.4348)	(0.3972)
cut2				
_cons	-4.4071	6.7289	0.7596 *	-0.5774
	(3.3944)	(7.6264)	(0.3992)	(0.3946)
sigma2_u				
_cons	0.000	0.000	0.000	0.000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
N	11	11	213	213
N_clust	3	3	22	22
p	0.0000	0.0000	0.0474	0.0438
chi2	483.2316	266.1440	6.0984	6.2582

Notes: We conduct four separate regressions (regressions 7, 8, 9 and 10) to assess the impact of EDA on both Risk and anticipated Direction in the *Pattern Task*. These regressions are performed to test hypothesis 2a) and 2b). We use fixed effects ordered probit regressions with robust standard errors due to the categorical ordinal nature of our independent variables and the panel nature of our data. Separate regressions were ran with regular oprobit models to compare results. We seek to measure the direct impact of the emotional reaction variables on both Risk and Direction to test our mediation model. For the regressions, we regress the independent variables on lcmValence_Mean and lcmValence_StdDev and one control variable to account for the condition and the view order of each graph in the Pattern Task (ViewOrderFinal). lcmValence_Mean represents the participant's average measured Valence when viewing each pattern. It was transformed lognormally and multiplied by 100,000 in our model. lcmValence_StdDev represents the participant's standard deviation of measured Valence when viewing each pattern. It was transformed lognormally and multiplied by 100,000 in our model. We therefore use 2 different metrics of Valence to test our hypothesis. We also show the cuts for each our ordered probit model and other relevant statistics. The number of observations (N) was of 11 for regressions 7 and 8 and 213 for regressions 9 and 10, which represents multiple trial data collected for 3 and 22 different participants (N_clust). Due to data quality, not all participants presented usable data for our analysis.. Levels of signficance of each of the variables with regards to their p-values in the regressions are identified by the * symbol: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001. The data in parentheses represents the coefficient's standard errors in the regressions. The regressions were done on Stata 17. Regression 7 : xtoprobit Answer_numeric ViewOrderFinal lcmValence_Mean, vce(robust). Regression 8 : xtoprobit Answer_order_3 ViewOrderFinal lcmValence_Mean, vce(robust). Regression 9 : xtoprobit Answer_numeric ViewOrderFinal lcmValence_StdDev, vce(robust). Regression 10: xtoprobit Answer_order_all ViewOrderFinal lcmValence_StdDev, vce(robust).

Table 11 – Emotional Reaction (Phasic) - *BluePanel*

Risk / Direction	H2a)_Risk (15)	H2b)_Direction (16)	H2a)_Risk (17)	H2b)_Direction (18)
ViewOrderFinal	-0.0015	0.0115	-0.0030	0.0118
	(0.0132)	(0.0095)	(0.0135)	(0.0089)
lcmphasic_Mean	0.0250	0.0238		
	(0.0237)	(0.0212)		
lcmphasic_StdDev			0.023076	0.026115
			(0.0258)	(0.0249)
cut1				
_cons	-0.8278 ***	-0.1790	-0.8979 ****	-0.2193
	(0.2204)	(0.2007)	(0.2241)	(0.1722)
cut2				
_cons	0.7304 ***	0.2398	0.6430 ***	0.2042
	(0.2352)	(0.1829)	(0.2167)	(0.1587)
sigma2_u				
_cons	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
N	194	194	192	192
N_clust	20	20	20	20
p	0.5680	0.3595	0.6317	0.3279
chi2	1.1313	2.0458	0.9187	2.2300

Notes: We conduct four separate regressions (regressions 15, 16, 17 and 18) to assess the impact of Phasic on both Risk and anticipated Direction in the Pattern Task. These regressions are performed to test hypothesis 2a) and 2b). We use fixed effects ordered probit regressions with robust standard errors due to the categorical ordinal nature of our independent variables and the panel nature of our data. Separate regressions were ran with regular oprobit models to compare results. We seek to measure the direct impact of the emotional reaction variables on both Risk and Direction to test our mediation model. For the regressions, we regress the independent variables on lcmphasic_Mean and lcmPhasic_StdDev and one control variable to account for the condition and the view order of each graph in the Pattern Task (ViewOrderFinal). lcmPhasic_Mean represents the participant's average measured Phasic EDA when viewing each pattern. It was transformed lognormally and multiplied by 100,000 in our model. lcmPhasic_StdDev represents the participant's standard deviation of measured Valence when viewing each pattern. It was transformed lognormally and multiplied by 100,000 in our model. We therefore use 2 different metrics of Valence to test our hypothesis. We also show the cuts for each our ordered probit model and other relevant statistics. The number of observations (N) was of 194 for regressions 15 and 16 and 192 for regressions 17 and 18, which represents multiple trial data collected for 20 different participants (N_clust). Due to data quality, not all participants presented usable data for our analysis.. Levels of signficance of each of the variables with regards to their p-values in the regressions are identified by the * symbol: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001. The data in parentheses represents the coefficient's standard errors in the regressions. The regressions were done on Stata 17. Regression 15 : xtoprobit Answer_numeric ViewOrderFinal lcmphasic_Mean, vce(robust). Regression 16 : xtoprobit Answer_order_3 ViewOrderFinal lcmphasic_Mean, vce(robust). Regression 17 : xtoprobit Answer_numeric ViewOrderFinal lcmphasic_StdDev, vce(robust). Regression 18 : xtoprobit Answer_order_3 ViewOrderFinal lcmphasic_StdDev, vce(robust).

As seen in tables 8, 9, 10 and 11 we find that none of the 16 physiological variables have a significant relationship with both the level of Risk and the anticipated Direction of the graph. None of the coefficients for our 8 regressions are significant at a 5% significance level. Since this second condition in our mediation analysis framework is not respected, we must stop our analysis and conclude that, according to the Baron and Kenny (1986) method, emotional reaction does not act as a mediator in explaining the relationship between chart characteristics and the level of Risk taken or the anticipated Direction when predicting the outcome of graphs. Although literature shows that emotions play a key role in explaining the decision-making process in financial market settings (Fenton-O'Creevy et al., 2012) or in a gambling setting (Studer and Clark, 2011), our results suggest that they do not in fact play a role in explaining decision-making in our study. These results support hypotheses 2a) and 2b) which state that emotions do not act as a mediator variable when explaining the relationship between chart characteristics and both the level of Risk taken and the anticipated Direction of the wait time when predicting the outcome of graphs in the *Pattern Task*.

5.3.2: Emotional Reaction—Conclusion

Overall, we found that emotional reaction does not act as a mediator variable in explaining the relationship between chart characteristics and Risk or Direction. These results support hypotheses 2a) and 2b) of our study. As none of our proxies for emotional reaction were found to exert a significant influence on the level of Risk of the anticipated Direction, we were unable to conclude that it acted as a mediator variable according to Baron and Kenny's (1986) model. Our results contradict existing literature which shows that emotions do play a key role in explaining risk behaviour and decision-making (Fenton-O'Creevy et al., 2012, Studer and Clark, 2011).

5.4: Risk-taking tendencies and Beliefs - *BluePanel*

We then looked at the impact of individual risk preferences and beliefs on both the level of Risk and the Direction taken when predicting the outcome of graphs. Four different variables were measured throughout the experiment to help characterize each participant's risk-taking preferences and beliefs. Participants were first asked to choose one of five different lotteries to play with each lottery getting progressively riskier, which allowed us to measure one aspect of the participant's risk preferences. This task was inspired by Eckel and Grossman's task. Participants were then asked to complete the Grable and Lytton Risk Tolerance Scale, a 13-point questionnaire designed to measure financial risk tolerance. As for the beliefs, participants were first shown a series of black and white images and asked to identify to what extent they saw certain objects in these images, which allowed us to measure their level of exhibited apophenia. Participants were also asked four questions to measure their beliefs in precognition. The Lottery, Financial Risk Tolerance, Apophenia and Precognition variables were therefore the main inputs for our third hypothesis.

The first proxy for risk preference that was used was the Lottery task, inspired by Eckel and Grossman's task. 14 participants chose to play the fifth and riskiest lottery while the rest of the participants were somewhat evenly distributed across the four other possible lotteries. Our second risk proxy was the Financial Risk Tolerance questionnaire. A minimum score of 13 and maximum of 44 could be recorded, which would represent a person selecting the more risk averse or the riskiest possible answers respectively to all 13 items in the questionnaire. The lowest score that was recorded for this task was of 17 while the highest score recorded was 42. An average score of 27.08 and standard deviation of 5.30 were recorded for this task.

As for beliefs, we first measured the participant's tendency to exhibit apophenia (tendency to perceive patterns in unrelated things). The sum of answers to each image the participants saw was taken as a score for the task. The higher the score, the higher the tendency to exhibit apophenia. A minimal score of 30 and maximum score of 210 could be obtained. The average score for the task was 80.05 and the standard deviation was 14.31. We then measured the participant's belief in precognition. We summed the score for each of the 4 questions (1 to 7 likert scale) as a measure of the belief. Scores for this task could therefore range from 4 to 28. The minimum and most frequently recorded score out of our 38 participants was of 4, while the maximum score was of 17. The average score was 6.31 with a standard deviation of 3.20.

5.4.1: Risk-taking tendencies and Beliefs—Risk

The impact of beliefs on the level of Risk taken in the *Pattern Task* was analyzed using a fixed effects ordered probit model with robust standard errors due to the categorical ordinal nature of our dependent variable. Results were once again validated by comparing the fixed effects ordered probit model with a simple ordered probit with clustering. The results were the same for both methods. Due to its ordinal nature (answers ranging from 1 to 5, each answer getting progressively riskier), the Lottery variable was coded as a quantitative discrete variable and therefore not converted to a set of binary variables. The Financial Risk Tolerance, Apophenia and Precognition variables were also coded as quantitative discrete variables. The View Order variable was included in our model to control for the nature of the graphs seen and the learning effect in the *Pattern Task*.

Below is the regression we used for our model:

Risk = β1 View Order + β2 Lottery + β3 Apophenia + β4 Financial Risk Tolerance + β5 Precognition +e **(19)**

Table 12 – Risk Preferences and Beliefs - *BluePanel*

Risk / Direction	H3a_Risk (19)	H3b_Direction (20)
View Order	-0.0138	0.0158
	(0.0107)	(0.0103)
Lottery	-0.0522	0.0579 *
	(0.0428)	(0.0309)
Apophenia	-0.0026	-0.0058 **
	(0.0042)	(0.0025)
Financial Risk Tolerance	0.0098	0.0142 **
	(0.0125)	(0.0062)
LogPrecognition	-0.1026	0.0118
	(0.1691)	(0.1312)
cut1		
_cons	-1.5082 ***	-0.0371
	(0.5043)	(0.4878)
cut2		
_cons	0.1292	0.3526
	(0.4901)	(0.4790)
sigma2_u		
_cons	9.53E-33	4.15E-35
	(0.0000)	(0.0000)
N	377	377
N_clust	38	38
p	0.471434	0.015411
chi2	4.563487	14.031471

Notes: We conduct two separate regressions (regressions 19 and 20), one for each of our two independent variables (Risk and Direction). These regressions are perfomed to test hypothesis 3a) and 3b) in our study. We use fixed effects ordered probit regressions with robust standard errors due to the categorical ordinal nature of our independent variables and the panel nature of our data. Separate regressions were ran with regular oprobit models to compare results. For both regressions, we regress the independent variables on variables used as a proxy for Risk Preferences and Beliefs (Lottery, Apophenia, Financial Risk Tolerance and Precognition) and one control variable to account for the condition and the view order of each graph in the *Pattern Task* (View Order). The Lottery variable represents the participant's level of risk when asked to chose one of five lotteries to play. The Apophenia variable measures the participant's tendecy to perceive patterns in unrelated things. The Financial Risk Tolerance variable measures the participant's risk preferences through a 13-item questionnaire. The precognition variable was transformed lognormally and measures the participant's belifs in the ability to predict the future. We also show the cuts for each our ordered probit model and other relevant statistics. The number of observations (N) was of 377, which represents multiple trial data collected for 38 different participants (N_clust). Levels of signficance of each of the variables with regards to their p-values in the regressions are identified by the * symbol: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001. The data in parentheses represents the coefficient's standard errors in the regressions. The regressions were done on Stata 17. Regression 19 : xtoprobit Risk ViewOrderFinal Lottery Apophenia Financial_Risk_Tolerance LogPrecognition, vce(robust). Regression 20 : xtoprobit Direction ViewOrderFinal Lottery Apophenia Financial_Risk_Tolerance LogPrecognition, vce(robust)

As seen in table 9, none of the four independent research variables in our model have a significant impact on the dependent variable. This confirms our hypothesis 3a) which states that risk preferences and beliefs do not have a significant impact on the level of Risk taken when predicting the outcome of graphs in the *Pattern Task*. Although many studies in various settings have shown that beliefs and individual risk preferences influence decision-making, we are unable to conclude that they exert an influence on the level of Risk taken in the *Pattern Task* of our study.

5.4.2: Risk Preferences and Beliefs—Direction

Once again, our model uses a fixed effects ordered probit model with robust standard errors as our dependent variable is classified as categorical ordinal. We also compare this model with a simple ordered probit with clustered standard errors. We get the same results (significance of coefficients) for both models.

Below is the regression we used for our model:

Direction = β1 View Order + β2 Lottery + β3 Financial Risk Tolerance + β4 Apophenia + β5 Precognition +e **(20)**

As seen in table 12, two of our independent variables have a significant impact on our dependent variable. First off the coefficient for Apophenia is significant (coef. = -0.0058 and standard error = 0.0025. These results indicate that participants with a higher score in the Apophenia taks and therefore exhibit more Apophenia have a higher predicted probability of believing that the wait time will decrease in the future. As seen in previous literature, participants exhibiting higher levels of apophenia have a tendency to find patterns in unrelated events or things (Paul et al. 2014, Fyfe et al., 2008). We see here that apophenia does have a significant impact on the anticipated Direction, suggesting that participants potentially identify trends in graphs when predicting their outcome. Second, we find that the Financial Risk Tolerance of participants has a significant impact on the anticipated Direction of the graph in the future (coef. = 0.0142 and standard error = 0.0062). This implies that participants exhibiting a higher financial risk tolerance will have a higher predicted probability of believing that the wait time will increase in the future, consistent with the logic that investors with a higher financial risk tolerance will tend to believe that markets will eventually go up. We therefore reject the hypothesis 3b) which suggests that beliefs and individual risk preferences do not have a significant impact on the anticipated Direction when predicting the outcome of graphs in the *Pattern Task*.

5.4.3: Risk Preferences and Beliefs—Conclusion

Overall, we found that none of the variables used as proxies for risk preferences and beliefs have a significant impact on the level of Risk taken in the *Pattern Task*. This supports the hypothesis 3a). On the other hand, we found that Apophenia and Financial Risk Tolerance have a significant impact on the anticipated Direction of the wait time in the *Pattern Task*. A higher tendency to exhibit apophenia and higher financial risk tolerance both increase the predicted probability of an anticipated increase in wait time in the future. This does not support the hypothesis 3b).

5.5: Financial Literacy—*BluePanel*

As the last step of our *BluePanel* study, we observed the impact of Financial Literacy on both the level of Risk taken and the anticipated Direction of the wait time when predicting the outcome of graphs in the *Pattern Task*. A combination of self-assessed financial literacy variables and questions on financial events were used as a proxy for Financial Literacy. Participants were first asked to self-assess their level of financial literacy on a Likert scale. Then participants were asked a series of questions on the GameStop events that took place in financial markets in early 2021 with participants answering each question on a 1 to 7 Likert scale. For this series of questions, participants were first asked to measure their level of familiarity with the situation (GameStop_Familiar) and if they believe that regulators should intervene in such a situation (GameStop Regulators). Then, participants were asked to assess the likelihood of such a situation happening again in the future (GameStop_Happen_Future) and to what extent they would be likely to purchase shares if it were to happen again (GameStop_Buy_Future).

Upon examination of the data, we found a certain level of correlation between the self-assessed financial literacy, the familiarity with the GameStop events and the tendency to believe that regulators should intervene. Financial_Literacy and GameStop_Familiar logically appear to be positively correlated. A higher financial literacy could easily lead individuals to be more aware of financial events and vice versa. GameStop_Regulator was negatively correlated with the two above variables. Lower awareness of financial events or a lower financial literacy could lead individuals to take a more defensive stance. We used the Cronbach Alpha test to assess the reliability of the coefficients and found an alpha of 0.7042, which is above the minimal acceptable value. This suggests that our coefficient presents an acceptable level of reliability. We therefore decided to group these three variables and create an average financial literacy score (Average Financial Literacy). This variable represents the average of the sum of the score for the three above-mentioned variables (the score for the GameStop_regulators was reversed due to its negative correlation with the other two variables).

The first variable to be included in our model was therefore the Average Financial Literacy. The average score came in at 4.35 with a standard deviation of 1.33. Scores range from 2 to 7 which is the maximum possible score for this variable. Next the perceived likelihood that such a situation would happen in the future, GameStop_Happen_Future, was included. The average score for this variable was 5.14 with a standard deviation of 1.40 suggesting a strong belief that such a situation will happen again. The desire to purchase shares if such a situation were to happen again in the future, GameStop_Buy_Future was finally included in our model. The average score for this variable was 3.42 with a standard deviation of 1.69.

5.5.1: Financial Literacy—Risk

We used a fixed effects ordered probit model with robust standard errors to assess the impact of financial literacy as our dependent variable, Risk, was of categorical nature. The results were validated by comparing our regression with a simple ordered probit with clustered standard errors. The results that were yielded were the same for both models. The Average Financial Literacy, GameStop_Happen_Future and GameStop_Buy_Future variables were coded as numeric discrete variables and therefore kept as is in our model. We also included the ViewOrder variable to control for the learning effect and the nature of the graph seen.

Below is the regression we used for our model:

Risk = β1 View Order + β2 Average Financial Literacy + β3 GameStop_Happen_Future + β4 GameStop_Buy_Future +e **(21)**

Our results in table 13 suggest that none of the three independent research variables in our model have a significant impact on our dependent variable Risk. This validates hypothesis 4a) which states that financial literacy does not have a significant impact on the level of Risk taken in the *Pattern Task*. Various studies have shown that a higher level of financial literacy usually translates into a higher risk tolerance when making financial decisions (Grable, 2000). Our study, however, does not allow us to conclude the same in the context of predicting the outcome of graphs.

Table 13 – Financial Literacy – *BluePanel*

Risk / Direction	H4a_Risk **(21)**	H4b_Direction **(22)**
ViewOrderFinal	-0.0107	0.0088
	(0.0102)	(0.0079)
Average Financial Literacy	0.0046	0.0769 **
	(0.0526)	(0.0299)
GameStop_Happen_Future	-0.0337	0.0244
	(0.0507)	(0.0312)
GameStop_Buy_Future	0.0225	0.0012
	(0.0401)	(0.0218)
cut1		
_cons	-1.2241 ****	0.2127
	(0.2782)	(0.2688)
cut2		
_cons	0.4081	0.6015 **
	(0.2731)	(0.2625)
sigma2_u		
_cons	0.0000	0.0000
	(0.0000)	(0.0000)
N	377	377
N_clust	38	38
p	0.8145	0.0949
chi2	1.5684	7.9112

Notes: We conduct two separate regressions (regressions 21 and 22), one for each of our two independent variables (Risk and Direction). These regressions are perfomed to test hypothesis 4a) and 4b) in our study. We use fixed effects ordered probit regressions with robust standard errors due to the categorical ordinal nature of our independent variables and the panel nature of our data. Separate regressions were ran with regular oprobit models to compare results. For both regressions, we regress the independent variables on variables used as a proxy for Financial Literacy (Average Financial Literacy, GameStop_Happen_Future, GameStop_Buy_Future) and one control variable to account for the condition and the view order of each graph in the *Pattern Task* (ViewOrderFinal). The Average Financial Literacy variable combines different variables to measure each participant's average level of financial literacy. The GameStop_Happen_Future represents the participant's perceived likelihood that an event similar to that of GameStop is will happen again in the future. The GameStop_Buy_Future variable measures the participant's willingness to purchase shares if the situation were to happen again in the future. We also show the cuts for each our ordered probit model and other relevant statistics. The number of observations (N) was of 377, which represents multiple trial data collected for 38 different participants (N_clust). Levels of signficance of each of the variables with regards to their p-values in the regressions are identified by the * symbol: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001. The data in parentheses represents the coefficient's standard errors in the regressions. The regressions were done on Stata 17. Regression 21 : xtoprobit Risk ViewOrderFinal AvgFinancial_Literacy GameStop_Happen_Future GameStop_Buy_Future, vce(robust). Regression 22 : xtoprobit Direction ViewOrderFinal AvgFinancial_Literacy GameStop_Happen_Future GameStop_Buy_Future, vce(robust).

5.5.2: Financial Literacy—Direction

We also used a fixed effects ordered probit model with robust standard errors to analyze the impact of financial literacy on the anticipated Direction of the wait time when predicting the outcome of graphs in the *Pattern Task*. A second simple ordered probit regression with clustered standard errors yielded similar results. The View Order variable was once again included in the model.

Below is the regression we used for our model:

Direction = β1 View Order + β2 Average Financial Literacy + β3 GameStop_Happen_Future + β4 GameStop_Buy_Future +e **(22)**

Results in Table 13 indicate one significant coefficient for the Average Financial Literacy variable (coef. = 0.0769 and standard error = 0.0299). This suggests that participants exhibiting a higher level of average financial literacy have a higher predicted probability of believing that the wait time will increase in the future when predicting the outcome of charts in the *Pattern Task*. As mentioned in section 5.5.2, multiple studies have linked higher financial literacy with higher financial risk tolerance. In this case, we see the same conclusion as with financial risk tolerance, where higher financial literacy leads participants to believe that the wait time will increase in the future.

5.5.3: Financial Literacy—Conclusion

When assessing the impact of financial literacy, we found that none of the variables used as a proxy exert an influence on the level of Risk taken in the *Pattern Task*. These results support the hypothesis 4a). On the contrary, we found that our measure for Average Financial Literacy significantly impacts the anticipated Direction of the wait time in the *Pattern Task*. A higher level of Average Financial Literacy increases the predicted probability of an anticipated increase in wait time when predicting the outcome of graphs. These results do not support the hypothesis 4b).

5.6: Chart Characteristics—*Mturk*

The chart characteristic variables remain the same for our second study and we once again looked at the impact of these characteristics on both the level of Risk and the Direction taken when predicting the outcome of these graphs. Instead of being shown 10 patterns, participants were only shown 5. However, the pool of 20 charts remained the same as in the *BluePanel* study. The graphs were grouped in the same categories as

in the *Bluepanel* study with regards to their General Trend, First Half Trend and Second Half Trend. Standard Deviation was also used as a variable. These General Trend, First Half Trend, Second Half Trend and Standard Deviation variables were therefore the main inputs in our model for our first hypothesis.
As for the Chart Characteristics Data, it remains the same as in the *BluePanel* study.

5.6.1: Chart Characteristics—Risk

The effect of chart characteristics on Risk in the *Pattern Task* was analyzed using a fixed effect ordered probit model with robust standard errors as our data was one again in panel format and our dependent variable was of categorical ordinal nature. Results were compared with an ordered probit model with clustered standard errors, and both yielded comparable results. The General Trend, First Half Trend and Second Half Trend variables were once again converted to binary variables and included in the regression due to their categorical nature. In this second study, participants were split into one of three groups. One group of participants was presented with two randomly generated graphs, another group was presented with manually created graphs and the other group with both types of patterns. Three binary variables were therefore created to reflect these groups and the nature of graphs and added as control variables in our model. A binary variable to reflect the view order of the graphs in the *Pattern Task* was also added to the model to control for learning effects.

Below is the regression we used for our model:
Risk = β1 Pattern Condition + β2 Random Condition + β3 View Order + β4 Descending General Trend + β5 Neutral General Trend + β6 Ascending First Half Trend + β7 Descending First Half Trend + β8 Ascending Second Half Trend + β9 Descending Second Half Trend + β10 Variability + e **(23)**

As seen in Table 14 below, we find that none of the chart characteristics in our model have a significant coefficient. This means that none of the variables in our model have a significant relationship with the level of Risk taken in the *Pattern Task* when predicting the outcome of charts. This confirms our hypothesis 5a), which states that chart characteristics do not have a significant impact on risk preferences and is consistent with the results we found in our model for the hypothesis 1a).

Table 14 – Chart Characteristics – *Mturk*

Risk / Direction	H5a_Risk **(23)**	H5b_Direction **(24)**
Pattern Condition	0.1138	0.0065
	(0.1557)	(0.1348)
Random Condition	-0.1513	-0.0411
	(0.1695)	(0.1338)
View Order	0.0340	-0.1070
	(0.1071)	(0.1154)
Descending General Trend	0.2532	-0.2284
	(0.2915)	(0.2896)
Neutral General Trend	0.3219	0.0767
	(0.2376)	(0.2388)
Ascending First Half Trend	0.2955	0.1114
	(0.2605)	(0.2472)
Descending First Half Trend	0.0495	-0.2360
	(0.1576)	(0.1495)
Ascending Second Half Trend	0.3261	-0.4406 *
	(0.2715)	(0.2435)
Descending Second Half Trend	-0.0771	-0.3178 *
	(0.1758)	(0.1796)
Variability	0.1187	0.0978
	(0.1295)	(0.1308)
cut1		
_cons	-0.4857	-0.6249
	(0.3956)	(0.4040)
cut2		
_cons	1.6186 ****	-0.2408
	(0.4166)	(0.4069)
sigma2_u		
_cons	0.2655 *	0.0000
	(0.1402)	(0.0000)
N	492	492
N_clust	246	246
p	0.1001	0.0168
chi2	15.9832	21.6906

Notes: We conduct two separate regressions (regressions 23 and 24), one for each of our two independent variables (Risk and Direction). These regressions are perfomed to test hypothesis 5a) and 5b) in our study. We use fixed effects ordered probit regressions with robust standard errors due to the categorical ordinal nature of our independent variables and the panel nature of our data. Separate regressions were ran with regular oprobit models to compare results. For both regressions, we regress the independent variables on seven variables used as a proxy for Chart Characteristics (Descending General Trend, Neutral General Trend, Ascending First Half Trend, Descending First Half Trend, Ascending Second Half Trend, Descending Second Half Trend, Variability)) and three control variables to account for the condition and the view order of each graph in the *Pattern Task* (Pattern Condition, Random Condition, View Order). The General Trend variables are binary variables to identify the graph's General Trend. The first half trends are binary variables to indentify the graph's first half trend. The second half trends are binary variables to indentify the graph's second half trend. Omited variables were chosen on the basis of correlation with other variables in the model. The Variability variables represents the variability of the pattern over the 35 day tome horizon. We also show the cuts for each our ordered probit model and other relevant statistics. The number of observations (N) was of 492, which represents multiple trial data collected for 246 different participants (N_clust). Levels of signficance of each of the variables with regards to their p-values in the regressions are identified by the * symbol: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001. The data in parentheses represents the coefficient's standard errors in the regressions. The regressions were done on Stata 17. Regression 23 : xtoprobit Risk dCondition_PATT dCondition_RAND dViewOrder2 dGenTrendDSC dGenTrendNEU dHalfASC dHalfDSC dHalf_0ASC dHalf_0DSC Std_dev, vce(robust). Regression 24 : xtoprobit Direction dCondition_PATT dCondition_RAND dViewOrder2 dGenTrendDSC dGenTrendNEU dHalfASC dHalfDSC dHalf_0ASC dHalf_0DSC Std_dev, vce(robust).

5.6.2: Chart Characteristics—Direction

For this other hypothesis, we once again used a fixed effects ordered probit model with robust standard errors which we then compared with a simple ordered probit with clustered standard errors. The significance of coefficients remains the same for both regressions. Although the dependent variable changes in this second model, as we are now looking at the impact of chart characteristics on the anticipated Direction of the wait time, it remains a categorical ordinal variable. The independent variables remain the exact same as above.

Below is the regression we used for our model:

Direction = β1 Pattern Condition + β2 Random Condition + β3 View Order + β4 Descending General Trend + β5 Neutral General Trend + β6 Ascending First Half Trend + β7 Descending First Half Trend + β8 Ascending Second Half Trend + β9 Descending Second Half Trend + β10 Variability + e **(24)**

As seen in Table 14, we once again find that none of the chart characteristics have an impact on the anticipated Direction of the wait time when predicting the outcome of graphs in the *Pattern Task*. None of the coefficients in our model were significant. These results support hypothesis 5b) which states that chart characteristics do not have a significant impact on the anticipated Direction of the graph in the future. These results contrast with the results found with our model with hypothesis 5b) where we found multiple variables having a significant impact on the anticipated Direction.

5.6.3: Chart Characteristics—Conclusion

For this first model in our *Mturk* study, we found that none of the chart characteristics variables have a significant impact on either the level of Risk taken or the anticipated Direction of wait time in the *Pattern Task*. This supports hypotheses 5a) and 5b) but contradicts the results found in section 5.2.3 with hypothesis 1b). This suggests that results differ when the setting of the study is slightly modified.

5.7: Emotional Reactions - *Mturk*

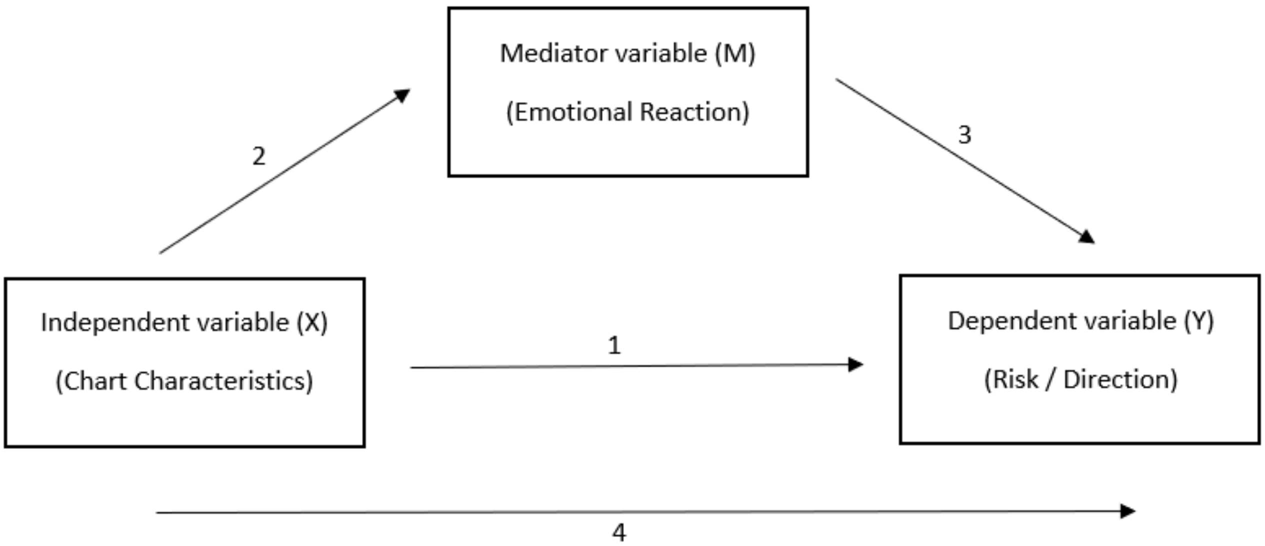
We then proceeded to assess the impact of emotional reactions on the level of Risk taken and the anticipated Direction when predicting the outcome of graphs in the *Pattern Task*. We once again wanted to see if emotional reactions act as a mediator variable in explaining the relationship between chart characteristics and the level of Risk and anticipated Direction. As the data was collected exclusively through an online questionnaire for this second study and we did not have access to any physiological data collection material, self-assessed emotional reaction was used for this second hypothesis. The intensity of emotions felt when viewing the charts was measured through a self-assessed arousal scale and the nature of the emotional reaction was measured through a self-assessed pleasure scale. Arousal and Pleasure are therefore used as our two main variables for our model.

Our first measured variable was Arousal, which represents the intensity of the emotion felt when viewing the different charts. The scores ranged from 0 to 100, on a scale that ranged from calm to excited. The average arousal for all trials came in at 53.80 with a standard deviation of 27.09. Our second measured variable was Pleasure, which represents the nature of the emotion felt when viewing the video. The scores once again ranged from 0 to 100, on a scale that ranged from sad to happy. The average came in at 57.26 with a standard deviation of 23.90.

5.7.1: Physiological Data Analysis

Both the Arousal and the Pleasure variables were coded as quantitative discrete variables and no transformations had to be mad to include them in our model. Our model for our sixth hypothesis was once again constructed around SOR theory and mediation analysis. The same model is applied but we observe the possibility that perceived emotional reaction (versus measured emotional reaction) acts as a mediator variable in explaining the relationship between chart characteristics and the level of Risk taken or the anticipated Direction of the graph in the future. We use Baron and Kenny's (1986) theory to identify mediator variables and once again break down our analysis in four steps that must each be validated to qualify emotional reaction as a mediator.

Figure 4 – Mediation Analysis - *Mturk*



This means that we must first assess the impact of chart characteristics on the level of Risk taken or on the anticipated Direction when predicting the outcome of graphs in the *Pattern Task* (Relationship 1 in figure 4). This relationship has already been established in sections 5.6.2 and 5.6.3 through our model for our fifth hypothesis. We have determined that none of the chart characteristics have an impact on neither the level of Risk taken nor the anticipated Direction of the graph. This first step in the Baron and Kenny process is therefore not validated. According to the theory, our mediation analysis stops here, and we conclude that emotional reaction does not act as a mediator variable in explaining the relationship between chart characteristics and the Risk and Direction variables. These results support hypotheses 6a) and 6b) which state that emotions do not act as a mediator variable when explaining the relationship between chart characteristics and both the level of Risk and the anticipated Direction of wait time.

We still found it interesting to observe the relationship between emotional reaction and the Risk and Direction variables even outside of the mediation context (Relationship 3 in figure 4). Although our hypothesis of no mediation is validated, there still might be a direct relationship between emotions and Risk/Direction that can be found to bring value to our analysis. We therefore regressed both Arousal and Pleasure on the two dependent variables, Risk and Direction. Variables controlling for the nature of the graphs presented (Condition) and for the learning effect (View Order) were included in our model. As our dependent variables are of categorical ordinal nature, we once again used a fixed effect ordered probit model with robust standard errors which we compared to a regular probit model with clustered standard errors. Both models yielded similar results. We illustrate our results in table 15 below.

Below are the regressions we used for our model:

Risk = β1 View Order + β2 Pattern Condition + β3 Random Condition + β4 Arousal +e **(25)**

Direction = β1 ViewOrder + β2 Pattern Condition + β3 Random Condition + β4 Arousal +e **(26)**

Risk = β1 ViewOrder + β2 Pattern Condition + β3 Random Condition + β4 Pleasure +e **(27)**

Direction = β1 ViewOrder + β2 Pattern Condition + β3 Random Condition + β4 Pleasure +e **(28)**

Table 15 – Emotional reaction – *Mturk*

Risk / Direction	H6a_Risk (25)	H6b_Direction (26)		H6a_Risk (27)	H6b_Direction (28)
View Order	0.0231	-0.0996	View Order	0.0257	-0.1039
	(0.1066)	(0.1136)		(0.1068)	(0.1143)
Pattern Condition	0.1906	-0.0798	Pattern Condition	0.1939	-0.0785
	(0.1446)	(0.1257)		(0.1467)	(0.1243)
Random Condition	-0.2539	-0.0099	Random Condition	-0.2615	-0.0291
	(0.1614)	(0.1289)		(0.1627)	(0.1271)
Arousal	0.0047 **	0.0062 ****	**Pleasure**	0.0007	0.0058 **
	(0.0022)	(0.0018)		(0.0024)	(0.0024)
cut1			cut1		
_cons	-0.9669 ****	-0.2970 **	_cons	-1.1827 ****	-0.2976 *
	(0.1735)	(0.1394)		(0.1865)	(0.1664)
cut2			cut2		
_cons	1.0940 ****	0.0801	_cons	0.8825 ****	0.0779
	(0.1678)	(0.1370)		(0.1783)	(0.1654)
sigma2_u			sigma2_u		
_cons	0.2289 *	3.07E-32	_cons	0.2522 *	1.27E-32
	(0.1310)	(0.0000)		(0.1348)	(0.0000)
N	492	492	N	492	492
N_clust	246	246	N_clust	246	246
p	0.0178	0.0114	p	0.1427	0.1311
chi2	11.9469	12.9662	chi2	6.8733	7.0914

Notes : We conduct four separate regressions (regressions 25, 26, 27 and 28), to measure the impacts of both arousal and pleasure on both of our independent variables. These regressions are perfomed to test hypothesis 6a) and 6b) in our study. We use fixed effects ordered probit regressions with robust standard errors due to the categorical ordinal nature of our independent variables and the panel nature of our data. Separate regressions were ran with regular oprobit models to compare results. We seek to measure the direct impact of the emotional reaction variables on both Risk and Direction to test our mediation model. For the regressions, we regress the independent variables on Pleasure and Arousal and three control variables to account for the condition and the view order of each graph in the Pattern Task (Pattern Condition, Random Condition, View Order). The Arousal variable measures the participant's perceived intensity of the emotional reaction for each graph seen. The Pleasure variable measures the participant's perceived nature of the emotional reaction for each graph seen. We also show the cuts for each our ordered probit model and other relevant statistics. The number of observations (N) was of 492, which represents multiple trial data collected for 246 different participants (N_clust). Levels of signficance of each of the variables with regards to their p-values in the regressions are identified by the * symbol: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001. The data in parentheses represents the coefficient's standard errors in the regressions. The regressions were done on Stata 17. Regression 25: xtoprobit Risk dViewOrder2 dCondition_PATT dCondition_RAND Arousal, vce(robust). Regression 26: xtoprobit Direction dViewOrder2 dCondition_PATT dCondition_RAND Arousal, vce(robust). Regression 27: xtoprobit Risk dViewOrder2 dCondition_PATT dCondition_RAND Pleasure, vce(robust). xtoprobit Direction dViewOrder2 dCondition_PATT dCondition_RAND Pleasure, vce(robust).

We start by looking at the impact of Arousal on both the Risk and Direction dependent variables. First, as seen in table 15, we find that Arousal has a significant impact on the level of Risk taken in the *Pattern Task* (coef. = 0.0047 and standard error = 0.0022). This coefficient implies that a higher level of self-reported arousal tends to lead to increase the predicted probability of Risk taken when predicting the outcome of graphs. Studies have shown that higher levels of arousal do affect the level of Risk taken, especially in gambling settings where higher arousal is linked to higher or increased bids (Adam et al., 2015, 2019). Our results support these conclusions, but they do not support our hypothesis 6a) which states that emotional reaction does not impact the level of Risk taken in the *Pattern Task*. Second, we find that arousal also has a significant impact on the anticipated Direction of the wait time (coef. = 0.0062 and standard error = 0.0018). Plainly, this suggests that a higher level of self-reported arousal tends to increase the predicted probability of anticipating an increase in wait time in the future. Once again, there appears to be a relationship between the level of arousal and the decision-making process which has been found to be the case in previous studies (Studer and Clark, 2011). This relationship is less straightforward to explain as it does not lead to a higher level of Risk taken but rather an anticipated Direction.

We then look at the impact of Pleasure on both the Risk and Direction dependent variables. As seen in table 15, we find that the coefficient for Pleasure is not significant in the model for Risk. This means that the self-reported level of pleasure does not have a significant impact on the level of Risk taken in the *Pattern Task*. These results contradict those found with arousal. As mentioned above, literature suggests that emotions do have an impact on the level of Risk taken, but in this case, not when predicting the outcome of graphs. We also find that pleasure has a significant impact on the anticipated Direction of the wait time in the future (coef. = 0.0058 and standard error = 0.0024). This relationship implies that a higher level of self-reported pleasure increased the predicted probability of an anticipated increase in the wait time when predicting the outcome of graphs in the *Pattern Task*.

5.7.2: Physiological—Conclusion

Overall, we found that for our *Mturk* study, Emotional Reaction does not act as a mediator variable in explaining the relationship between chart characteristics and both the level of Risk taken and the anticipated Direction of the wait time in the *Pattern Task*. According to Baron and Kenny's (1986) model, we are unable to conclude that Emotional Reaction acts as a mediator variable since none of the chart characteristics have a significant impact on the Risk or Direction variables. This supports hypotheses 6a) and 6b). We pushed our analysis further and looked at the direct impact of Arousal and Pleasure on the Risk and Direction. Consistent with existing literature, we found that arousal has a significant impact on both the level of Risk taken and the anticipated Direction of wait time. A higher level of self-reported arousal increases the predicted probability of higher Risk being taken in the *Pattern Task* and increases the predicted probability of an anticipated increase in wait time in the future. We also found that a higher level of pleasure increases the predicted probability of an anticipated increase in wait time in the future.

5.8: Beliefs - *Mturk*

During our *Mturk* study, we once again looked at the impact of beliefs on both the level of Risk taken and the Direction taken in the *Pattern Task* when predicting the outcome of graphs. Two variables were measures to help us characterize each participant's beliefs, namely Apophenia and Precognition. The precognition variable was measured in the exact same manner as in the *BluePanel* study. As for the Apophenia variable, participants were presented with 5 (versus 10 in the *BluePanel* study) black and white images and asked to identify to what extent they saw certain objects in these images.

First, the participant's tendency to exhibit apophenia was measured. Once again, the sum of answers to all five images was used as a score for this task. The lowest and highest scores measured were of 27 and 77 respectively (minimum possible score of 15 and maximum possible score of 105) while the average score was 44.04 and standard deviation was 10.44. Second, for precognition, the sum of the answers to each of the four questions was summed to give a global score. The lowest and highest score recorded corresponded to the minimum and maximum possible score of 4 and 28 for the task. The average score was 14.02 and standard deviation was 7.75.

5.8.1: Beliefs—Risk

A fixed effects ordered probit model with robust standard errors was used to measure the impact of beliefs on the level of Risk taken in the *Pattern Task*. We once again compared our results with an ordered probit model with clustered standard errors which yielded similar results. Both the Apophenia and the Precognition variables were coded as quantitative discrete variables in our model. View order and condition variables were once included in our model to control for both the nature of the graphs that were seen and the learning effect when completing the *Pattern Task*.

Below is the regression we used for our model:

$$\text{Risk} = \beta 1 \text{ View Order} + \beta 2 \text{ Pattern Condition} + \beta 3 \text{ Random Condition} + \beta 4 \text{ Apophenia} + \beta 5 \text{ Precognition} + e \qquad \textbf{(29)}$$

Our results in table 13 show that neither the Apophenia nor Precognition variable have a significant impact on the level of Risk taken in the *Pattern Task*. None of the coefficients in our model are significant. This supports our hypothesis 7a) which states that beliefs do not have an impact on the level of Risk taken in the

Pattern Task. These results are also consistent with those found with our model for hypothesis 3a) where none of the variables were significant.

Table 16 – Beliefs – *Mturk*

Risk / Direction	H7a_Risk (29)	H7b_Direction (30)
Pattern Condition	0.1734	-0.0731
	(0.1497)	(0.1239)
Random Condition	-0.2747 *	-0.0281
	(0.1609)	(0.1282)
View Order	0.0262	-0.0953
	(0.1066)	(0.1140)
Apophenia	-0.0070	0.0011
	(0.0075)	(0.0060)
Precognition	0.0170 *	0.0078
	(0.0098)	(0.0085)
cut1		
_cons	-1.2979 ****	-0.4668 **
	(0.3051)	(0.2329)
cut2		
_cons	0.7682 ***	-0.0940
	(0.2960)	(0.2299)
sigma2_u		
_cons	0.2412 *	5.44E-32
	(0.1340)	(0.0000)
N	492	492
N_clust	246	246
p	0.0667	0.7424
chi2	10.3181	2.7240

Notes: We conduct two separate regressions (regressions 29 and 30), one for each of our two independent variables (Risk and Direction). These regressions are perfomed to test hypothesis 7a) and 7b) in our study. We use fixed effects ordered probit regressions with robust standard errors due to the categorical ordinal nature of our independent variables and the panel nature of our data. Separate regressions were ran with regular oprobit models to compare results. For both regressions, we regress the independent variables on variables used as a proxy for Beliefs (Apophenia and Precognition) and three control variables to account for the condition and the view order of each graph in the Pattern Task (Pattern Condition, Random Condition, View Order). The Apophenia variable measures the participant's tendecy to perceive patterns in unrelated things. The precognition variable was transformed lognormally and measures the participant's belifs in the ability to predict the future. We also show the cuts for each our ordered probit model and other relevant statistics. The number of observations (N) was of 377, which represents multiple trial data collected for 38 different participants (N_clust). Levels of signficance of each of the variables with regards to their p-values in the regressions are identified by the * symbol: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001. The data in parentheses represents the coefficient's standard errors in the regressions. The regressions were done on Stata 17. Regression 29 : xtoprobit Risk dCondition_PATT dCondition_RAND dViewOrder2 Apophenia Precognition, vce(robust)). Regression 30 : xtoprobit Direction dCondition_PATT dCondition_RAND dViewOrder2 Apophenia Precognition, vce(robust).

5.8.2: Beliefs—Direction

Once again, our model uses a fixed effects ordered probit model with robust standard errors as our dependent variable is classified as categorical ordinal. We also compare this model with a simple ordered probit with clustered standard errors. We get the same results (significance of coefficients) for both models. The View Order and Condition variables were once again included in our model as control variables.

Below is the regression we used for our model:

Direction = $\beta1$ View Order + $\beta2$ Pattern Condition + $\beta3$ Random Condition + $\beta4$ Apophenia + $\beta5$ Precognition +e **(30)**

The results shown in table 16 once again indicate that none of the research variables in our model have a significant impact on the dependent variable. This means that the coefficients for both Apophenia and Precognition are not significant. This supports our hypothesis 7b) which states that beliefs do not have an impact on the anticipated Direction of the wait time when predicting the outcome of graphs in the *Pattern Task*. These results differ from those found with our model for the hypothesis 3b) where we found that Apophenia significantly impacted the anticipated Direction.

5.8.3: Beliefs—Conclusion

Overall, we find that neither Apophenia nor Precognition have a significant impact on both Risk and Direction in the *Pattern Task*. These results support hypotheses 7a) and 7b) but contradict the results found in section 5.4.3 where Apophenia was found to significantly impact the anticipated Direction of the wait time in the future.

5.9: Financial Literacy—*Mturk*

As the last step for our *Mturk* study, we assessed the impact of Financial Literacy on the level of Risk taken and on the anticipated Direction of the chart in the future in the *Pattern Task*. With the *Mturk* study being a shortened version of the *BluePanel* study, only the self-assessed Financial Literacy variable was kept in our model and all GameStop related variables were removed. The average score for the self-assessment of Financial Literacy was of 5.07 with a standard deviation of 1.40.

5.9.1: Financial Literacy—Risk and Direction

We used a fixed effects ordered probit model with robust standard errors to assess the impact of financial literacy as our dependent variable, Risk, was of categorical nature. The results were validated by comparing our regression with a simple ordered probit with clustered standard errors. The results that were yielded were the same for both models. The Average Financial Literacy, GameStop_Happen_Future and GameStop_Buy_Future variables were coded as numeric discrete variables and therefore kept as is in our model. We once again used a fixed effects ordered probit model with robust standard errors which we compared with a simple ordered probit model with clustered standard errors. Both yielded the same results. The View Order and Condition variables were included in the model to control for the learning effect and the nature of the charts seen.

Below are the two regressions we used for our model:

Risk = β1 View Order + β2 Pattern Condition + β3 Random Condition + β4 Financial Literacy +e **(31)**

Direction = β1 View Order + β2 Pattern Condition + β3 Random Condition + β4 Financial Literacy +e **(32)**

Table 17 – Financial Literacy – Mturk

Risk / Direction	H8a_Risk **(31)**	H8b_Direction **(32)**
Pattern Condition	0.1845	-0.0695
	(0.1460)	(0.1237)
Random Condition	-0.2733 *	-0.0123
	(0.1635)	(0.1278)
View Order	0.0263	-0.0960
	(0.1066)	(0.1138)
Financial Literacy	0.0704	-0.0171
	(0.0433)	(0.0358)
cut1		
_cons	-0.8708 ****	-0.7035 ****
	(0.2444)	(0.2014)
cut2		
_cons	1.1957 ****	-0.3313
	(0.2526)	(0.2027)
sigma2_u		
_cons	0.2447 *	0.0000
	(0.1335)	(0.0000)
N	492	492
N_clust	246	246
p	0.0587	0.8759
chi2	9.0997	1.2132

Notes: We conduct two separate regressions (regressions 31 and 32), one for each of our two independent variables (Risk and Direction). These regressions are perfomed to test hypothesis 8a) and 8b) in our study. We use ordered fixed effects ordered probit regressions with robust standard errors due to the categorical ordinal nature of our independent variables and the panel nature of our data. Separate regressions were ran with regular oprobit models to compare results. For both regressions, we regress the independent variables on a variable used as a proxy for Financial Literacy and three control variables to account for the condition and the view order of each graph in the Pattern Task (Pattern Condition, Random Condition, View Order). The FinancialLiteracy variable measures each participant's self-reported financial literacy. We also show the cuts for each our ordered probit model and other relevant statistics. The number of observations (N) was of 377, which represents multiple trial data collected for 38 different participants (N_clust). Levels of signficance of each of the variables with regards to their p-values in the regressions are identified by the * symbol: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001. The data in parentheses represents the coefficient's standard errors in the regressions. The regressions were done on Stata 17. Regression 31 : xtoprobit Risk dCondition_PATT dCondition_RAND dViewOrder2 FinancialLiteracy, vce(robust). Regression 32 : xtoprobit Direction dCondition_PATT dCondition_RAND dViewOrder2 FinancialLiteracy, vce(robust).

Our results in table 17 suggest that the Financial Literacy variable does not have a significant impact on neither the Risk nor the Direction variable. These results validate hypothesis 8a) and 8b) which states that Financial Literacy does not have an impact on the level of Risk taken or on the anticipated Direction of graphs in the *Pattern Task*. In our model for hypothesis 4a) we found that none of the financial literacy variables had a significant impact on Risk, while in our model for hypothesis 4b), we found that average financial literacy did have a significant impact on Direction. Our results therefore differ from one study to the other.

5.9.2: Financial Literacy—Conclusion

Overall, for this fourth model in our *Mturk* study, we found that Financial Literacy does not impact either Risk or Direction in the *Pattern Task*. These results support hypotheses 8a) and 8b) but contradict the results found in section 5.5.3 where average financial literacy was found to significantly impact the anticipated Direction of the wait time. This once again suggests that results differ from one study to another, showing a lack of consistency.

6. Hypothesis Summary

We now present a table of our confirmed or refuted hypotheses in the table below:

Table 18
Summary of our research hypothesis—*BluePanel*

Hypothesis	Description	Supported/Not supported
Hypothesis 1a	Chart characteristics, as measured by the chart's general, first half and second half trends, as well as the chart's volatility, do not impact the individual's risk preferences when predicting the outcome of graphs.	**Supported**
Hypothesis 1b	Chart characteristics, as measured by the chart's general, first half and second half trends, as well as the chart's volatility, do not impact the anticipated direction of the graph's outcome.	Not supported
Hypothesis 2a	Emotional reactions, as measured by valence, phasic, EDA and HRV do not act as a mediator in explaining an individual's risk preferences when predicting the outcome of graphs.	**Supported**
Hypothesis 2b	Emotional reactions, as measured by valence, phasic, EDA and HRV do not act as a mediator in explaining an individual's anticipated direction of the graph's outcome.	**Supported**
Hypothesis 3a	Beliefs and risk preferences, as measured by lottery preferences, financial risk tolerance, apophenia tendencies and beliefs in precognition, do not impact the individual's risk preferences when predicting the outcome of graphs.	**Supported**
Hypothesis 3b	Beliefs and risk preferences, as measured by lottery preferences, financial risk tolerance, apophenia tendencies and beliefs in precognition, do not impact the anticipated direction of the graph's outcome.	Not supported
Hypothesis 4a	Financial knowledge, as measured by self-assessed financial literacy and knowledge surrounding the GameStop events, does not impact the individual's risk preferences when predicting the outcome of graphs.	**Supported**
Hypothesis 4b	Financial knowledge, as measured by self-assessed financial literacy and knowledge surrounding the GameStop events, do not impact the anticipated direction of the graph's outcome.	Not supported

Table 19
Summary of our research hypothesis—*Mturk*

Hypothesis	Description	Supported/Not supported
Hypothesis 5a	Chart characteristics, as measured by the chart's general, first half and second half trends, as well as the chart's volatility, do not impact the individual's risk preferences when predicting the outcome of graphs.	**Supported**
Hypothesis 5b	Chart characteristics, as measured by the chart's general, first half and second half trends, as well as the chart's volatility, do not impact the anticipated direction of the graph's outcome.	**Supported**
Hypothesis 6a	Emotional reactions, as measured by perceived pleasure and arousal, do not act as a mediator in explaining an individual's risk preferences when predicting the outcome of graphs.	**Supported**
Hypothesis 6b	Emotional reactions, as measured by perceived pleasure and arousal, do not act as a mediator in explaining an individual's anticipated direction of the graph's outcome.	**Supported**
Hypothesis 7a	Beliefs, as measured by apophenia tendencies and beliefs in precognition, do not impact the individual's risk preferences when predicting the outcome of graphs.	**Supported**
Hypothesis 7b	Beliefs, as measured by apophenia tendencies and beliefs in precognition, do not impact the anticipated direction of the graph's outcome.	**Supported**
Hypothesis 8a	Financial knowledge, as measured by self-assessed financial literacy, does not impact the individual's risk preferences when predicting the outcome of graphs.	**Supported**
Hypothesis 8b	Financial knowledge, as measured by self-assessed financial literacy, does not impact the anticipated direction of the graph's outcome.	**Supported**

7. Discussion and Conclusion

Throughout this study, we collected data on over 300 participants in hopes of better understanding the mechanism behind each participant's decision-making process when confronted with various chart patterns. Our goal was to see if the chart characteristics, the emotional reaction to charts, the participants' beliefs, individual risk preferences or their financial literacy impacted both the level of Risk taken and the anticipated Direction of the chart in the future.

We created a new experimental task, the Pattern Task, in which a series of graphs was displayed, and a neutrally framed scenario was created to remove all potential financial biases. Participants were told that the charts represented the evolution over a 35-day period of the average daily wait time to speak to an agent when calls were placed to various companies' customer service departments. The goal of the task was to predict what the average daily wait time would be in 5 days. Through physiological data collection material and a series of questionnaires, we also measured the participants' emotional reactions, beliefs, risk preferences and financial literacy to assess the impact of these factors on the decision-making process in the Pattern Task.

Our results first indicate that neither chart characteristics, beliefs, risk preferences nor financial literacy have a significant impact on the level of Risk taken in the Pattern Task for both the *BluePanel* and the *Mturk* experiments. In the *BluePanel* experiment, we also find that emotional reaction does not act as a mediator in explaining the relationship between chart characteristics and the level of Risk taken as neither chart characteristics nor emotional reaction had direct relationships with risk. In our *Mturk* experiment, we find that emotional reaction once again does not act as a mediator since none of the chart characteristics have a significant relationship with the level of Risk taken in the Pattern Task, thus once again failing to validate one of Baron and Kenny's (1986) conditions for moderation. These results therefore validate hypothesis 1a), 2a), 3a) 4a), 5a), 6a), 7a) and 8a) in our study. As discussed in section 2, the above-mentioned factors have been found to have a significant impact on Risk taken by individuals or on decision-making. Our results, however, indicate otherwise. The level of Risk is therefore not influenced by any of the factors that were included in our models, indicating that the decision-making appears to be completely random throughout the Pattern Task.

We also find that chart characteristics, beliefs, risk preferences and financial literacy do not significantly impact the anticipated Direction of the chart in the future in our *Mturk* experiment. Emotional reaction was also found not to act as a mediator in explaining the relationship between chart characteristics and the anticipated Direction as the absence of a direct relationship between chart characteristics and anticipated

Direction violated one of Baron and Kenny's (1986) conditions. These results validate hypothesis 5b), 6b), 7b) and 8b) in our study. Although the anticipated Direction had not been explicitly linked to any of the factors, our literature review had shown that the above-mentioned factors did impact the decision-making process of individuals in various situations. Once again, it appears as if in our study, they do not have an impact on the decision-making process of individuals throughout the Pattern Task, which is in line with the results found for the level of Risk. Decision-making appears to be random in the Pattern task with regards to anticipated Direction in the *Mturk* experiment.

Results found for the anticipated Direction in the *BluePanel* experiment are less straightforward and differ from the above-mentioned results for the other variables. We first find that emotional reaction does not act as a mediator in explaining the relationship between chart characteristics and the anticipated Direction of the charts in the future. This is the case since emotional reaction does not have direct impact on the anticipated Direction in the Pattern Task, therefore violating one of Baron and Kenny's (1986) conditions. These results validate hypothesis 2b) in our study. Although emotional reaction had been found to influence decision-making and risk preferences in previous studies (Adam et al. 2015), it appears as if in the context of our study, it does not exert influence on the answers in the Patten Task.

As for the chart characteristics, we first find that the chart's general trend has a significant impact on the anticipated Direction of the chart in the future. Our model shows that charts with descending or neutral general trends yield answers in the *Pattern Task* that are significantly different from charts exhibiting an ascending trend. Upon further examination of the data, we find the presence of a trend reversal when anticipating the future movement of the wait time. For example, participants exposed to ascending patterns had a higher predicted probability of anticipating a descending pattern in the future. These results are in line with existing literature on the beliefs in trend reversal in stock markets (Andreassen, 1988) and also trend reversal in markets is a result of individuals changing their expectations on stock prices (Achelis, 2000). We also found similar results for the first half trend in our model. Ascending first half trends yielded significantly different answers than neutral first half trends. Although these results are less straightforward to interpret, it appears as if the trend in the first portion of the graph influences the anticipated Direction of the graph in the future. This contrasts with the trend in the second half of the graph which has been found not to significantly influence the anticipated Direction of the graph in the future. Finally, with regards to chart characteristics, we found that the chart's overall variability, as measured through the standard deviation of the wait time, had a significant impact on the participant's answers in the *Pattern Task*. A higher variability increases the predicted probability of anticipating a downward trend in the future. Existing literature has shown that retail investors cause volatility in financial markets (Brandt et al., 2009, but the impact of volatility on the behavior of retail investors is difficult to pinpoint. Our study's results with regards to the volatility of patterns are therefore difficult to interpret and tie to existing theories. Overall, we find that several chart characteristics have a significant impact on the anticipated Direction of the graph in the future in our *BluePanel* study. These results contradict those found in our *Mturk* study. It is also difficult to tie these results to existing literature as the logic behind the interpretation remains unclear. These results therefore do not support the hypothesis 1b).

As for the link between Risk Preferences / Beliefs and anticipated Direction in the *BluePanel* study, we first find that Apophenia has a significant impact on the anticipated Direction of the graph in the Pattern Task. Our model shows that participants exhibiting higher levels of apophenia or, in other words, tend to perceive patterns in unrelated situations, will have a higher predicted probability of anticipating a decrease in wait time in the future. Previous literature has shown that Apophenia and Pareidolia does influence a person's thought process and our results suggest the same (Paul et al. 2014, Foster & Kokko, 2009). It is, however, difficult to explain why higher levels of apophenia lead to an anticipated downward Direction of charts. Second, we find that Financial Risk Tolerance has a significant impact on the anticipated Direction of the graph in the *Pattern Task*. Participants exhibiting a higher level of financial risk tolerance have a higher predicted probability of anticipating an increase in wait time in the future. A significant relationship between Financial Risk Tolerance and Risk would have been easier to interpret as multiple studies have already explored this theme (Qadan, 2019). However, our previous results have shown that such a relationship does not exist in both our studies. It is once again difficult to interpret the significance of our results in this case, apart from the fact that Financial Risk Tolerance does have a significant impact on the participant's decision-making process in general. These results therefore do not support the hypothesis 3b).

As for the link between Financial Literacy and anticipated Direction in the *BluePanel* study, we find that Average Financial Literacy has a significant impact on the anticipated Direction of the graphs in the Pattern Task. As a reminder, Average Financial Literacy was measured through a combination of self-assessed financial literacy, self-assessed knowledge of the GameStop events that occurred in early 2021 and self-assessed belief that regulators should intervene in a situation similar to that of GameStop. Our results indicate that participants exhibiting higher levels of financial literacy have a higher predicted probability of anticipating an increase in wait time in the future. Hundreds of existing studies have found a significant impact between Financial Literacy and Risk Tolerance (Grable, 2000, Mishra, 2018). In our study, we find that it rather impacts the anticipated Direction, making the interpretation of our results less straightforward. We can, however, conclude that Average Financial Literacy does impact the decision-making process of participants in our *BluePanel* study. These results therefore do not support the hypothesis 4b).

Our hypothesis and model to assess the impact of emotional reaction on the decision-making process made use of Baron and Kenny's (1986) mediation theory. We explored the significance of emotional reaction as a mediator in explaining the relationship between Chart Characteristics and both Risk and anticipated Direction. We did, however, also observe the direct impact of emotional reaction on Risk and anticipated Direction. Interestingly, results from our *Mturk* study show that self-reported Arousal and Pleasure do not act as a mediator variable, but rather have a direct impact on the decision-making process in the Pattern Task. Arousal was found to have a significant impact on both the level of Risk taken and the anticipated Direction when predicting the outcome of graphs. Higher levels of Arousal lead to a higher predicted probability of exhibiting a higher level of Risk in the *Pattern Task* and also anticipating an upward trend for the chart in the future. Pleasure was also found to significantly impact the anticipated Direction, with higher reported levels of pleasure leading to a higher predicted probability of anticipating an upward trend for the chart in the future. Our results can be tied with existing literature on emotional reaction which found that emotions did influence the decision-making process and the level of Risk taken (Kruger et al., 2010, Coated & Herbert, 2007). These results found in our Mturk Studies are not tied to any of our hypotheses directly but are still interesting to keep in mind for further studies.

We are aware that the results and interpretations drawn from this research are subject to many various limitations due to our research model. First off, our sample consisted of 38 participants for the first study (laboratory experiment) and 246 participants for our second study (online experiment), which is relatively small. We must therefore be careful when generalizing our results to the larger population. Our second research was conducted in hopes of increasing statistical power and gathering more participants. However, the fact that the study was conducted online on the Amazon Mturk platform meant that we could not entirely replicate the experiment in our first study. Several variables were removed from the second model and most importantly, physiological data could not be collected by using laboratory tools, which forced us to measure the participant's perceived emotional reaction. The fact that the study was conducted at home by each participant without the presence of a moderator also meant less supervision for the participants of the second study.

Our first study's panel was also mainly composed of students since the recruitment process was done internally at HEC's Tech3Lab. The Covid-19 related sanitary restrictions at the time of conducting the experiment prevented us from having participants in the research lab. As previously mentioned, experiments were conducted at home by participants with the help of physiological data collection tools that were delivered to each participants' residence. To facilitate material transportation and setup, Tech3Lab students and researchers were asked to recruit relatives or people in their entourage. In an ideal world, a traditional recruitment process would have been better for both collecting a larger sample of participants and to avoid the concentration of participants in one specific age group, revenue group or level of education.

This study contributes to the literature by presenting a laboratory experiment that examines technical and chart pattern analysis. Very few studies have observed the impact of financial decision-making in a laboratory setting while measuring the participants' real emotional reactions. We also contribute to the existing literature surrounding non-expert chart analysis. Other interesting aspects of our study included the measuring of each participant's tendency to exhibit apophenia as well as their tendency to believe in precognition. Few studies have combined such psychological characteristics with finance-related topics in hopes of better understanding how people's beliefs influence their decision-making or risk preferences.

This study also opens the door to new possibilities in the world of finance. Getting a better understanding of the individual investor's decision-making process will be of great help in the upcoming years as self-brokerage platforms become increasingly popular and accessible to the public. A larger scale study would have allowed us to get more participants and therefore a more representative view of reality. More complex, thorough, and well-known behavioral questionnaires and tests such as the Rorschach test would also potentially allow for a better measurement of people's true personality and personal characteristics, which in turn could help develop a strong model for understanding decision-making. In a normal non-pandemic setting, a trading technical analysis simulation software could also be quite interesting to leverage when analyzing behavior and individual personality in a stock market setting for individual investors versus trained professionals. Investor behavior is key in understanding movements in stock markets, and it will become crucial for finance professionals to understand the decision-making process of retail/novice investors which will continue to make up a significant proportion of stock market participants in the upcoming years.

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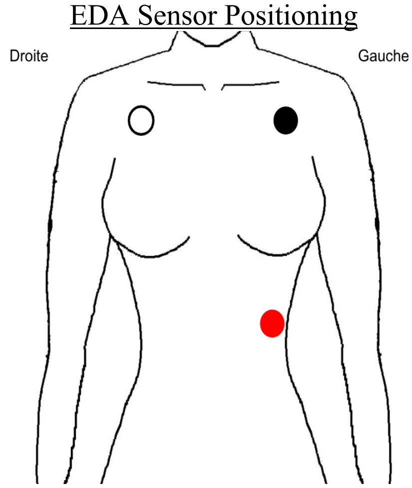
Annexes

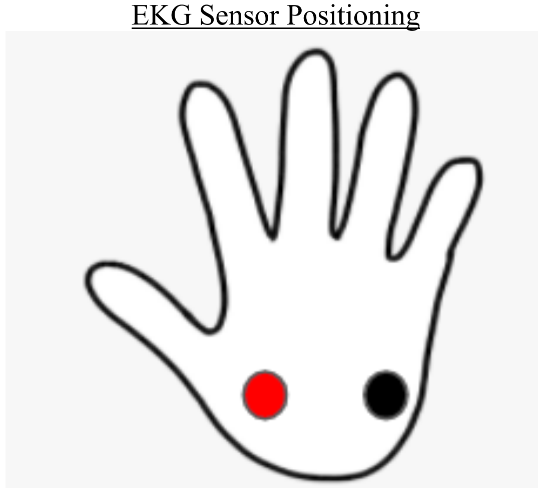
Annex 1 – Physiological Data Collection

COBALT Bluebox data collection device

EDA Sensor Positioning



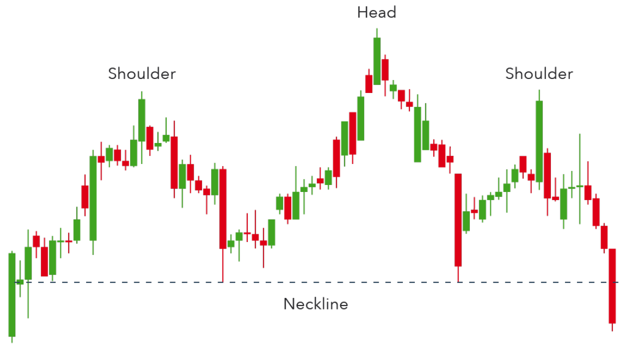
EKG Sensor Positioning

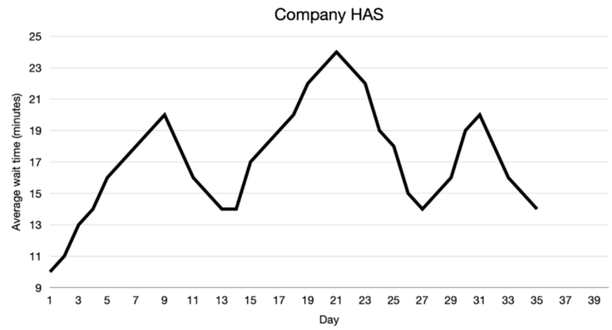


Annex 2 – Technical Analysis Patterns

Source for images : https://www.ig.com/en/trading-strategies/10-chart-patterns-every-trader-needs-to-know-190514

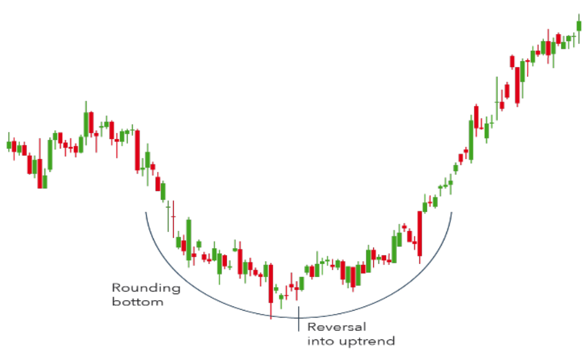
Head and shoulder

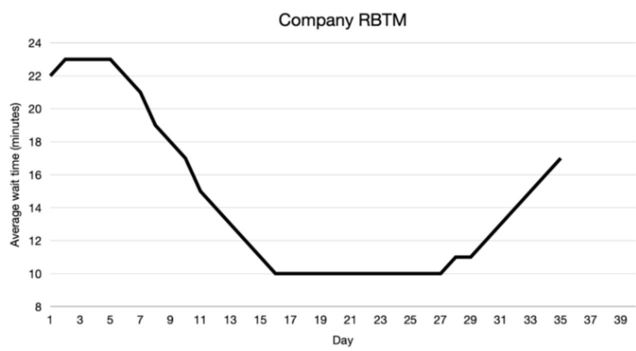




The head and shoulder pattern is characterized by its three peaks, as seen above. According to the study of technical analysis, once the price reaches the neckline after the 2nd shoulder, it should continue its downtrend. In other words, this pattern marks the end of a bullish (upwards) trend and a transition to a bearish (downwards) trend. Once the price reaches the second shoulder, traders should prepare for the price to drop and therefore sell shares. For this study, the pattern was replicated up until the 35th day where the neckline is reached on the downward trend.

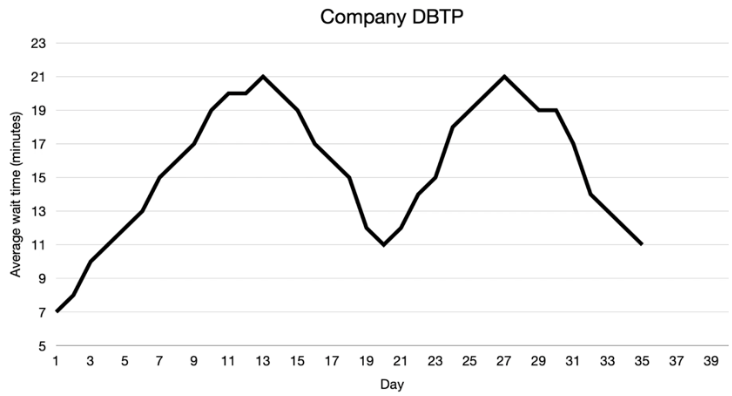
Rounding bottom





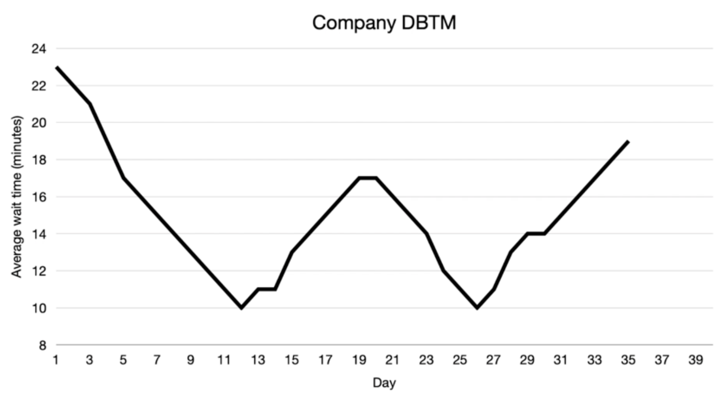
As the name implies, a rounding bottom pattern is characterised by a downward rounding trend followed by an upwards recovery. According to the study of technical analysis, the stock price will decline until it reaches the midpoint of the round bottom and then the trend will reverse. It marks a bullish trend reversing into a bullish trend. The trader's goal would be to buy the stock once it reaches the bottom of the curve and the stock price is expected to increase thereafter and follow a bullish trend. For this study, the pattern was replicated up until the 35th day, halfway through the upward reversal trend.

Double top



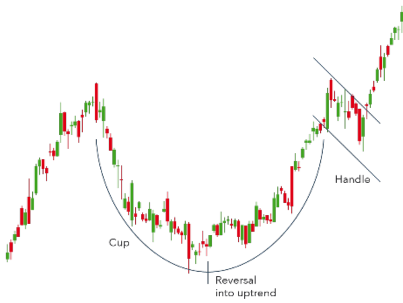
The double top bottom is similar in nature to the head and shoulder patterns, but with two peaks instead of three. It usually signifies a trend reversal. In other words, the stock will be on an upwards (bullish) trend and once it has passed the two tops, the trend should reverse and the stock price should then decrease below the neckline in a downwards (bearish trend). Arriving at the second top, traders should sell the stock in anticipation of a steady decline below the neckline thereafter. For this study, the pattern was replicated up until the 35th day where the neckline is reached on the downward trend.

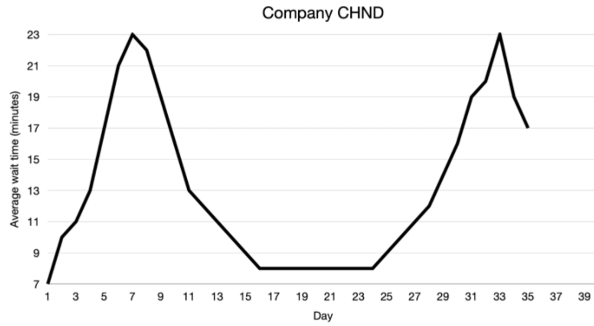
Double Bottom



The double bottom is the exact opposite of the double top pattern, meaning that it has two downward instead of upward peaks. Just as the double top, it usually signifies a trend reversal. The stock will be on a downwards (bearish) trend and once it passes the two bottoms, the trend should reverse and the stock price should then increase past the neckline in an upwards (bullish) trend. Arriving at the second bottom, traders should buy the stock in anticipation of a steady increase past the neckline thereafter. For this study, we replicated the pattern up until the 35th day when the neckline is reached on the upward trend.

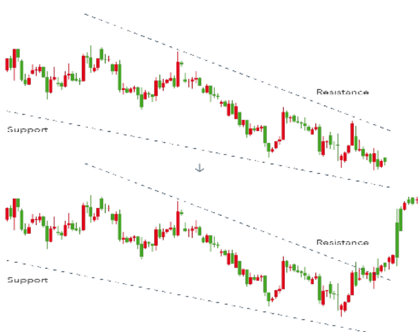
<u>Cup and Handle</u>

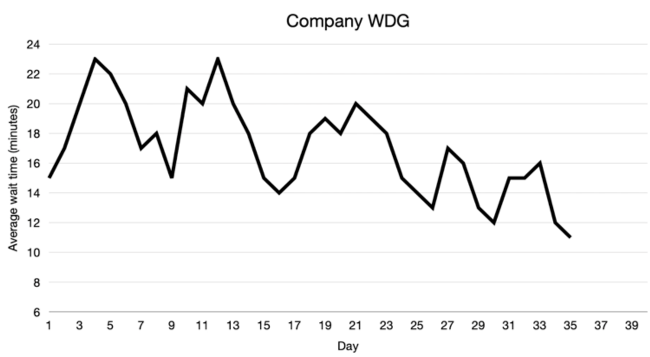




The cup and handle is similar to the rounding bottom pattern. The stock will be on a bullish trend until it temporarily reverses back to a bearish trend. The difference with the rounding bottom is that once the bearish trend is reversed and the stock price is back to the level of the previous upwards trend, there is a slight decrease in the share price in the form of a "handle". Therefore, at the bottom of the handle, the trader should purchase the stock because the study of technical analysis suggests a continuing uptrend after. For this study, we replicated the pattern up until the 35th day when the bottom of the handle is reached.

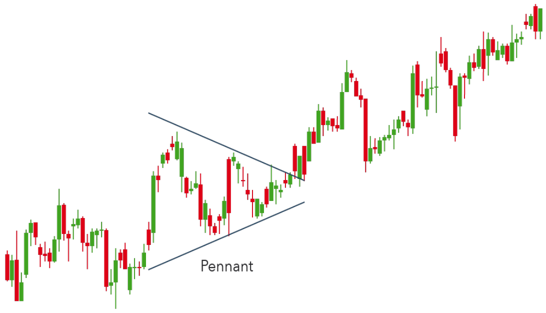
<u>Wedge</u>

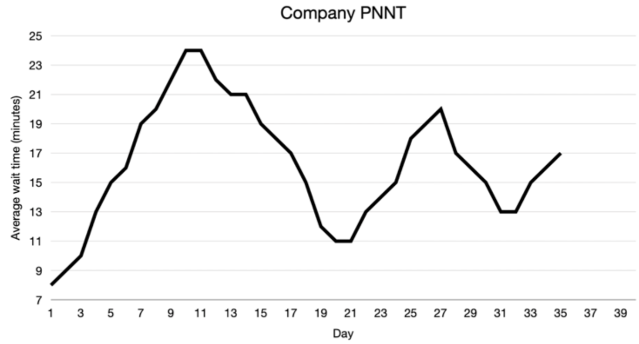




Wedges can either be rising or falling. It is characterized by a steepening trend, whether it is bullish or bearish. Usually, when studying technical analysis, we presume that for the rising wedge, the price will increase until a certain point where the trend will reverse into a bearish trend. For the falling wedge, we presume that the price will decrease steadily and more tightly until a certain point where the trend will reverse into a bullish trend. Therefore a trader should buy when the falling wedge reaches a low point and sell when a rising wedge reaches a high point. For this study, we replicated the pattern up until the 35th day when the bearish trend reaches its lowest point, just before the reversal.

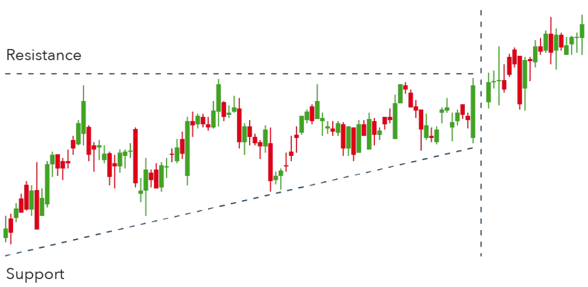
<u>Pennant or Flags</u>

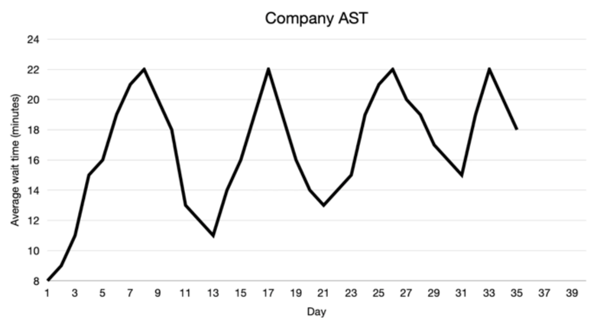




Pennants and flags are similar to wedges but the main difference is that they are horizontal. They can either be bullish or bearish and can mean a reversal or a continuation. In the case of the image above, it represents a bullish trend where the pattern tightens before increasing again in the future. Therefore, for a trader, it is difficult to make a decision when such a pattern presents itself. Remaining neutral can be the preferred alternative. For this study, we replicated the specific pennant portion of the upward trend up until the 35th day, right before the continuation pattern starts.

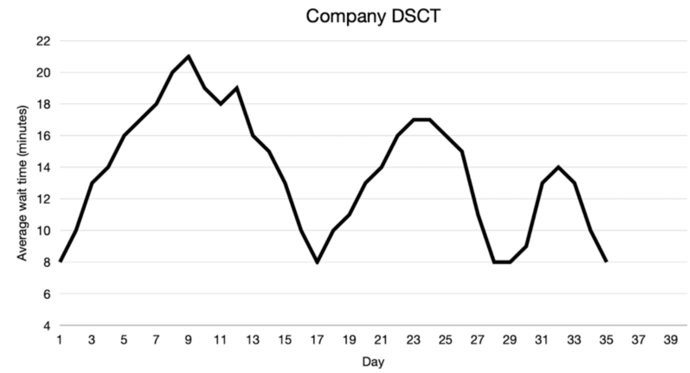
<u>Ascending triangle</u>





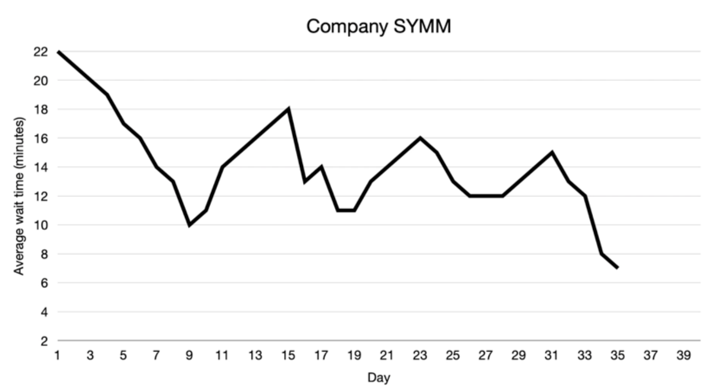
The ascending triangle pattern is a continuation pattern that shows a steady upward (bullish) trend and a price increase thereafter. The main difference with the wedge is that the resistance line at the top is steady and the support line at the bottom is ascending. It usually has two or more tops that reach the resistance line, but the number of tops can vary. After seeing at least two identical tops and a continuation of the upwards trend, a trader should purchase the stock in anticipation of a price increase. For this study, we replicated an ascending triangle pattern with 4 tops up until the 35th day, right before the resistance line is broken.

Descending triangle



Descending triangles will be characterized by gradually declining peaks until the support line is eventually broken through. It is the opposite of an ascending triangle trend. It usually signifies the continuation of a bearish (downward) trend. Therefore, traders should enter a short position when they notice such a pattern and especially when the support line is broken through. For this study, we replicated the descending triangle pattern up until the 35th day, right before the support line at the bottom is broken.

Symmetrical triangle



Symmetrical triangles show a converging and horizontal trend in a stock chart. When observed individually, they are normally associated with a continuation pattern. Therefore, in a bearish market as the picture below shows, the symmetrical triangle will be a temporary slow-down in the trend until the bearish trend continues. Therefore, traders should take a short position in anticipation of the continuation of the original trend. If we are in a bullish market the exact opposite should happen. For this study, we replicated the symmetrical triangle pattern up until the 35th day as the trend begins its downwards trend

Annex 3 – Randomisation Details

Participants in the Technical condition presented with 10 chart patterns replicating well-known chart patterns frequently observed on financial markets and analysed in technical analysis theory. The first 35 days of the chart were manually created to replicate the desired patterns. The five following days, which represent the outcome of the graph, were simulated using the NormInv Excel function. The probability aspect of this function was created by the Rand() function in order to create a random variable with a normal distribution. The mean was set to 0 and the standard deviation was set to 15% to represent a daily graph standard deviation of 15%.

Participants in the Random condition were presented with randomly generated chart patterns. The full 40 day chart was randomly generated using the NormInv Excel function. The probability aspect of this function was also created by the Rand() function in order to create a random variable with a normal distribution. The mean was set to 0 and the standard deviation was set to 15% to represent a daily graph standard deviation of 15%. The starting point of the graph was usually between 10 and 15 minutes.

For both groups, the outcome of the pattern over the final 5 day period is randomly generated, so the actual chart pattern has no impact on the outcome, even if the participants try to predict based on the observed pattern.

Annex 4 – Apophenia

Source : http://www.kickvick.com/everyday-things-pareidolia/

Plane *On a scale of 1 to 7, to what extent do you agree with the following statements:*

	1	2	3	4	5	6	7
I see a butterfly in this picture.	○	○	○	○	○	○	○
I see a smiling face in this picture.	○	○	○	○	○	○	○
I see a plane in this picture.	○	○	○	○	○	○	○
I see a tree in this picture.	○	○	○	○	○	○	○

Source : https://sites.google.com/site/ribboneyes/home/final-exam/apophenia

Horse Cloud *On a scale of 1 to 7,* to what extent do you agree with the following statements:

	1	2	3	4	5	6	7
I see a cloud in this picture.	○	○	○	○	○	○	○
I see a boat in this picture.	○	○	○	○	○	○	○
I see a horse in this picture.	○	○	○	○	○	○	○
I see a building in this picture.	○	○	○	○	○	○	○

Source : http://www.kickvick.com/everyday-things-pareidolia/

Binoculars *On a scale of 1 to 7, to what extent do you agree with the following statements:*

	1	2	3	4	5	6	7
I see a crying face in this picture.	○	○	○	○	○	○	○
I see a cat in this picture.	○	○	○	○	○	○	○
I see a unicorn in this picture.	○	○	○	○	○	○	○
I see binoculars in this picture.	○	○	○	○	○	○	○

Source: https://www.wanderwoman.ca/iceberg-pareidolia/

Iceberg Camel* On a scale of 1 to 7, *to what extent do you agree with the following statements:*

	1	2	3	4	5	6	7
I see a flower in this picture.	○	○	○	○	○	○	○
I see a ghost in this picture.	○	○	○	○	○	○	○
I see an iceberg in this picture.	○	○	○	○	○	○	○
I see a camel in this picture.	○	○	○	○	○	○	○

Source : https://imgur.com/niQs94s

Tree On a scale of 1 to 7, *to what extent do you agree with the following statements:*

	1	2	3	4	5	6	7
I see a cake in this picture.							
I see a face in this picture.							
I see a car in this picture.							
I see a tree in this picture.							

Source : https://imgur.com/niQs94s

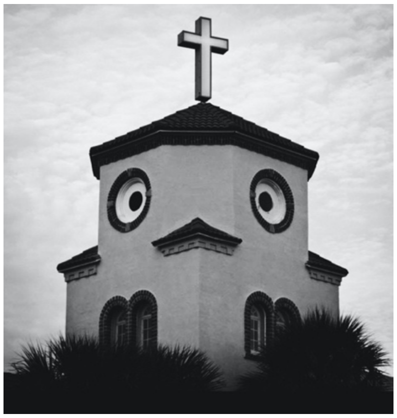
Cloud face On a scale of 1 to 7, *to what extent do you agree with the following statements:*

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)
I see a face in this picture. (1)							
I see a cloud in this picture. (2)							
I see a sunflower in this picture. (3)							
I see a television in this picture. (4)							

Source : https://old.reddit.com/r/Pareidolia/comments/8plboc/lady_in_white_waterfall/

Waterfall Dress On a scale of 1 to 7, *to what extent do you agree with the following statements:*

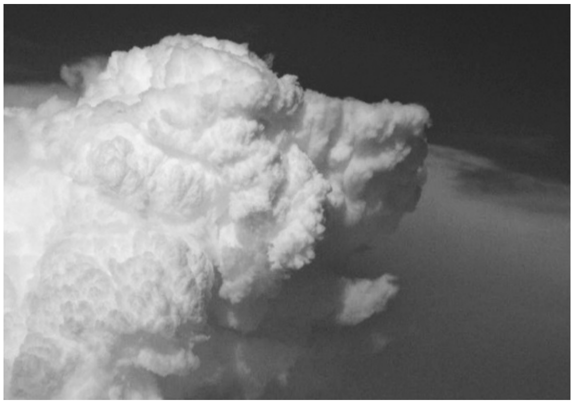
	1	2	3	4	5	6	7
I see a waterfall in this picture.	○	○	○	○	○	○	○
I see an elephant in this picture.	○	○	○	○	○	○	○
I see a bike in this picture.	○	○	○	○	○	○	○
I see a woman in a dress in this picture.	○	○	○	○	○	○	○



Source : https://imgur.com/gallery/6H2VVCj

Church *On a scale of 1 to 7, to what extent do you agree with the following statements:*

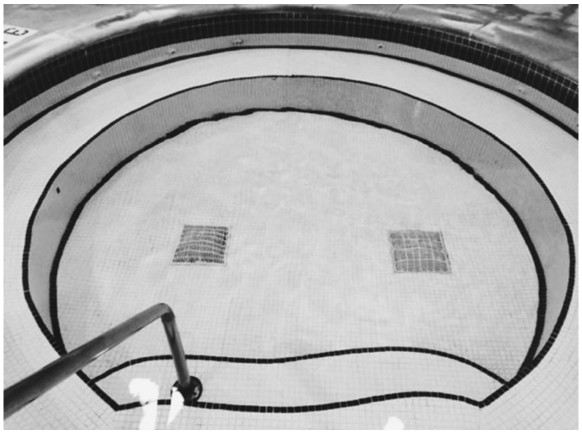
	1	2	3	4	5	6	7
I see a face in this picture.	○	○	○	○	○	○	○
I see a lightbulb in this picture.	○	○	○	○	○	○	○
I see a church in this picture.	○	○	○	○	○	○	○
I see a croissant in this picture.	○	○	○	○	○	○	○



Source : Credit : http://www.kickvick.com/everyday-things-pareidolia/

Cloud Dog   On a scale of 1 to 7, *to what extent do you agree with the following statements:*

	1	2	3	4	5	6	7
I see a clock in this picture.	○	○	○	○	○	○	○
I see a dog in this picture.	○	○	○	○	○	○	○
I see a cloud in this picture.	○	○	○	○	○	○	○
I see a phone in this picture.	○	○	○	○	○	○	○



Source : Credit : http://www.kickvick.com/everyday-things-pareidolia/

Pool   On a scale of 1 to 7, *to what extent do you agree with the following statements:*

	1	2	3	4	5	6	7
I see a pool in this picture.	○	○	○	○	○	○	○
I see a lion in this picture.	○	○	○	○	○	○	○
I see a face in this picture.	○	○	○	○	○	○	○
I see a spider in this picture.	○	○	○	○	○	○	○

Annex 5 – *BluePanel* Questionnaire

Preparation

Introduction Welcome to this Tech3Lab study.
Participant number Please select your participant number.

▼ 01 ... 24

Patterns

General instructions Today, you will have the opportunity to play 2 different games. In the first game, you will be asked to predict the average daily wait time when a call is placed to the customer service department. In the second game, you will be asked to choose between different prizes in a lottery.

Play wisely as your answers in these games will allow you to accumulate coupons for the draw of a 100$ Amazon gift card among all participants.
When you are ready, move to the next page to read the instructions for the first game.

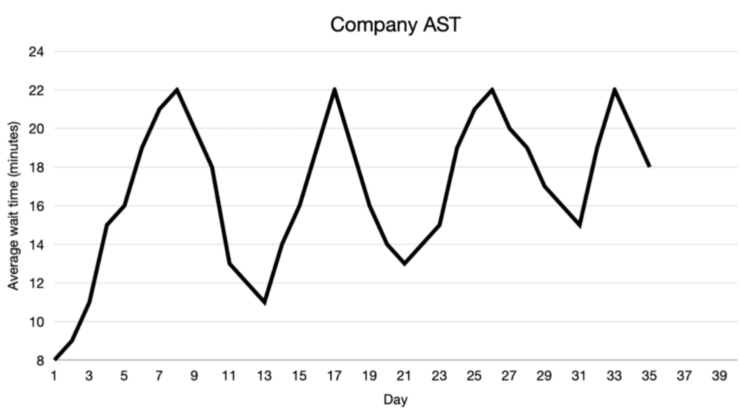
Patterns - P1 **Game 1 : Wait time prediction** You will now be shown a series of graphs illustrating the average daily wait time to speak to an agent when a call is placed to a company's customer service department. The average wait time will be shown over a period of 35 days. You will be shown graphs for 10 different companies. For each company, you are asked to predict the evolution of the average daily wait time on the 40th day (5 days later).

To predict evolution of the wait time, you will have to choose one of the 5 following options :

1) On the 40th day, the average daily wait time will have increased by more than 4 minutes
2) On the 40th day, the average daily wait time will have increased by 1 to 4 minutes
3) On the 40th day, the average daily wait time will have remained at the same level
4) On the 40th day, the average daily wait time will have decreased by 1 to 4 minutes
5) On the 40th day, the average daily wait time will have decreased by more than 4 minutes.

For each outcome that you predict correctly, you will be rewarded with 10 coupons for the draw of the 100$ Amazon gift card. If you do not predict the average daily wait time correctly, you will not be awarded any coupons for the draw of the Amazon gift card for that trial. You will start the game with 10 coupons for the draw. You will therefore earn between 10 and 110 coupons for the 100$ Amazon gift card draw in this game depending on the number of correct answers you get. Please be sure to watch the entire video depicting the evolution of the wait time and answer the question before you move on to the next page that will show you the actual outcome. Do you have any questions for the moderator? When you are ready, click on the link below to access the videos and the questions:
https://uxstimuli.web.app/?id=1&project=tvdj2xbmnD4JMDtKUe1a

Graph example :



E&G
Game 2

You now have the opportunity to add some coupons for the 100$ Amazon gift card draw to those you've earned in the previous game! The second game consists of choosing one of the five "heads or tails" lotteries below!

Each lottery has a different payoff depending on if you land on heads or on tails. For example, with lottery 1, you will earn a guaranteed 10 coupons for the 100$ Amazon gift card draw if you get either heads or tails. For lottery 2, you will earn 18 coupons if get tails, but only 6 coupons get heads. Lotteries 4 and 5 allow you to earn a lot of coupons if you get tails, but you will lose some coupons if you get heads. In other words, the riskier the lottery, the more coupons you earn if you land on tails, but the more you lose if you land on heads.

You must only choose one lottery. After your choice is made, you can move on to the next page to see the result of the lottery.
Do you have any questions for the moderator?

Which lottery do you choose?

- ○ Lottery 1
- ○ Lottery 2
- ○ Lottery 3
- ○ Lottery 4
- ○ Lottery 5

The coin is flipped and lands on :

TAILS

Congratulations! You win 10 additional coupons for the 100$ Amazon gift card draw !
You can proceed to the next page.

Part 3 - Images

You will now be shown a series of images. For every new image, please answer the related questions before moving on to the next image.

On a scale of 1 to 7, to what extent do you agree with the following statements:

	1	2	3	4	5	6	7
I see a butterfly in this picture.	◯	◯	◯	◯	◯	◯	◯
I see a smiling face in this picture.	◯	◯	◯	◯	◯	◯	◯
I see a plane in this picture.	◯	◯	◯	◯	◯	◯	◯
I see a tree in this picture.	◯	◯	◯	◯	◯	◯	◯

Financial Questions

Part 4 - Finance

You will now answer a series of finance related questions. Please answer the questions honestly and to the best of your abilities. Make sure to answer every question before moving on to the next page.

Page Break

On a scale of 1 to 7, to what extent do you agree with the following statement

	1	2	3	4	5	6	7
I possess a high level of financial literacy.	◯	◯	◯	◯	◯	◯	◯

Accounts Which of the following accounts do you possess (you may select more than one)?

◯ Cash account

◯ Savings account

◯ Registered Retirement Savings Plan (RRSP) account

◯ Tax-Free Savings account (TFSA)

◯ Margin account

◯ Other

What is your current primary employment status?

- Student
- Part-time worker (Less than 35 hours per week)
- Full-time worker (35 hours per week or more)
- Retired
- Unemployed
- Other

Page Break

The following 13 questions are designed to measure your financial risk preferences. Please answer these questions honestly and to the best of your abilities.

In general, how would your best friend describe you as a risk taker?

- A real gambler
- Willing to take risks after completing adequate research
- Cautious
- A real risk avoider

You are on a TV game show and can choose one of the following, which would you take?

- 1000$ in cash
- A 50% chance at winning 5,000$
- A 25% chance at winning 10,000$
- A 5% chance at winning 100,000$

You have just finished saving for a "once-in-a-lifetime" vacation. Three weeks before you plan to leave, you lose your job. You would:

- Cancel the vacation
- Take a much more modest vacation
- Go as scheduled, reasoning that you need the time to prepare for a job search
- Extend your vacation, because this might be your last chance to go first-class

If you unexpectedly received $20,000 to invest, what would you do?

- Deposit it in a bank account, money market account, or an insured Certificat of deposit
- Invest it in safe high quality bonds or bond mutual funds
- Invest it in stocks or stock mutual funds

In terms of experience, how comfortable are you investing in stocks or stock mutual funds?

- Not at all comfortable
- Somewhat comfortable
- Very comfortable

When you think of the word "risk," which of the following words comes to mind first?

- Loss
- Uncertainty
- Opportunity
- Threat

Some experts are predicting prices of assets such as gold, jewels, collectibles, and real estate (hard assets) to increase in value; bond prices may fall, however, experts tend to agree that government bonds are relatively safe. Most of your investment assets are now in high interest government bonds. What would you do?

- ○ Hold the bonds
- ○ Sell the bonds, put half the proceeds into money market accounts, and the other half into hard assets
- ○ Sell the bonds and put the total proceeds into hard assets
- ○ Sell the bonds, put all the money into hard assets, and borrow additional money to buy more hard assets

Given the best and worst case returns of the four investment choices below, which would you prefer?

- ○ $200 gain best case; $0 gain/loss worst case
- ○ $800 gain best case; $200 loss worst case
- ○ $2,600 gain best case; $800 loss worst case
- ○ $4,800 gain best case; $2,400 loss worst case

In addition to whatever you own, you have been given $1,000. You are now asked to choose between:

- ○ A sure gain of $500
- ○ A 50% chance to gain $1,000 and a 50% chance to gain nothing

In addition to whatever you own, you have been given $2,000. You are now asked to choose between:

- ○ A sure loss of $500
- ○ A 50% chance to lose $1,000 and a 50% chance to lose nothing

Suppose a relative left you an inheritance of $100,000, stipulating in the will that you invest ALL the money in ONE of the following choices. Which one would you select?

- A savings account or money market mutual fund (1)
- A mutual fund that owns stocks and bonds (2)
- A portfolio of 15 common stocks (3)
- Commodities like gold, silver, and oil (4)

If you had to invest $20,000, which of the following investment choices would you find most appealing?

- 60% in low-risk investments, 30% in medium-risk investments, 10% in high-risk investments
- 30% in low-risk investments, 40% in medium-risk investments, 30% in high-risk investments
- 10% in low-risk investments, 40% in medium-risk investments, 50% in high-risk investments

Your trusted friend and neighbor, an experienced geologist, is putting together a group of investors to fund an exploratory gold mining venture. The venture could pay back 50 to 100 times the investment if successful. If the mine is a bust, the entire investment is worthless. Your friend estimates the chance of success is only 20%. If you had the money, how much would you invest?

- Nothing
- One month's salary
- Three month's salary
- Six month's salary

Over the past few weeks, there have been growing talks in the media about a stock market situation involving the company GameStop (stock market ticker : GME). Please answer the following questions with regards to the GameStop situation.

On a scale of 1 to 7, to what extent do you agree with the following statement:

	1	2	3	4	5	6	7
I am familiar with the GameStop situation that took place in January 2021.	○	○	○	○	○	○	○

Do you own share of GameStop ?

- Yes
- No

On a scale of 1 to 7, to what extent do you agree with the following statement:

	1	2	3	4	5	6	7
Stock market regulators should intervene when a situation such as the GameStop situation occurs on the stock market.	○	○	○	○	○	○	○

On a scale of 1 to 7, to what extent do you agree with the following statement:

	1	2	3	4	5	6	7
It is likely that a similar situation will happen again in the future?	○	○	○	○	○	○	○

On a scale of 1 to 7, to what extent do you agree with the following statement:

	1	2	3	4	5	6	7
If a similar situation were to happen again with another company, I would join the movement and buy some shares?	○	○	○	○	○	○	○

Precognition

For the final part of the experiment, you will answer questions on precognition. You can move to the next page when you are ready.

Precognition On a scale of 1 to 7, to what extent do you agree with the following 4 statements? Please use the scales below to answer the question for each statement.

	1	2	3	4	5	6	7
Astrology is a way to accurately predict the future.	○	○	○	○	○	○	○
The horoscope accurately tells a person's future.	○	○	○	○	○	○	○
Some psychics can accurately predict the future.	○	○	○	○	○	○	○
Some people have an unexplained ability to predict the future.	○	○	○	○	○	○	○

Annex 6 – *Mturk* Questionnaire

Preparation

Intro Welcome to this short survey!

Today, you will be asked to perform various tasks and answer questionnaires.
Please be sure to answer every question before moving on to the next page.
Mturk ID Please enter your Mturk identification number.

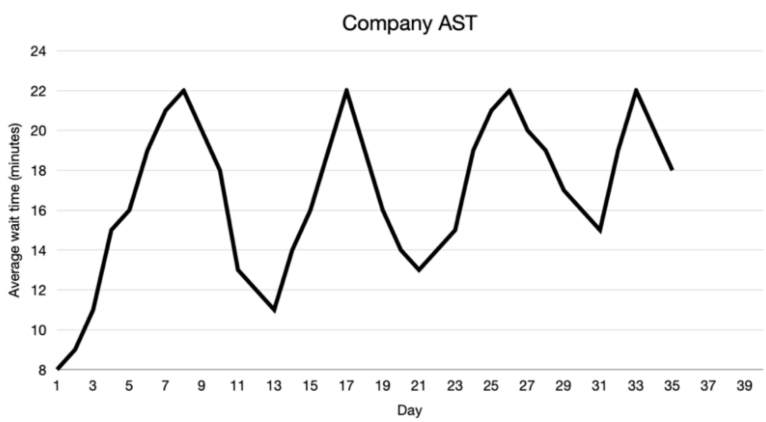
____

Part 1 - Videos

You will now be shown graphs illustrating the average daily wait time to speak to an agent when a call is placed to a company's customer service department. You will be shown the graph of average daily wait time for two different companies. You are asked predict the evolution of the wait time over the following 5 days.
When you are ready, move to the next page to view the videos and predict the outcome.

Patterns

The graph below shows the average daily wait time to speak to an agent from the AST company when a call is made to the customer service department. The average wait time when the graph curve stops is 18 minutes.



In your opinion, the average wait time 5 days later will have :

- ◯ Increased by more than 4 minutes
- ◯ Increased by 1 to 4 minutes
- ◯ Remained at the same level
- ◯ Decreased by 1 to 4 minutes
- ◯ Decreased by more than 4 minutes

On what day does the graph curve stop in the video?

- ◯ Day 15
- ◯ Day 35
- ◯ Day 65

Arousal represents the intensity of the emotion felt when viewing the video. The scale below goes from calm to excited.

Please move the slider to rate your level of arousal when viewing the above video.	

Pleasure represents the nature of the emotion felt when viewing the video. The scale below goes from sad to happy.

Please move the slider to rate your level of pleasure when viewing the above video.	

Apophenia

Part 2 - Images

You will now be shown a series of images. For every new image, please answer the related questions before moving on to the next image.

On a scale of 1 to 7, *to what extent do you agree with the following statements:*

	1	2	3	4	5	6	7
I see a flower in this picture.	○	○	○	○	○	○	○
I see a ghost in this picture.	○	○	○	○	○	○	○
I see an iceberg in this picture.	○	○	○	○	○	○	○
I see a camel in this picture.	○	○	○	○	○	○	

Attention check

Please put the slider on 45.

	0 10 20 30 40 50 60 70 80 90 100

Financial and Socio-demographics Questions

Part 3 - General

You will now answer a series of finance and socio-demographics related questions. Please answer the questions honestly and to the best of your abilities.

Age What is your age?

	15 20 25 30 35 40 45 50 55 60 65 70 75 80

What is your gender?

○ Female

○ Male

○ Other

In what country do you currently reside?

○ Canada

○ United-States of America

○ Other

Display This Question:

If In what country do you currently reside? = United-States of America

Or In what country do you currently reside? = Other

What is your estimated personal annual income in US dollars?

- Less than $20 000
- $20 000 to $39 999
- $40 000 to $59 999
- $60 000 to $79 999
- More than $80 000

Display This Question:

If In what country do you currently reside? = Canada

What is your estimated personal annual income in Canadian dollars?

- Less than 20 000$
- 20 000$ to 39 999$
- 40 000$ to 59 999$
- 60 000$ to 79 999$
- More than 80 000$

What is the highest level of education you have completed?

- Some high school or less
- High school diploma or GED
- Some college, but no degree
- Associates or technical degree
- Bachelor's degree
- Graduate or professional degree (MA, MS, MBA, PhD, JD, MD, DDS)

What is your current marital status?

- Married
- Living with a partner
- Widowed
- Divorced/Separated
- Never been married

On a scale of 1 to 7, to what extent do you agree with the following statement

	1	2	3	4	5	6	7
I possess a high level of financial literacy.	○	○	○	○	○	○	○

Part 4 - Precognition

You will now answer 4 questions on precognition.

Precognition On a scale of 1 to 7, to what extent do you agree with the following 4 statements? Please use the scales below to answer the question for each statement.

	1	2	3	4	5	6	7
Astrology is a way to accurately predict the future.	○	○	○	○	○	○	○
The horoscope accurately tells a person's future.	○	○	○	○	○	○	○
Some psychics can accurately predict the future.	○	○	○	○	○	○	○
Some people have an unexplained ability to predict the future.	○	○	○	○	○	○	○

Completion Code Here is your ID : ${e://Field/RandomID}

Copy this value to paste into Mturk.

When you have copied this ID, please click the next button to submit your survey.