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Biases at the Bank : Gender Differences in Behavioural Biases among UK Investment Bankers

Rosy Cilia[1] and Florian Meier[2*]

[1]*Heriot Watt University, UK.*

[2]*Associate Professor in Accounting and Finance, Heriot Watt University Dubai, Dubai, UAE.*

***Corresponding Authors**

Florian Meier,
Associate Professor in Accounting and Finance, Heriot Watt University Dubai, Dubai, UAE.

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Abstract
This study examines gender differences in behavioural biases among UK investment bankers, a professional group rarely explored in behavioural finance research. Using an online survey of 72 bankers, we assess four cognitive biases - overconfidence, herding, loss aversion and overreaction - through the lenses of prospect theory and heuristics theory. The results show that males exhibit significantly higher overconfidence, while no meaningful gender differences emerge for herding, loss aversion or overreaction, suggesting that professional expertise may moderate commonly observed disparities. Additional analysis reveals that herding decreases with age among female bankers, indicating a gender specific demographic influence. Further, inter-bias relationships differ across genders: males show a strong negative association between overconfidence and loss aversion, whereas females display a positive link between herding and overreaction. Overall, the findings highlight that cognitive biases persist even in sophisticated professional settings, offering implications for risk management, training and the design of diverse decision making teams.

Keywords: Behavioural Finance, Investment Bankers, Gender, Cognitive Biases, Overconfidence, Herding, Loss Aversion, Overreaction, Prospect theory, Heuristics theory.

JEL Classifications: G11; G24; G40; G41

Introduction

Understanding the cognitive processes determining investor decisions has gained prominence, especially over recent decades, as technological advancements have lowered barriers to engage in financial markets (Cruciani, 2017). With more market participants increasing the volume of trading, a wealth of studies have attempted to uncover the psychological factors that influence investment decisions. While the finance literature had been dominated by traditional decision theory and the assumptions of market efficiency and rational investors (Ackert, 2014), this theory has increasingly been challenged. For example, Kumar and Choudhary (2023) states that traditional theories overlook the stock market's 'tumultuous bubbles', often caused by irrationality and imperfections of the market.

As a response, behavioural finance theory has emerged and attempts to expand on traditional theories by incorporating behavioural elements into the decision-making process. Central to behavioural finance is the belief that behavioural biases directly impact one's decision-making. These biases consist of both cognitive and emotional deviations from rational thought, with their presence in many everyday decisions echoing their real-world implications (Rehan & Umer, 2017). Further, many studies have highlighted that these biases do not uniformly align across gender (Onsomu, 2014; Hsu et al., 2021), hence, the present study aims to examine these biases and their proposed gendered differences.

More precisely, despite an abundance of studies employing behavioural finance theories to ascertain the influence of cognitive biases on financial decision-making (Korte, 2003; Nikolić, 2018; Kumar & Goyal, 2015), there is a dearth of research into biases among financial professionals. While several studies employ retail investors or students as their sample populations (e.g., Metawa et al., 2019; Lazar & Sundar, 2017), they were also calling for the examination of more professional samples. Additionally, although gendered differences in behavioural biases have been widely documented among retail investors (Zheng et al., 2021; Cueva et al., 2019), research has not yet documented whether these relationships remain in a professional setting or if experience, training and heightened expertise, moderate these disparities.

In this light, the present study opts for a more professional sample, surveying investment bankers. As highlighted by Painter (2010), investment bankers are highly trained professionals operating on the frontline of financial markets, making them an ideal demographic for studying this issue. Finally, despite the growing number of studies on gender and decision-making, studies in a United Kingdom (UK) context remain notably limited. The UK is a leading financial centre for Europe with a diverse community of professionals, making undeniable progress in gender equality in recent times (Fox, 2018; Darnell & Gadiesh, 2013). It is, therefore, a prime geographical context for research into this question.

The objective of this study is to examine the presence of behavioural biases within the UK investment banking industry, and whether the documented gender differences remain within this professional setting, despite their heightened expertise, training and experience. We specifically investigate the following two research questions:

1. Does the presence of behavioural biases remain within the professional setting of the UK investment banking industry?
2. Are there significant gender differences in the manifestation of behavioural biases within the investment banking context?

This study uses both prospect theory and heuristics theory as theoretical lens and examines four cognitive biases to assesses participants' levels of overconfidence, herding, loss aversion and overreaction', along with gender differences among them. Based on an online survey to assess the presence of behavioural biases and their gendered differences among a sample of 72 UK investment banking professionals, the study finds overconfidence emerging as significantly more pronounced among male investment bankers. On the other hand, no statistically significant gender disparities were observed in levels of herding, loss aversion and overreaction. Further analysis revealed that herding has a significant association with age and industry experience, particularly among female participants. Herding tendencies, however, tend to diminish as age increases. Furthermore, overconfidence was negatively correlated with loss aversion among male participants. Interestingly, we also found a positive relationship between herding and overreaction, but solely among the female subsample. These findings underscore the presence of gender differences in behavioural biases within a professional setting, offering a unique perspective to the existing body of literature.

This research contributes to the growing body of behavioural finance literature by extending evidence to a sample of financial professionals, investment bankers, arguably one of the most sophisticated market participants. The study contributes by demonstrating the presence of biases and behavioural finance theories in institutional settings, where their effects could be devastating given the significant amounts and responsibilities involved. The findings have implications for investment institutions, regulators and risk managers, who can harness the conclusions of this study to prevent cognitive biases from entering corporate investment settings. Additionally, investment bankers themselves can educate on these biases and ensure they adopt the necessary procedures to avoid their presence in decision-making. The study's results also open a new avenue for future research within similar contexts.

The paper will proceed as follows: Section two discusses the literature, followed by the methodology in section three. Section four presents the results and section five offers a discussion. The paper concludes in section six.

Literature Review

Traditional Decision Theory

Traditional decision theory is based on the belief that investors act both rationally and within their best interests (De Bondt et al., 2013). Its foundations are primarily built on Efficient Market Hypothesis (EMH) and Utility theory. EMH argues that markets are efficient, as asset prices reflect all available information as and when released (Naseer & Bin Tariq, 2015). It is therefore impossible for an individual investor to outperform the market (Fama, 1965; Kamoune & Ibenrissoul, 2022). Conversely, utility theory is grounded on the belief that individuals, when faced with risk, base their decisions on the expected utility across different options (Kapoor & Prosad, 2017). Both EMH and utility theory form the backbone to traditional finance theories. They perceive investors as being fully rational which, according to Barberis and Thaler (2003), is an individual's ability to update their beliefs in response to new information and generate decisions that maximise utility based on these beliefs. Since market bubbles and mispricing cannot really be explained by the classic approach, behavioural finance has emerged as a response to calls for a theory to provide a better understanding of both the mechanics of the market and investor psychology.

Behavioural Finance Theory

Behavioural finance explores how psychological biases shape decision-making and the resulting impacts on financial markets (Alquraan et al., 2016), aiming to address the anomalies that traditional theories cannot explain. For instance, Shiller (1981) highlights that traditional theories fail to explain many anomalies such as bubbles and crashes, suggesting markets are not efficient and investors are not fully rational. Similar to traditional theories, behavioural finance is primarily composed of two theories, heuristics theory and prospect theory. Those two form the underlying theoretical lens for our study.

Heuristics Theory

Heuristics theory, proposed in the 1950s yet further developed by psychologists Daniel Kahneman and Amos Tversky in the 1970s, aims to address the irrationality of investors' decisions, often omitted by traditional theories (Chakraborty, 2023). Heuristics asserts that individuals make decisions based on 'rules of thumb', rather than complex calculations (Venkatapathy & Sultana, 2016). In other words, investors are irrational in the sense that they may not always make decisions by accounting for all available information, but rather, they will use mental shortcuts to make decisions, introducing a psychological bias into the decision-making process. Though these mental shortcuts can accelerate decision-making, they may also result in misjudgement or bias (Dale, 2015). Such misjudgements can be detrimental to both market sentiment and one's portfolio. While heuristics theory was groundbreaking, it does not fully indulge in the mechanics of decision-making within risky environments (Gowda, 1999), which is the domain of prospect theory.

Prospect Theory

Prospect theory, initially developed as an alternative to utility theory, is aimed at understanding investors' decision-making under risk (Edwards, 1996). Unlike utility theory, prospect theory believes that psychological biases play a role in investors' decisions. Kahneman and Tversky (1979) critique utility theory and perform a series of tests to illustrate real-life deviations from the theories' beliefs. The findings demonstrated that individuals weigh up options of gains and losses differently, in the sense that a loss has a larger impact than a gain. Furthermore, emotional and psychological factors play a key role in decision-making, contradicting utility theory and its assumption of complete rationality. Prospect theory has become a staple in behavioural finance to date, and numerous behavioural biases that underpin decision-making have been identified, offering a deeper understanding of how decisions can deviate from rationality.

Behavioural Biases

Behavioural biases are a key component of behavioural finance embedded deep within the human mind. Essentially, biases serve as decision-making behaviours that are connected to how an individual processes information and arrives at their decision (Byrne & Utkus, 2013). Though they can enable effective decision-making, they can also lead to flawed judgements. Typically, biases stem from mental shortcuts (heuristics theory), as well as an investor's emotional perception towards potential gains or losses (prospect theory) (Chakraborty, 2023). Over time, studies have investigated these behavioural biases in many different contexts and, particularly, the role that gender plays (Rajdev & Raninga, 2016; Jaiswal & Kamil, 2012). Although specific findings vary across the field, the consensus is that biases do not uniformly align across men and women, resulting in different investment decisions. Exploring the role of gender can therefore provide deeper market insights and allow investors to understand their biases. Although they may not be completely removed, being aware of them may prevent their interference with decision-making (Byrne & Utkus, 2013). Table 1 defines the four key biases that the present study will examine to investigate the role of gender and the effects on decision-making. The following sections discuss each bias individually, their gender-based empirical findings, and formulate the hypotheses.

Table 1: Definitions of Behavioural Biases

Behavioural Bias	Definition	Relevant Literature
Overconfidence	Overconfidence refers to the overestimation or inflation of one's skills or abilities in a given task.	Jaiswal & Kamil (2012)
Herding	An individual's tendency to replicate the actions or decisions of another individual or group, rather than relying on their own beliefs or knowledge.	Hwang & Salmon (2004)
Loss Aversion	An individual is loss averse if they feel more pain in losing something, than satisfaction of gaining something of an equal value.	Kahneman & Tversky (1979)
Overreaction	When investors respond excessively in relation to new information, causing short-term momentum in the direction of the reaction.	Daniel *et al*., (1998)

Source: Developed from Dickason, Ferreira and Nel (2017)

Gender and Overconfidence

Overconfidence is arguably the most prominent behavioural bias among the literature and can prove detrimental to one's decision-making (Jaiswal & Kamil, 2012). Overconfidence can be closely tied into heuristics theory as investors may place added reliance on their own abilities rather than performing analysis of available information, thus, creating a mental shortcut. Empirically, many studies have found that overconfidence manifests differently across gender (Barber & Odean, 2001; Cueva et al., 2019; Nyhus et al., 2024).

Seen as a foundational study investigating gender differences in investment decisions, Barber and Odean (2001) used data spanning over 35,000 US households from a large US brokerage firm. By utilising the gender of who opened the account and their transactional data, the authors provide empirical evidence that men exhibit higher levels of overconfidence compared to women. Those findings are congruent with more recent evidence by, for instance, Cueva et al. (2019) and Hassan et al. (2014), based on an experimental study of trading simulations with 192 undergraduate students in Spain, and a survey of 391 investors in Pakistan, respectively. Hassan et al. (2014) also surveyed respondents with little expertise, finding males were more overconfident. Experimental evidence by Cueva et al. (2019) further confirms this relationship. Although a vast majority of findings indicate a positive relationship between men and overconfidence, there are also conflicting results. For example, while Deaves et al. (2009) fail to find a direct relationship between gender and overconfidence in an experimental study on students in Canada and Germany, other studies such as Lawrence et al. (2024) and Nyhus et al. (2024) both conclude females exhibit higher levels of overconfidence than males. The latter two studies employ a survey, the first in Scandinavia and the second in the US, on a general population with no specified level of expertise.

This highlights the need for further investigation of the overconfidence bias. Moreover, the studies are similar in their recommendations for future research suggesting different geographical contexts and further exploration of biases. The present study aims to explore multiple biases in a UK context, which has limited coverage in previous research. Based on previous empirical evidence, we form the following hypothesis:

H_1**:** *Males exhibit significantly higher levels of overconfidence compared to females in investment decisions.*

Gender and Herding

Similar to overconfidence, herding can serve as an effective heuristic as it simplifies decision-making, allowing a mental shortcut rather than considering all available information. Empirical evidence suggests that herding behaviour is not symmetrical across different genders (Jamil & Khan, 2016; Sabir et al., 2020), and also that if individuals lack confidence they are more prone to herding behaviour (Zheng et al., 2021; Jamshidinavid et al., 2012). That being said, if the literature within overconfidence holds true, then presumably women will be more prone to herd behaviour, as males were found to exhibit higher levels of confidence.

Numerous studies affirm the validity of this hypothesis. Specifically, Zheng et al. (2021) and Zainul and Suryani (2021) both find that females demonstrate higher levels of herding compared to males. This based on a sample of over 1.5 million investors within the Chinese stock market, and less than 400 investors in an Indonesian context, respectively. Likewise, Yuliawati et al. (2021) surveys 65 investors in Indonesia, again indicating females are more prone to herding than males. They, however, also highlight that both genders are highly susceptible to herding behaviour, which illustrates that although women may be more dominant in herding behaviour, the herding phenomenon affects both genders. This is supported by Jaiswal and Kamil (2012) and Gupta and Goyal (2024) in the Indian context, with their questionnaires highlighting a minor difference in herding behaviour between genders. It is to be noted, though, that the sample ratio across the latter two studies is approximately a 70:30 split between males and females. Consequently, the gender imbalance could affect the results. Contrary evidence, while present, is scarce. Lazar and Sundar (2017) investigate herding behaviour among 400 investors from the Bombay stock exchange. Although it adopts a similar methodology and sample size to Zainul and Suryani (2021) the findings indicate conflicting views, as male investors were more susceptible to herding than females. This study also presents a much greater ratio of males to females which might explain the opposite findings. Although the majority of the literature assesses the existence of herding across gender there is little consideration of further variables that may influence results. This demonstrates the need to explore variables that influence results, which the present study will aim to address. The present study will also utilise the UK as a geographical context which, once again, is neglected among the literature. Given the existing evidence, females were the more prevalent gender to partake in herd behaviour as opposed to males. Thus, it can be hypothesised that:

H_2*: *Females exhibit significantly higher levels of herding compared to males in investment decisions.

Gender and Loss Aversion

Loss aversion is a broad concept that can fit numerous definitions (Schmidt & Zank, 2005). Unlike the previous biases, loss aversion is highly tied to prospect theory as it addresses the tendency to add more weight to the prospects of losses, than the prospect of gains when making decisions (Kahneman & Tversky, 1979). Although there is empirical evidence that loss aversion is present among investors, studies considering the role of gender are largely inconclusive with no definite pattern prevailing.

For instance, Holger (2014) and Brooks and Zank (2005) both conduct experimental studies on students to assess the existence of loss aversion, the former in Germany and the latter in the UK, both finding women to exhibit higher levels of loss aversion than their male counterparts. Similarly, Harzer et al. (2016) and Bouchouicha et al. (2019) also utilise students as their sample population, however both present conflicting results to the former two studies. Harzer et al. (2016) replicate the original questionnaire of Kahneman and Tversky (1979) at a university in Brazil, finding that gender is not significant in the presence of loss aversion. Bouchouicha et al. (2019) conducts an experimental study across 30 countries and finds that results vary depending on the definition of loss aversion, with some definitions having males exhibit higher levels and others female. Although each of these studies are focused on students, they are all based in separate geographical contexts. The differences in these results indicate the global inconsistencies in the measurement of loss aversion, thus, highlighting the need for further examination.

Unlike the previous biases, loss aversion has been studied in the UK, though it remains limited. Dawson (2023) and Brooks and Zank (2005) both provide empirical findings in a UK context indicating that females display greater levels of loss aversion than males. In addition, Blake et al. (2021) surveys UK residents also identifying women to be slightly more loss averse, however with control variables, gender provided no significant difference in results. Taken together, these inconsistent findings indicate the need for further examination of loss aversion in different contexts and cultures, and various influences. Furthermore, many studies utilised student populations as their sample, suggesting the need for more diverse and professional samples to be covered. In response, the present study focuses on examining investment bankers in a UK context. Harnessing investment bankers as opposed to other professionals, such as corporate bankers, will provide valuable contributions as their first-hand market experience and high stakes decision-making could provide new findings to the field. Since the literature highlights no prevailing pattern between gender and loss aversion, can be hypothesised that:

H_3*: *There is no significant difference in loss aversion levels between males and females in investment decisions.

Gender and Overreaction

De Bondt and Thaler (1985) set the foundations for overreaction in their seminal paper titled, 'Does the stock market overreact?'. The paper challenges the belief of efficient markets, inciting that the stock market is prone to overreaction from investors, which can lead to the mispricing of assets. Like loss aversion, overreaction falls within the framework of prospect theory, as perceptions of losses and gains may lead investors to place added weight to information that will have little significance.

Empirically, the concept of overreaction has had much exploration, with academics testing the theory and exploring how different types of news influences the market (Chan, 2003; Metawa et al., 2019). However, there have been few empirical contributions focusing on the role of gender. Their results generally show males prevailing as the gender more prone to overreaction (Jaiswal & Kamil, 2012; Strydom et al., 2019). Firstly, Metawa et al. (2019) survey 384 Egyptian investors and identify that gender alongside age and other demographics have a significant impact on overreaction. This study, however, suffers from a skewed gender ratio, with 80% of participants being male, which might influence the results. More balanced ratios can be found within Strydom et al. (2019) demonstrating that gender is significant. They survey students within an Australian context, providing empirical findings indicating that males tend to overreact, whereas females adopt a more conservative position and are able to adjust their beliefs accordingly. Similar findings are presented by Jaiswal and Kamil (2012) who survey investors in India, showing that females are significantly less prone to overreaction than males. Although males are overwhelmingly identified as being more prone to overreaction, Jamil and Khan (2016) find no significant correlation with gender in a multiple bias study adopting a structured questionnaire within the Middle East. Nevertheless, the majority of studies suggest that males display considerably higher levels of overreaction than females. Additionally, while there were a handful of studies on gender and overreaction, this bias has not been as extensively covered compared to other biases. Therefore, the present study will examine overreaction as its final bias to address this gap, and it can be hypothesised that:

***H_4*: Males exhibit significantly higher levels of overreaction compared to females in investment decisions.**

Methodology

Data Collection and Questionnaire Design

The study adopts a quantitative methodology to examine gender differences in behavioural biases among UK investment bankers, in line with prior literature (Yuliawati et al., 2021; Hassan et al., 2014; Harzer et al., 2016).[1] We employed an online closed-ended questionnaire comprised of 25 closed-ended questions, distributed evenly across five sections.

The first section of the survey was allocated to gathering demographic information, including gender, age, educational background, industry experience, and a question on self-assessment of financial literacy. The latter was measured on a Likert scale of 1-5, with higher values indicating higher self-assessed skill. The four subsequent sections were each allocated to a specific behavioural bias, enabling the presence of each bias to be assessed independently. Each bias had five questions which asked participants to indicate their agreement on a Likert scale from 1-5, with higher scores representing a higher tendency of the respective bias. That means, each of the four biases could score a maximum of 25 in terms of agreement, indicating a high presence of the respective bias. Table 2 details the variables and their measurement method.

Table 2: Summary of Variables

Biases	**Measurement Method**
Overconfidence	5-item Likert Scale, 1 (Lower) – 5 (Higher)
Herding	5-item Likert Scale, 1 (Lower) – 5 (Higher)
Loss Aversion	5-item Likert Scale, 1 (Lower) – 5 (Higher)
Overreaction	5-item Likert Scale, 1 (Lower) – 5 (Higher)
Demographic Variables	**Measurement Method**
Gender	Female =1, Male = 2
Age	Categorical groups (e.g. 18-25, 26-35)
Industry Experience	Categorical groups (e.g. Less than 1 year, 1-2 years)
Educational Background	Categorical groups (e.g. High School, College)
Financial Literacy	5-item Likert Scale, 1 (Lower) – 5 (Higher)

Each bias was allocated two occurrence questions, two agreement questions and one likelihood question, to ensure measurement was consistent across different contexts (See Appendix 1). Following the creation of the survey and approval from the university's ethics committee, a pilot test was conducted with five members of the target sample to test the instrument. Our pilot participants did not raise any issues; thus, the survey was considered ready for distribution to the target audience.

Sampling

The target population consisted of those who currently worked within the UK investment banking industry. A mixed approach to sampling was employed, combining convenience sampling and snowball sampling. Initially, convenience sampling was adopted, which involves selecting participants based on accessibility, proximity or availability (Etikan et al., 2016). First, the survey was distributed to previous connections within the industry, both via email and LinkedIn. To increase sample size, snowball sampling was then used, where participants share the survey onto further relevant candidates. It is employed when samples are not easily accessible (Ghaljaie et al., 2017), like our target audience consisting of busy professionals who may be difficult to access. Numerous prior studies within the field also opted for a similar approach (Aigbovo & Ilaboya, 2019; Adil et al., 2022; Athur, 2014). Following the initial distribution of the

[1]While some studies within this field used an experimental design (e.g., Bouchouicha et al., 2019; Cueva et al., 2019; Deaves, Lüders & Luo, 2009), those can be much more time consuming when compared with a survey. Given that the present study targets a professional sample in investment bankers, an industry known for long working hours and demanding jobs, it is unlikely that they would have the time or availability to participate in an experiment. Hence, the survey is deemed a more practical approach.

survey, responses were then collected over a four-week period to enable enough time for the snowball sample to take effect and to follow up on invitations as response rates depleted. The target population for this study was 100 investment bankers to enable diverse and statistically meaningful insights, with 79 responses received at survey closure, which translates to a 79% response rate. Given that the target population are very busy professionals in demanding jobs, this was deemed sufficient enough to address the aims of the present study and provide meaningful insights into an industry that has received little prior exploration.

Data Analysis

The initial 79 survey responses were cleaned and 7 incomplete responses removed, resulting in a final sample of 72 responses. Consistent with previous studies (Metawa et al., 2019; Gupta & Goyal, 2024), each bias was assessed by summing the relevant survey scores, with a total possible score of 25. A higher score represents a higher presence of the respective bias. The analysis included a combination of descriptive and inferential statistics, t-tests, correlations and regression models.

Ethical Considerations

Ethical approval from the university's ethics committee was obtained before data collection. Both a participant information sheet and consent form were given to participants prior to the survey, to obtain informed consent. Participants could withdraw at any time. To ensure confidentiality, anonymity and security, all responses were completely anonymous.

Data Analysis and Findings

Descriptive Statistics

Demographic Variables

The descriptive statistics for demographic variables are displayed in Table 3. As we can see, the sample was relatively balanced in terms of gender with a slightly higher representation of female participants (55.6%, n=40) compared to males (44.4%, n=32). The age range of participants was well distributed across different age brackets with the majority falling within 18-25 (29.2%, n=21) and 26-35 (25%, n=18) years. Industry experience levels of participants show a strong dispersion, with the majority displaying more than ten years of experience (34.7%, n=25), while education levels were evenly distributed across higher-level education (university and professional qualifications) and lower-level education (high school and college), with a 50:50 split. Crosstabulation (not reported) revealed that older participants tended to have lower levels of education, possibly due to entering the industry at a time where a degree was less necessary. Since younger participants with university degrees made up the sample majority, the overall distribution of educational levels was balanced. Overall, the results illustrate a high level of experience, both academically and professionally with reciprocal findings in financial literacy as the majority of the participants rated themselves as 4 (52.8%, n=38) and 5 (23.6%, n=17) out of 5, indicating high self-belief in their financial knowledge.

Table 3: Descriptive Statistics of Sample Demographics

Variable	Frequency (n)	Percentage (%)
Gender		
Female	40	55.6
Male	32	44.4
Age		
18-25	21	29.2
26-35	18	25.0
36-45	13	18.1
46-55	9	12.5
Above 55	11	15.3
Industry Experience		
Less than 1 year	13	18.1
1-2 years	12	16.7
3-5 years	12	16.7
6-10 years	10	13.9
More than 10 years	25	34.7
Educational Background		
High school or equivalent	29	40.3
College	7	9.7
University undergraduate degree	21	29.2
University postgraduate degree	9	12.5
Professional qualification (e.g. ACCA, ICAS)	6	8.3
Self-Assessment of Financial Literacy (1=Low, 5=High)		
1	1	1.4
2	4	5.6
3	12	16.7
4	38	52.8
5	17	23.6
		N=72

Behavioural Biases

The present study assessed participants' tendencies to display certain behavioural biases, namely, overconfidence, herding, loss aversion, and overreaction. Table 4 presents the descriptive statistics for each behavioural bias.

Table 4: Descriptive Statistics of Behavioural Biases

Bias	**Min**	**Max**	**Mean**	**StDev**
Overconfidence	9	25	15.708	3.514
Herding	9	23	14.458	2.945
Loss Aversion	9	23	18.250	2.900
Overreaction	8	22	16.055	3.236

Overconfidence displayed a mean of 15.708 and the highest standard deviation (SD=3.514), suggesting that while some participants exhibited high overconfidence, others displayed much lower levels. Herding had the lowest mean value (M=14.458, SD=2.945), indicating that it was less prevalent than overconfidence, with a lower variation in the responses signalling greater consistency across participants. Finally, loss aversion (M=18.250, SD=2.900) and overreaction (M=16.055, SD=3.236) displayed the highest mean scores signalling their increased presence among participants. Interestingly, loss aversion had the lowest variation, suggesting uniformly high levels of loss aversion.

Preliminary Data Validity and Assumption Testing

To assess the internal consistency of the behavioural bias measures, Cronbach's Alpha was computed. Typically, in social science research, an alpha above 0.65 is regarded as acceptable, while any values below this may be viewed as sufficient depending on the context (Vaske, et al., 2017). Our reliability test revealed that all four measures scored above the level of 0.65. More specifically, overconfidence, herding, loss aversion and overreaction, have a coefficient of 0.808, 0.681, 0.758 and 0.684, respectively. This demonstrates strong internal consistency and indicates a reliable measure, further reinforcing the significance of the results presented. In addition, extensive testing revealed no violations of assumptions underlying statistical analysis, such as linearity, homoscedasticity, or multicollinearity. Hence, we can proceed with our statistical analyses with confidence in the validity and accuracy of the results (Garson, 2012).

Hypothesis Testing: Independent Sample T-tests

To test the four hypotheses, we conducted independent samples t-tests to check for significant differences in the mean scores of males and females, with p-values representing the significance of the difference. Additionally, Cohen's d was calculated to measure the effect size and evaluate the practical significance of the findings. A general rule of thumb for Cohen's d, is that 0.2 is considered a low effect size, 0.5 considered moderate and 0.8 is considered a high effect size (Becker, 2000). Table 5 displays the results.

Table 5: Independent Sample t-tests and Cohen's d Results for Gender Differences in Behavioural Biases

Behavioural Bias	**Female**		**Male**		**Mean Difference**	**t-value**	**p-value (p)**	**Cohen's d**
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**				
Overconfidence	14.850	3.068	16.781	3.782	-1.931	-2.393	0.019**	-0.568
Herding	14.975	2.966	13.813	2.833	1.163	1.686	0.096*	0.400
Loss Aversion	18.600	2.790	17.813	3.021	0.788	1.147	0.255	0.272
Overreaction	15.725	2.810	16.469	3.707	-0.744	-0.968	0.336	-0.230

***, **, and * denote significance levels 1%, 5%, and 10%, respectively.

The first hypothesis posited that males would display greater levels of overconfidence than females. The results support H1 as they show that males indeed displayed higher levels of overconfidence when compared to their female counterparts, with a statistically significant difference (5% level). This further reinforces the existence of gender differences in overconfidence as reported in prior research. Additionally, Cohen's d (0.568) suggests a moderate effect size, indicating that males demonstrate significantly higher overconfidence levels than females. Hypothesis two asserts that females display greater levels of herding. While we find that females displayed a slightly higher level of herding compared to males, the difference is only moderately significant (10% level). Cohen's d also presents a low effect size of 0.400, suggesting a minimal real-world impact and further reinforcing the low significance. Thus, based on these findings, H2 is rejected.

Hypothesis three assumed that neither gender demonstrated a significant difference in levels of loss aversion, suggesting the two are equally loss averse. The results are as expected. While with males on average exhibiting lower levels of loss aversion than females, the difference is insignificant. Low effect size (d = 0.272) also indicates an immaterial real-world effect. Hence, H3 of no significant difference is supported. The fourth and final hypothesis suggested that males exhibit a significantly higher level of overreaction when compared to females. We find a mean difference across genders, with males displaying slightly higher overreaction tendencies than females. This suggest that males are more prone to overreaction within the UK investment banking industry. The difference, however, is insignificant, coupled with a low effect size. Consequently, H4 is rejected.

Influence of Demographic Variables on Biases

To probe the data further, we investigate the potential influence of demographic variables on the biases in question. Firstly, Pearsons's correlation analysis was conducted, examining age, education level, industry experience and financial literacy, against each bias. The results of the Pearson's correlation analysis can be seen in Table 6. Panel A presents the results for the full sample, Panel B the analysis split by gender.

For the full sample shown in Panel A, we see a significant negative correlation (1% level, respectively) between herding and age and herding and industry experience. No significant correlations were visible between financial literacy or educational background and any of the four biases, suggesting these factors do not meaningfully influence behavioural biases within this sample. The results indicate that as an individual gets older or gains greater levels of industry experience, their herding tendencies significantly decrease. To determine whether these correlations hold for both male and female, a gender-split Pearson's correlation was conducted.

As we can see from Panel B, when controlling for gender, the negative correlations between herding and age (1% level) and industry experience (5% level) remain significant only among the female participants. Thus, it can be ascertained that younger and less experienced female investment bankers are more prone to herding behaviour than their older and more experienced counterparts. In contrast, males exhibited no significant relationships between overconfidence, loss aversion, herding or overreaction, and any of the demographic variables. These results suggest that the influence of demographic characteristics is exclusive to the female gender, particularly in relation to herding.

To explore this finding further, we ran a regression analysis on significant correlations only, to assess whether age and industry experience independently predict herding. Since no significant correlations were observed among male participants, the regression was conducted exclusively on the female subsample.

Table 6: Correlation of Behavioural Biases and Demographics

Variable	Overconfidence	Herding	Loss Aversion	Overreaction
Panel A Correlations across Full Sample				
Age	-0.069	-0.433***	0.206	-0.124
Industry Experience	-0.041	-0.349***	0.119	-0.188
Educational Background	0.054	0.089	-0.094	-0.086
Financial Literacy	0.020	-0.128	-0.070	-0.124
Panel B Gender-Split Correlations				
Female				
Age	0.055	-0.612***	0.278	-0.241
Industry Experience	0.054	-0.350**	0.283	-0.277
Educational Background	0.190		-0.193	-0.159
Financial Literacy	0.128		-0.094	-0.209
Male				
Age	-0.293		0.170	-0.045
Industry Experience	-0.200		-0.043	-0.132
Educational Background	-0.084		0.013	-0.041
Financial Literacy	-0.012		-0.079	-0.038

***, **, and * denote significance levels 1%, 5%, and 10%, respectively.

Table 7: Regression with Herding as a Dependent Variable Among Females

Variable	
Age	-0.596***
	(-3.873)
Industry Experience	-0.030
	(-0.195)
R2	0.376
F-value	11.137
N	40

***, **, and * denote significance levels 1%, 5%, and 10%, respectively.

The results (Table 7) reveal that only age remained a significant determinant of herding 1% level); industry experience was insignificant. While rather exploratory due to the small sample size (N=40), this implies that age was the primary determinant in predicting herding tendencies, with older females displaying a reduced tendency to follow the actions or advice of others. For completeness, we also ran the same regression on the full sample and the male subsample. The results (not reported) remained consistent, as age continued to significantly predict herding in the full sample, while there were no significant predictors in the male subsample. This solidifies the results of the prior correlation and highlights the gendered nature of the relationship.

Table 8: Correlation of Interrelationships Between Behavioural Biases

Variable	Overconfidence	Herding	Loss Aversion	Overreaction
Panel A Correlations across Full Sample				
Overconfidence	1			
Herding	-0.160	1		
Loss Aversion	-0.478***	-0.052	1	
Overreaction	0.197	0.210	-0.077	1
Panel B Gender-Split Correlations				
Female				
Overconfidence	1			
Herding	-0.139	1		
Loss Aversion	-0.250	-0.255	1	
Overreaction	0.052	0.316**	0.149	1
Male				
Overconfidence	1			
Herding	-0.085	1		
Loss Aversion	-0.664***	0.131	1	
Overreaction	0.268	0.168	-0.248	1

***, **, and * denote significance levels 1%, 5%, and 10%, respectively.

Next, the relationships between the four biases will be explored to investigate whether the presence of one bias amplifies the presence of another. In line with the previous section, to first assess the relationships between biases, Pearson's correlation analysis was adopted. Table 8 presents the results of the analysis, where each bias was evaluated one by one against the remaining three biases, to assess whether a higher tendency of one influenced a greater tendency of another.

The results for the full sample (Panel A) indicate a significant negative correlation between loss aversion and overconfidence at the 1% level. This suggests that as one's overconfidence tendencies increase, a corresponding decrease may be seen within their levels of loss aversion. Additionally, a weak significant positive correlation can also be observed between herding and overreaction (10% level), which suggests that individuals prone to increased herd behaviour may also exhibit heightened overreaction, indicating the need for deeper examination. A further gender-split correlation was conducted to examine whether these relationships uphold their significance when controlling for gender (Panel B). The gender-split correlation presents two notable findings. Firstly, the initial significant relationship between loss aversion and overconfidence, only remains significant among the male subsample (1% level). This indicates that males display a significant inverse relationship between loss aversion and overconfidence, suggesting that those with lower overconfidence exhibit higher levels of loss aversion. To explore further, we ran a univariate regression (not tabulated) with overconfidence as the dependent variable and herding as the independent variable. The results confirm loss aversion as a strong negative predictor of overconfidence for males only, both in full and split gender subsamples.

Secondly, the near significant relationship between herding and overreaction initially observed, becomes significant when controlling for gender, with female participants displaying a significant positive correlation between herding and overreaction (5% level). This suggests that females who are more prone to overreaction also exhibit heightened herd behaviour, following the recommendations and actions of others. This result was further confirmed by running a univariate regression (not tabulated) for both the full and split gender subsamples, which showed that overreaction was a significant positive predictor of herding only among the female participants within this study.

Discussion

This study aimed to examine gender differences in behavioural biases among UK investment bankers, primarily framed by four hypotheses and further analysis. The first hypothesis examined the notion that males tend to exhibit greater levels of overconfidence than their female counterparts. The results show that males indeed displayed significantly higher overconfidence levels compared to the female participants, thus supporting hypothesis one. Notably, these findings affirm much of the existing scholarly research within the area. Specifically, Barber and Odean (2001) found that male investors tend to overestimate their financial literacy, leading to heightened levels of trading and reduced returns. Similarly, Cueva et al. (2019) also find that males display greater overconfidence levels in financial decision-making. Our study evidences the existence of those differences even within professional settings. One potential explanation for these differences has been attributed to psychological and cognitive differences across genders, such as a difference in risk perceptions (Hassan et al., 2014). This suggests that females display reduced risk tolerance which has corresponding reductions in their levels of overconfidence. Although this may explain the differences, deeper exploration within professional settings may be necessary to ascertain the reality of this relationship. Nonetheless, it remains evident that these disparities retain their prominence across multiple contexts, underscoring the necessity to educate on their presence within professional settings.

Hypothesis two was aimed at examining whether females displayed greater levels of herding than males, as pertained by much of the existing literature (Zheng et al., 2021; Zainul & Suryani, 2021; Yuliawati et al., 2021). The insignificant results of our study, however, contradict these findings, despite an overall difference in herding levels across gender. The partial support for the hypothesis indicates that although females may have displayed greater levels of the bias, the difference was not substantial enough to indicate a strong disparity. It is to be noted that the conflicting findings may be resultant of the present study context being in a more professional setting. For instance, both Zheng et al. (2021) and Zainul and Suryani (2021) utilise investors as their sample, however, fail to mention their level of expertise. This implies that both samples will include varied levels of expertise from novice traders to full time investors. Hence, the heightened expertise of those working within the investment banking industry in our study may subdue the prevalent gender differences observed among the literature.

Additionally, there were a minority of studies that also presented uncommon findings. Lazar and Sundar (2017) concluded that males present higher herding tendencies, whereas Jaiswal and Kamil (2012) refer to the difference being minor, rather than significant. The present study's results compliment these findings, displaying little to no difference in herding across gender among financial professionals, further adding to the controversy within the field of herding. Once again, there have been several explanations postulated for the reduction in gendered differences, such as millennial investors challenging the stereotypical norms of herding across genders (Gupta & Goyal, 2024). Our results may be an indication of this, due to the large number of millennials within our sample. However, further exploration of this is necessary to uncover the extent of this relationship.

Our third hypothesis was that there is no significant difference in the levels of loss aversion among gender. We find a slight, yet insignificant, difference in the mean scores among males and females, thus supporting the hypothesis. This indicates that loss aversion does not meaningfully vary across men and women and is in line with various prior findings. While loss aversion was proposed as a universal bias, affecting all individuals regardless of their demographic (Kahneman & Tversky, 1979), empirical studies do not support this. For example, many studies have concluded females to be more loss averse, due to their heightened risk perceptions (Holger, 2014; Brooks & Zank, 2005). Conversely, others have found little to no significance in gender influencing levels of loss aversion (Harzer et al., 2016; Bouchouicha et al., 2019). These conflicting findings leave many questions regarding the significance of gender in altering one's levels of loss aversion. Notably, the present study's results align with the latter and the views of Kahneman and Tversky (1979), in that gender is indeed insignificant in loss aversion, but rather it seems universal. Hence, it can be assumed that rather than gender being a key driver there may be more significant factors that were not examined, such as industry experience, financial literacy or overall market conditions (Brooks & Zank, 2005; Schmidt & Zank, 2005). These insights further emphasize that loss aversion is a broad cognitive bias rather than a gendered trait, affirming the importance to deeper examine what factors influenced the documented disparities among the literature.

The last hypothesis, which posited that males tend to show higher levels of overreaction bias compared to females, was not supported. We do not find a significant difference and a minimal Cohen's d effect size. These results indicate that neither gender display significantly larger levels of overreaction within the UK investment banking industry, presenting contrary results to the literature. This is similar to loss aversion, where De Bondt and Thaler (1985) do not attribute the bias to a specific gender but instead uses it as a more generalised principle with regards to asset pricing and market behaviour. By contrast, the limited number of contemporary studies examining this bias empirically attribute variance in the results to demographics, namely gender, with males often demonstrating heightened overreaction (Jaiswal & Kamil, 2012; Strydom et al., 2019). Our results conflict with these findings, illustrating that gender is not a significant predictor of overreaction within the context of this study. This could be attributable to many factors such as the level of professionalism required to work within the investment banking industry, potentially limiting the presence of the emotional tendency to overreact. Additionally, Metawa et al. (2019) proposes that gender alone may not be the best predictor of overreaction, despite its influence, and should be considered alongside age, investing exposure, and risk perceptions for a deeper understanding.

Following the results of the hypothesis testing, we also carried out a deeper examination of the impact of different demographic characteristics on behavioural biases, and interrelationships between the different biases. First, further analysis how different demographic characteristics shape financial decision-making and cognitive biases shows that only herding displays significant relationships with demographics. This indicates that loss aversion, overconfidence and overreaction are not sensitive to demographic variables such as age, industry experience, financial literacy or education level. These findings refute the numerous prior studies that attribute the disparities within these biases to demographic variables (Hassan et al., 2014; Metawa et al., 2019; Jamshidinavid et al., 2012). Herding proved to be strongly correlated to both age and industry experience, among females only. More specifically, when controlling for other variables only age remained significant, suggesting that as the females within this study aged their herding tendencies decrease, and industry experience was merely incidental due to its correlation with age. While prior studies involving age are scarce, this is consistent with Sabir et al. (2020) who find that as one's age increases, the herding tendencies decrease but contradicts Zheng et al. (2021) who suggest that as age increases herding increases in tandem. While our study's conclusions align with the former, the relationship is due to females. This suggests the need for further exploration, due to the scarcity of demographic analysis within the field. Overall, the findings indicate that as one's age increases, their decision-making shifts from reliance on others to rationality, with females mostly displaying this relationship. This signifies that heightened experience and maturity can overrule herding tendencies within the investment banking context.

Second, we analysed whether biases have the potential to influence one another, in the sense that a heightened presence of one could influence the tendency to display another. For the entire sample, we uncovered a significant negative relationship only between loss aversion and overconfidence, suggesting that participants displaying increased levels of one, would exhibit reduced levels of the other. These findings greatly align with prospect theory (Kahneman & Tversky, 1979), believing that individuals with heightened sensitivity to losses will exhibit reduced confidence in their financial decisions. This further underscores our results in that biases do not operate in isolation, but rather they interact in a complex manner. An additional gender-split analysis revealed that these relationships among biases are not uniform across gender, with only males presenting a significant relationship between loss aversion and overconfidence. The female subsample presented a significant positive relationship between herding and overreaction, a relationship that was not previously present when not controlling for gender. Although several studies have examined interplay between biases and uncovered similar relationships (Hassan et al., 2014; Hoitash & Krishnan, 2008), to the researchers' knowledge, the present study may be unique in examining these interrelationships across genders, marking new and valuable contributions to the field that would benefit from further examination in future research.

Conclusion

This study examined gendered differences in behavioural biases within a professional setting, compared to the usually used non-professional participants. Specifically, the four biases of overconfidence, herding, loss aversion, and overreaction were all investigated within the UK investment banking industry, via distribution of an online survey. The analysis uncovered several intriguing relationships, demonstrating a combination of conflict and congruence with the existing literature.

Firstly, prior literature demonstrated that both overconfidence and overreaction were attributable to the male gender (Cueva et al., 2019; Jaiswal & Kamil, 2012), whereas herding was more pronounced among females, and loss aversion was determined to be independent of gender (Zainul & Suryani, 2021; Harzer et al., 2016). We tested four hypotheses based on these principles and find only overconfidence and loss aversion being supported. This implies that although professional contexts may not eliminate biases or their gender differences, the heightened experience, exposure and professionalism may reduce their presence and the documented disparities. Additionally, it was revealed that herding was inversely correlated with age among females, with no such relationship being observable among males. Notably, the correlation between herding and age had been uncovered before, however never attributed to solely females, marking new and valuable contributions to the field.

Further analysis examined the interplay between biases, highlighting an inverse relationship between loss aversion and overconfidence within the male gender, and a positive correlation between levels of overreaction and herding among females. These gendered results once again mark new and invaluable contributions to behavioural finance literature, emphasising the role of gender in shaping the manifestation of cognitive biases. Overall, the findings of the present study have significant implications for industry professionals, as well as making significant contributions to the field of behavioural finance, reinforcing the validity of such theories in modern day financial decision-making. Ultimately, this study has evidenced that professionalism alone does not eliminate behavioural biases, with their presence strongly evidenced within this study. Furthermore, emotional and cognitive biases do not operate in isolation but rather they are complex phenomena, driven by a combination of personal experience, demographic variables and interconnections with other psychological traits. The conclusions of this study broaden the horizons of the field laying the foundations for future research, to deeper explore these relationships in similar contexts and raise further awareness on the presence of cognitive biases and their broader significance in real-world decisions.

This study makes several important contributions. First, many of the prior studies within the behavioural finance area have predominantly relied on less professional samples, such as retail investors or students, leaving a gap for a sample of professionals. In response, we provide evidence that cognitive biases persist, even within professional settings, reinforcing the applicability of both prospect theory and heuristics theory within the modern world. The findings on gender differences challenge existing evidence, whilst putting forward new relationships such as the inverse herding and age relationship uncovered among females, or the negative correlation of loss aversion and overconfidence only present within males. Despite a voluminous body of literature, these findings are unique, presenting new relationships and perspectives.

Second, from a practical perspective the results have implications for multiple parties, including financial professionals, investment firms and risk managers. The persistence of biases within professional settings underscores the need for mechanisms to be constructed to mitigate their interference with portfolio management. Therefore, it is paramount that the correct training be provided to educate on these biases, raising awareness of their broader implications. Finally, the evidence of gender influences on these biases suggest that firms should adjust their risk management strategies, focusing on the composition of diverse decision-making teams, to mitigate the influence of cognitive biases. Overall, this study has bridged the gap between the current literature and more professional samples, offering valuable insights to both industry and academia.

The study is subject to several limitations. Firstly, whilst the final sample of 72 investment bankers is considered sufficient for the objectives of this study, it is relatively small in comparison to the general population of investment bankers within the UK. This may limit the generalisability of the results. Secondly, the combination of convenience and snowball sampling is effective in gathering participants within the niche industry of investment banking, yet reliance on accessibility may run the risk of sampling bias. Nonetheless, the present study provided meaningful insights into the gendered differences in behavioural biases among UK investment bankers. As an area with limited coverage, this study has built strong foundations for future research. For instance, studies could expand beyond UK investment banking, into other areas of the financial sector or geographical contexts to explore other contexts. Moreover, considering the conclusions drawn with regards to age and industry experience, longitudinal or experimental studies could be considered; to investigate how bias tendencies evolve over time. Finally, future research could examine the influence of different variables such as hierarchical positioning or risk perceptions.

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Appendix 1: Questionnaire

Demographics

Gender

What gender do you identify as?
Enter answer

Age

What age range group do you fit into?
Under 18, 18-25, 26-35, 36-45, 46-55, Above 55

Industry Experience

How long have you currently worked within the financial sector?
Less than 1 year, 1-2 years, 3-5 years, 6-10 years, More than 10 years

Educational Background

What is your highest level of education completed?
High school or equivalent, College, University undergraduate degree, University postgraduate degree, Professional qualification (e.g. ACCA, ICAS), Other (please specify)

Financial Literacy

On a scale of 1 to 5, how would you rate your financial literacy?
1, 2, 3, 4, 5

Overconfidence

How often do you take on tasks because you feel like you can perform them better than others?
Always, Often, Sometimes, Rarely, Never

When faced with a challenging decision, how often do you believe your judgement is better than the average person?
Always, Often, Sometimes, Rarely, Never

How likely are you to stick with a decision even though evidence suggests it may beincorrect?
Very likely, Likely, Neither likely nor unlikely, Unlikely, Very unlikely

To what extent do you agree with the following statement? When making decisions, I am more confident compared to others around me.
Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree

To what extent do you agree with the following statement? When making decisions, I rely more on my own expertise than external data or advice.
Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree

Herding

Do you ever change your decision based on trends or popular opinions on social media?
Always, Often, Sometimes, Rarely, Never

When faced with uncertainty, how often do you rely on advice or actions of those around you?
Always, Often, Sometimes, Rarely, Never

A group of your peers are excited about a new investment, how likely are you to participate without conducting your own analysis?
Very likely, Likely, Neither likely nor unlikely, Unlikely, Very unlikely

To what extend do you agree with the following statement? When making decisions, it is important for me to align my decision with the majority.
Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree

To what extent do you agree with the following statement? I feel more confident with my decisions, when they are aligned with others.
Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree

Loss Aversion

How often do you avoid taking risks to prevent a potential loss?
Always, Often, Sometimes, Rarely, Never

When faced with the possibility of losing resources, how often do you feel a sense of discomfort or stress?
Always, Often, Sometimes, Rarely, Never

You are given two options:
1. **a 100% chance to earn £100, or,**
2. **a 50% chance of losing £50 to potentially earn £200.**

How likely are you to chose the option 1?
Very likely, Likely, Neither likely nor unlikely, Unlikely, Very unlikely

To what extent do you agree with the following statement? The fear of losing money has an impact on my decision-making.
Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree

To what extent do you agree with the following statement? The regret from a loss weighs more heavily than the satisfaction from a gain of an equal value.
Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree

Overreaction

When receiving negative feedback, how often would you make immediate changes and rethink previous decisions?
Always, Often, Sometimes, Rarely, Never

When things don't go as planned, how often do you drastically alter your approach?
Always, Often, Sometimes, Rarely, Never

You hear a rumour about an issue within a company you are investing in, how likely are you to assume the company is in trouble and act quickly?
Very likely, Likely, Neither likely nor unlikely, Unlikely, Very unlikely

To what extent do you agree with the following statement? I often alter my decision based on short-term trends.
Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree

To what extent do you agree with the following statement? I often react impulsively to minor issues, thinking they are more serious than they actually are.
Strongly agree, Agree, Neither agree nor disagree, Disagree, Strongly disagree