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Individual Investor Risk Tolerance from a Behavioural Finance Perspective in Gauteng, South Africa

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ABSTRACT

The investment behaviour of individuals is unconsciously influenced by their thoughts, emotions, personal beliefs or past experiences to the degree that even individual investors with considerable knowledge may diverge from logic and reason. These influences, which can be classified as behavioural finance biases, may affect the manner in which risk is perceived and understood. This study aims to establish the relationship between the behavioural finance biases and the risk tolerance of individual investors within Gauteng, South Africa. This study also aims to identify the behavioural finance biases that drive individual investment decisions. Positive, statistically significant relationships were established between the behavioural finance biases and individual investor risk tolerance. Furthermore, the investment decisions of individual investors are driven to a rather great extent by the behavioural finance biases. The significance of these findings will contribute to facilitate the more practical and accurate profiling of individual investors' risk tolerance to ensure the successful implementation of investment strategies not only within South Africa, but also internationally.

Keywords: Individual Investors, Risk Tolerance, Risk Profiling, Behavioural Finance, Investment Decisions, Gauteng, South Africa
JEL Classifications: D81, G41

1. INTRODUCTION

Behavioural finance investigates how the unpredictable nature of human psychology has an effect on investment decision-making and occasionally brings about emotionally driven behaviours that result in market anomalies that as a whole may either be speculative bubbles or bad bear markets (Rossini and Maree, 2015). Behavioural finance comprises three elements, which are knowledge of finance, economics and cognitive psychology when investment decisions are made by individual investors (Lintner, 1988; Zindel et al., 2014). The financial decision-making environment is characterised by complexity and uncertainty as financial markets are neither strictly efficient nor strictly inefficient (Fakhry, 2016). According to traditional finance theories, it is believed that individual investors behave rationally, take all available information into account and capitalise on available opportunities to maximise their wealth when making investment decisions. However, in reality, individual investors do not behave rationally and investment decisions are driven by emotions, such as greed and fear (Muhammad, 2009). Therefore, numerous systematic deviations in individual investment decision-making from the principle of rationality, based on traditional finance theories, were revealed by behavioural finance research (Klement, 2015).

Traditional finance theories are focused on recognising rational solutions for decision problems as a result of investors' behaviour through the development of assumptions and tools (Baker and Nofsinger, 2002). On the other hand, behavioural finance comprises finance concepts and cognitive psychology as to comprehend and forecast systematic financial market implications of the psychological process of decision-making (Olsen, 1998). Furthermore, while traditional finance theories examine how individuals behave with regard to wealth maximisation, the behavioural finance theory examines how individuals truly behave in a financial environment (Kourtidis et al., 2011). De

Bondt et al. (2008) asserted that the behavioural finance theory is not essentially derived from the assumption of rational market participants and efficient markets. However, it is believed that individual investors behave normal in the manner that they act rationally, but with a limited available set of information.

Pompian (2016) stated that behavioural finance aspires to comprehend and explain investors' actual behaviour rather than theorising about investor behaviour. It is believed that the investment decision-making and risk-taking behaviour of individual investors are better comprehended by employing models in which individuals are not fully rational. The investment behaviour of individuals is unconsciously influenced by their thoughts, emotions, personal beliefs or past experiences to the degree that even individual investors with considerable knowledge may diverge from logic and reason. These influences, which can be classified as behavioural finance biases, may affect the manner in which risk is perceived and understood (Curtis, 2004).

When individual investors make investment decisions on how much risk to take (risk appetite) or how much loss can be tolerated without placing financial goals at risk (risk capacity), unknown risks can cause individual investors to behave irrationally (Pompian, 2016). In a behavioural finance context, individual investors should take into consideration their likely reaction towards known risks, and particularly unknown risks, to acquire a comprehensive depiction of their risk tolerance. If individual investors are able to comprehend and measure the risks they are taking (i.e. known risks), the results from their investment decisions can be accepted. Nonetheless, behavioural finance becomes apparent in the unknown risks. Therefore, when the risks individual investors accepted consist of outcomes that are beyond their expectation and comprehension (i.e. unknown risks) it brings about uncertainty and behavioural problems are often set in motion (Pompian, 2016). The ability to understand individual investors' bounded rationalities and imperfections, as well as how individual investors and markets behave, provide the possibility to adjust financial behaviours to make better investment decisions and improve economic outcomes (Massol and Molines, 2015).

2. LITERATURE REVIEW

According to Byrne and Utkus (2013), investment decision-making biases, also known as behavioural finance biases, relate to the manner in which information is processed by individual investors and the preferences they have when making investment decisions. Hence, behavioural finance concentrates on the concerns of emotional factors and social interactions that influence the risk judgement and decision-making of individual investors (Pompian, 2016). A summary of the primary investment decision-making biases is provided in Table 1.

The majority of research compiled on behavioural finance originates from the field of cognitive psychology, which is the study of how individual investors think, reason and make investment decisions. Numerous researchers only concentrated on cognitive issues and did not take note of the emotional factors of risk perceptions and investment decisions (Loewenstein et al., 2001; Mazzoli and Marinelli, 2011). Nonetheless, this brought about a new understanding in the behavioural finance field known as "risk as feeling" and the examination of the influence of emotions in risk perception and investment decision-making (Slovic et al., 2004). Pompian (2012) asserted that emotional factors (emotional biases) are more difficult to rectify than cognitive errors, because emotional factors originate from impulse or intuition rather than conscious estimates. Furthermore, concerning emotional factors or biases, it may only be feasible to recognise the biases and adapt to it instead of rectifying it (Lucarelli et al., 2015).

Table 1: Investment decision-making biases

Investment decision-making biases	Theories	Biased effects
Cognitive issues	Heuristics: Availability heuristic Representativeness	Ease of recall bias Base rate neglect Sample size neglect Gambler's fallacy effect Trend chasing Halo effect
	Framing	Soothing effect Narrow framing Money illusion Preference reversals Context effects
	Overconfidence	Miscalibration Self-attribution bias Hindsight bias Cognitive dissonance Rationalisation Confirmation bias
	Anchoring Ambiguity aversion Perceived control	Conservatism Familiarity bias Locus of control Illusion of control
Preferences	Mental accounting Prospect theory	Sequential choices Utility over gains/losses Risk aversion/seeking over Gains/losses Loss aversion Small probabilities overweighting Certainty effect
Emotional factors	Current feelings and mood Anticipation of future feelings	Misattribution bias Risk/loss aversion House money effect Break-even effect Omission bias Endowment effect Status quo bias
Social interactions	Person-to-person contagion Media contagion	Herding Rigid thinking Fundamental attribution error False consensus effect

Source: Mazzoli and Marinelli (2011); Dickason (2017). Dickason (2017) and Ferreira (2018) highlighted several behavioural finance biases in their studies. These behavioural finance biases are described in Table 2 and attended to in the study

Emotional factors can cause individual investors to make suboptimal investment decisions. The effect of emotional factors upon the decision-making process is distinguishable in current feelings and mood, as well as the anticipation of future feelings (Mazzoli and Marinelli, 2011). Firstly, with regard to current feelings and mood, the emotions and moods individual investors experience presently influence their perceptions of risk, judgements and choices in investment decisions. When making investment decisions, individual investors are more optimistic in their judgements and choices when they are in a happy mood and experience joyful emotions (Lerner et al., 2015; Dickason, 2017). On the other hand, when individual investors are in a bad mood, they are more decisive in their strategies to evaluate information and consequently, it may bring about incorrect judgements or misattribution biases. In view of that, preceding affective states may cause individual investors to allocate their optimism about a choice to the incorrect sources. In addition, feelings and moods tend to influence abstract judgements more than specific judgements for which individual investors have concrete information (Ross, 1977). Secondly, the anticipation of future feelings may also influence individual investors' perceptions of risk, judgements and choices in investment decisions.

Table 2: Behavioural finance bias

Behavioural finance bias	Description
Representativeness	Individual investors classify new information and make investment decisions based on their perceptions of past experiences or known events
Overconfidence	Individual investors have a tendency to overestimate their investment capabilities
Anchoring	Individual investors have a tendency to rely on a single piece of information when making investment decisions, regardless of the fathomless information available
Gambler's fallacy	Individual investors inaccurately predict financial market movements as they base their investment decisions on future market trends
Availability bias	Individual investors base their investment decisions on the most recently available information
Loss aversion	Individual investors have a greater inclination to avoid losses rather than to achieve gains and therefore, have a tendency to hold onto non-performing investments with the anticipation that investments will produce positive returns in the future
Regret aversion	Individual investors tend to manage situations to avoid feelings of regret or embarrassment of reporting a loss as a result of poor investment decisions
Mental accounting	Individual investors group information regarding particular events and keep track of gains and losses concerning investment decisions in separate mental compartments
Self-control	Individual investors exercise self-control to lessen the temptations of taking bigger financial risks to avoid large financial losses and to protect their investments

Source: Kannadhasan (2006); Byrne and Brooks (2008); Mazzoli and Marinelli (2011); Singh (2012); Pompian (2016); Dickason (2017); Ferreira (2018)

As indicated in Table 3, Pompian (2016) classified individual investors into behavioural investor types based on their level of risk tolerance and a primary type of bias, either cognitive or emotional. Accordingly, individual investors are categorised into four risk profiling categories, namely conservative, moderate (balanced), growth (moderately aggressive) and aggressive, which display different types of behavioural biases.

According to Pompian (2016), conservative individual investors have low risk tolerance levels (indicating low risk appetite and risk capacity) and are primarily driven by emotional biases, such as the endowment bias, loss aversion and status quo. On the other hand, conservative individual investors are also subject to cognitive biases, such as anchoring and mental accounting. Moderate individual investors displaying moderate risk tolerance levels are primarily driven by cognitive biases, such as the hindsight bias, framing, cognitive dissonance and the recency bias. However, moderate individual investors also experience emotional reactions when they realise that judgement errors were made in investment decisions and accordingly, they are also subject to the regret aversion bias (Zindel et al., 2014).

Furthermore, growth (moderately aggressive) individual investors display medium to high levels of risk tolerance and are primarily driven by cognitive biases, such as conservatism, availability, confirmation, representativeness and self-attribution (Pompian, 2012). These types of individual investors believe in themselves and their investment decisions. They also attempt to outperform the financial markets and may hold more concentrated investment portfolios. However, they can be unperceptive to contrary thinking and therefore, education and information about their cognitive biases are fundamental to change their behaviour and make better investment decisions (Pompian, 2012). Lastly, aggressive individual investors that have high risk tolerance levels (indicating high risk appetite and risk capacity) are primarily driven by emotional biases, namely the self-control bias and affinity bias. Moreover, aggressive individual investors are also subject to

Table 3: Risk tolerance and types of biases

Investor description	Conservative	Moderate	Growth	Aggressive
Risk tolerance	Low	Medium	High	Very high
Bias types	Primarily emotional	Primarily cognitive	Primarily cognitive	Primarily emotional
Biases	Endowment Loss Aversion Status quo Anchoring Mental accounting	Hindsight Framing Cognitive dissonance Recency Regret	Conservatism Availability Confirmation Representativeness Self-attribution	Overconfidence Self-control Affinity Illusion of control Outcome

Source: Pompian (2016)

cognitive biases, such as the overconfidence bias, outcome bias and illusion of control bias. These types of individual investors display overconfidence in their own abilities to make investment decisions and are likely to believe that they can control the outcomes of their investments (Pompian, 2016).

Moreover, Dickason and Ferreira (2018a) conducted a study whereby they examined which behavioural finance biases are associated with a certain level of risk tolerance and investor personality (risk profiling category). Figure 1 presents a graphical illustration of the findings of the study by demonstrating the investor risk tolerance levels and investor personality according to each behavioural finance bias.

As indicated in Figure 1, it was found in the study that conservative individual investors with low levels of risk tolerance are subject to biases, such as loss aversion and mental accounting. Alternatively, conservative individual investors with medium levels of risk tolerance are subject to the anchoring bias. However, moderate individual investors with medium levels of risk tolerance were driven by the regret aversion bias. Furthermore, moderate-to-growth individual investors with medium levels of risk tolerance were found to be subject to the availability, representativeness, overconfidence and gambler's fallacy biases. Lastly, individual investors that were found to be driven by the self-control bias were aggressive individual investors with high levels of risk tolerance (Dickason and Ferreira, 2018a).

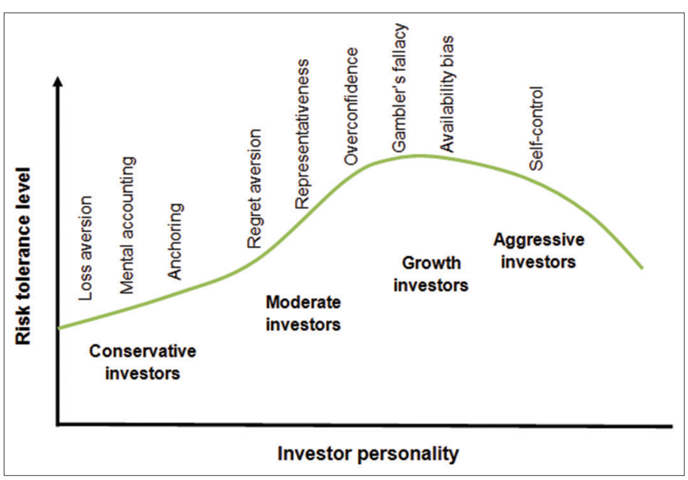
3. METHODOLOGY

This section addresses the methodology employed in the research study. The purpose and design, sample, research instrument and statistical analysis of the study are discussed.

3.1. Research Purpose and Design

The main aim of this study is to establish the relationship between the behavioural finance biases and individual investor risk tolerance. This study also aims to identify the behavioural finance biases that drive individual investment decisions. This study comprises a descriptive research design, whereby a positivist research paradigm was implemented. A descriptive research design was followed as it is used to explain the characteristics, attitudes, perceptions and behaviours of individuals and to establish the differences between numerous groups (Malhotra et al., 2017). Positivism presumes that only reliable knowledge, based on experience and attained through scientific methods, is considered to be truthful knowledge. Positivism attends to human behaviour that is passive, controlled and determined by the external environment, based on reality (Dudovskiy, 2016). According to Creswell (2003), the positivist research paradigm commences with the process of theory, the collection of data that supports or rejects the theory and accordingly, the implementation of the necessary amendments before additional tests are performed. Given that scientific measures and empirical testing methods are employed in this study to attain insights and knowledge, the positivist research paradigm is mainly associated with quantitative research studies (Frels and Onwuegbuzie, 2013).

Figure 1: Risk tolerance, investor personality and behavioural finance biases



Source: Dickason and Ferreira (2018a)

Hence, a quantitative research approach was followed in this study, which allowed for the systematic and objective gathering of information from the representative sample using a self-administered questionnaire. The quantitative research approach is reliant on the collection and analysis of numerical data to illustrate, describe, predict or control variables and phenomena of interest (Williams, 2007; Creswell and Clark, 2011; Plano Clark and Ivankova, 2016). The underlying phenomenon being investigated is usually measured once in its present state of existence with the aim to establish relationships among variables. It also involves the classification of the characteristics of an underlying phenomenon, which is determined on an observational basis or through the investigation of the relationship between two or more variables. Also, hypotheses are only developed subsequent to collection of the data (Maree and Pietersen, 2007). By following a quantitative research approach, the collection and analysis of data were more time efficient. The objective measurement and the statistical analysis of the data provided quantifiable, accurate and unbiased results that enabled the researcher to test existing theories, establish and verify relationships among variables and create generalisations that contribute to theory (Johnson and Onwuegbuzie, 2004; Flick, 2011; Plano Clark and Ivankova, 2016).

3.2. Research Study Sample

The target population for this research study consisted of individual investors from an investment company within the South African context. The sampling frame of this study comprised a purposive sample of individual investors from the South African investment company. By following a purposive sampling method, individuals that have other products, for example, insurance products, but no investments were eliminated from the sample frame. Purposive sampling, a non-probability sampling method, entails the most characteristic and representative elements of the population that are most valuable for the study (Grinnell and Unrau, 2008; Babbie, 2010). The inclusion criteria for individual investors were as follows:

- Older than 18 years
- A current investor (a screening question was asked); and
- Lives in Gauteng.

The individual investors from the investment company should be 18 years and older, a current investor with some form of a formal investment product with the investment company and should live in Gauteng. Gauteng province was selected for this research study, as it encompasses the greatest portion of the South African population (Stats, 2021). The individual investors from the South African investment company had to meet the inclusion criteria to ensure that every individual chosen to partake in the study makes a valuable contribution (Quinlan, 2011). For that reason, the individual investors chosen to participate in the study were chosen with a purpose (Babbie, 2010).

Given that the sample was selected using purposive sampling, a sample size of 463 individual investors (n = 463) was selected, whereby all the inclusion criteria were met to obtain the representative sample. This sample size is in line with the sample sizes utilised in comparable studies, namely Eckel and Grossman (2002); Grable and Joo (2004); Strydom et al. (2009); Sages and Grable (2010); Olweny et al. (2013); Shusha (2017); Dickason and Ferreira (2018b), Abdillah et al. (2019), as well as Shah et al. (2020). Moreover, the selected sample size of this study was efficient for the analysis of the study, as it sufficiently met all the requirements for the statistical analysis employed that facilitated the investigation of the underlying phenomena and achievement of the empirical objectives.

3.3. Research Instrument

The primary quantitative data for this research study were collected through a self-administered questionnaire, which consisted of two sections, and entailed the electronic distribution of the questionnaire to individual investors in the database of the South African investment company. The first section of the questionnaire focused on the self-report on risk tolerance and consisted of a 20-item scale. Self-reported risk tolerance is a measurement of the willingness of an individual to take risks (Hanna et al., 2001). This section included financial risk events derived from theory and existing risk scales, namely the Grable and Lytton's risk tolerance scale (GL-RTS), the Survey of Consumer Finances (SCF) and the domain-specific risk-taking (DOSPERT) scale, where individual investors were asked to indicate the amount of financial risk they are willing to take when making an investment decision (Yao et al., 2004; Blais and Weber, 2009; Gilliam et al., 2010; Discovery, 2019; AMP, 2020; Liberty, 2021; Sanlam, 2021). This approach allowed the researcher to examine the level of risk tolerance individual investors are willing to take and how they behave towards risk in different financial risk events by asking a combination of questions from existing theory and risk scales.

The GL-RTS considers various facets of financial risk tolerance and is used to measure financial risk tolerance based on three primary factors, namely investment risk, risk comfort and experience, and speculative risk (Grable and Lytton, 2001; Gilliam et al., 2010; Kuzniak et al., 2015). The SCF, which is a single-question measure, is utilised to determine the perceptions of individual investors towards financial risk tolerance (Kuzniak et al., 2015). It is only a direct measure for investment choice attitudes and experiences, since it does not incorporate all the variables of financial risk tolerance (Grable and Lytton, 2001). The DOSPERT scale is a psychometric scale developed to measure individual differences in risk attitudes, namely the self-reported degree of risk-taking and perceived attitudes, which is the trade-off between perceived risk and benefits (Blais and Weber, 2009). However, only the financial domain of the DOSPERT scale was included in the self-report on risk tolerance scale. The self-report on risk tolerance was measured on a six-point Likert scale (1 = strongly disagree, 6 = strongly agree).

The second section of the questionnaire, which focused on the behavioural finance biases, consisted of a nine-item scale with statements to illuminate upon the behavioural finance biases that drive individual investors' investment decisions. The extent to which the behavioural finance biases drive individual investors' investment decisions was measured using a six-point Likert scale (1 = strongly disagree, 6 = strongly agree). This section of the questionnaire, which was adapted from Dickason (2017) and Ferreira (2018), consisted of statements that were derived from theory. The inclusion of the behavioural finance scale in this study enabled the researcher to firstly, identify the behavioural finance biases that drive individual investment decisions. Secondly, it allowed the researcher to establish the relationship between the behavioural finance biases and individual investor risk tolerance.

3.4. Statistical Analysis

The quantitative data were analysed using the statistical package, SPSS, Version 26 for Microsoft Windows® (IBM SPSS, 2020). The statistical analysis of this study employed reliability analysis, factor analysis, descriptive analysis, namely frequencies and percentages, as well as measures of central tendency and dispersion, and inferential analysis, namely non-parametric Spearman's rho correlation.

3.4.1. Factor analysis and reliability of the self-report on risk tolerance scale

According to Pallant (2020), factor analysis is a data reduction technique that is generally utilised to reduce or summarise a large number of variables into a smaller and more manageable number of variables. Factor analysis techniques are used to a great extent by researchers engaged in the development and evaluation of tests and scales. It produces a more efficient representation of the original set of observations, which provides evidence of construct validity for an instrument (Hinkin, 1998; Plucker, 2003). Factor analysis, namely exploratory factor analysis (EFA), was conducted on the self-report on risk tolerance scale to identify the financial risk events that influence the risk tolerance of individual investors. This factored the most significant financial risk events according to three newly established risk tolerance categories, namely high risk, average risk and low risk, to report on the risk tolerance of individual investors in the sample. In order to validate the internal consistency of the self-report on risk tolerance scale, the Cronbach's alpha values and average inter-item correlation were calculated for the three factors, namely low risk, average risk and high risk.

Before EFA can be performed, the suitability of the data for factor analysis should be assessed by means of sample size determination, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and the Bartlett's test of sphericity. Concerning the sample size, a sample size of at least 150 is recommended and a ratio of at least five items per variable is required (Pallant, 2020). In this study, the sample (463) yielded a ratio of five items for each variable. Regarding the KMO measure of sampling adequacy, the index ranges from 0 to 1, with values greater than 0.5 indicating sampling adequacy, while values below 0.5 indicate that the sample size is not adequate for factor analysis (Malhotra et al., 2017; Sarstedt and Mooi, 2019). However, Pallant (2020) suggested a minimum KMO value of 0.6 for a good factor analysis. Bartlett's test of sphericity should be statistically significant at $p < 0.05$ for factor analysis to be considered suitable (Sarstedt and Mooi, 2019; Pallant, 2020). It was ensured that the dataset is suitable for factor analysis in this study. Principal component analysis was utilised to extract the factors and the rotation method applied was Oblimin with Kaiser Normalisation. Factor loadings of 0.3 or greater were deemed suitable for the extraction of factors (Pallant, 2020).

With reference to Table 4, the KMO and Bartlett's test of sphericity generated satisfactory results for factor analysis. The KMO index attained a value of 0.851, which is greater than the minimum value of 0.5 and displays great sampling adequacy (Malhotra et al., 2017). Bartlett's test of sphericity had an approximate chi-square statistic of 2757.082 with 136 degrees of freedom and was statistically significant ($p = 0.000 < 0.05$). This denoted that the variables are related and that the data are suitable for factor analysis relating to the self-report on risk tolerance scale.

The pattern matrix of factors for the self-report on risk tolerance scale is presented in Table 5. The percentage of variance and eigenvalue for each of the factors are also illustrated. As mentioned earlier, principal component analysis was used to extract the factors and the rotation method applied was Oblimin with Kaiser Normalisation. The item loadings on the three factors are shown in Table 5. A minimum of five items per factor were grouped, with all items loading above 0.3 on the three factors. This was deemed satisfactory, as the criteria of three or more items loadings on each factor with factor loadings of 0.3 or greater were met (Pallant, 2020).

As presented in Table 5, three factors with eigenvalues greater than 1.0 were extracted and explained 54.817% of the variance. Thus, factors with eigenvalues <1.0 were not considered (Mooi et al., 2018). The three factors were deemed appropriate and best fit to explain the newly developed self-report on risk tolerance scale (Pallant, 2020). Factor one, labelled as average risk, comprised seven variables that explained 28.316% of the variance with an eigenvalue of 4.814. The items that are loaded into this factor relate to the financial risk events that indicate the propensities of individual investors to take average risks when making investment decisions. Factor two, labelled as high risk, comprised five variables that explained 13.875% of the variance with an eigenvalue of 2.359. The items that are loaded into this factor relate to the financial risk events that indicate the propensities of individual investors to take high risks when making investment decisions. Factor three, labelled as low risk, comprised five variables that explained 12.626% of the variance with an eigenvalue of 2.146. The items that are loaded into this factor relate to the financial risk events that indicate the propensities of individual investors to take low risks when making investment decisions.

In order to validate the internal consistency of the self-report on risk tolerance scale, the Cronbach's alpha values were calculated for the three factors, namely low risk, average risk and high risk. Table 6 demonstrates the values of the Cronbach's alpha coefficient and average inter-item correlation per factor relating to the self-report on risk tolerance scale.

It is evident from Table 6 that the three factors extracted generated acceptable Cronbach's alpha values of greater than 0.6, which indicates that all three factors consist of sufficient reliability (Malhotra et al., 2017). The first factor, average risk, has a Cronbach's alpha value of 0.837, signifying very good reliability, while the average inter-item correlation was 0.419, indicating a strong relationship among the items. The second factor, high risk, has a Cronbach's alpha value of 0.797, which indicates good

Table 4: KMO and Bartlett's test of sphericity for the self-report on risk tolerance scale

KMO and Bartlett's test of sphericity		Self-report on risk tolerance
KMO measure of sampling adequacy		0.851
Bartlett's test of sphericity	Approx. Chi-square	2757.082
	Degree of freedom (df)	136
	Significance (Sig.)	0.000

Table 5: Pattern matrix for self-report on risk tolerance

Item	Factors		
	1	2	3
C10	0.830		
C6	0.830		
C2	0.810		
C4	0.712		
C8	0.592		
C9	0.455		
C15	0.444		
C1		0.793	
C18		0.743	
C11		0.690	
C20		0.673	
C5		0.644	
C16			0.761
C19			0.729
C12			0.628
C14			0.604
C13			0.551
Eigenvalue	4.814	2.359	2.146
% of Variance	28.316	13.875	12.626
Cumulative %	28.316	42.192	54.817

Table 6: Reliability of the self-report on risk tolerance scale

Section C: Self-report on risk tolerance	Number of items	Cronbach's alpha	Average inter-item correlation
Factor 1: Average risk	7	0.837	0.419
Factor 2: High risk	5	0.797	0.441
Factor 3: Low risk	5	0.679	0.299

reliability, while the average inter-item correlation was 0.441, indicating a strong relationship among the items. The third factor, low risk, has a Cronbach's alpha value of 0.679, which denotes fair reliability, while the average inter-item correlation was 0.299, indicating a rather strong relationship among the items (Quinlan et al., 2015; Pallant, 2020). Therefore, it can be concluded that the newly developed self-report on risk tolerance scale consists of satisfactory internal consistency reliability and is deemed reliable.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1. Behavioural Finance Biases that Drive Individual Investment Decisions

Descriptive statistics, namely frequencies and percentages, as well as measures of central tendency and dispersion, were applied to identify the behavioural finance biases that drive individual investment decisions. The extent to which the behavioural finance biases drive individual investors' investment decisions was measured using a six-point Likert scale (1 = strongly disagree, 6 = strongly agree). Table 7 reports on the frequencies and percentages of the behavioural finance biases in the second section of the questionnaire.

As demonstrated in Table 7 and relating to the representativeness bias, the majority of the sample (43.6%), representing 202 out of the 463 participants, specified that they somewhat agree that their investment decisions are driven by this behavioural finance bias. The minority of the sample (3.7%), representing 17 out of the 463 participants, specified that they strongly disagree that their investment decisions are driven by the representativeness bias. In relation to the overconfidence bias, 129 out of the 463 participants, which represents the majority of the sample (27.9%), specified that they somewhat agree that their investment decisions are driven by this behavioural finance bias. The minority of the sample (3.5%), representing 16 out of the 463 participants, specified that they strongly agree that their investment decisions are driven by the overconfidence bias.

On the contrary, the majority of the sample (33.3%), which is 154 out of the 463 participants, stated that they disagree that their investment decisions are driven by the anchoring bias, while the minority of the sample (0.6%), which is 3 out of the 463 participants, stated that they strongly agree that their investment decisions are driven by this behavioural finance bias. Pertaining to the gambler's fallacy bias, the majority of the sample (43.6%) indicated that they somewhat agree that their investment decisions are driven by this behavioural finance bias, while the minority of the sample (4.3%) stated that they strongly disagree that their investment decisions are driven by this behavioural finance bias. Similarly, the majority of the sample (40.2%) indicated that they somewhat agree that their investment decisions are driven by the availability bias and the minority of the sample (2.4%) stated that they strongly disagree that their investment decisions are driven by this behavioural finance bias.

With regard to the loss aversion bias, 144 out of the 463 participants, which represent the majority of the sample (31.1%),

Table 7: Frequencies and percentages for behavioural finance biases

Representativeness – D1		
	Frequency (*f*)	**Percentage (%)**
Strongly disagree	17	3.7
Disagree	35	7.6
Somewhat disagree	50	10.8
Somewhat agree	202	43.6
Agree	135	29.2
Strongly agree	24	5.2
Total	463	100
Overconfidence – D2		
	Frequency (*f*)	**Percentage (%)**
Strongly disagree	50	10.8
Disagree	86	18.6
Somewhat disagree	114	24.6
Somewhat agree	129	27.9
Agree	68	14.7
Strongly agree	16	3.5
Total	463	100
Anchoring – D3		
	Frequency (*f*)	**Percentage (%)**
Strongly disagree	77	16.6
Disagree	154	33.3
Somewhat disagree	135	29.2
Somewhat agree	71	15.3
Agree	23	5.0
Strongly agree	3	0.6
Total	463	100
Gambler's fallacy – D4		
	Frequency (*f*)	**Percentage (%)**
Strongly disagree	20	4.3
Disagree	52	11.2
Somewhat disagree	77	16.6
Somewhat agree	202	43.6
Agree	91	19.7
Strongly agree	21	4.5
Total	463	100
Availability bias – D5		
	Frequency (*f*)	**Percentage (%)**
Strongly disagree	11	2.4
Disagree	34	7.3
Somewhat disagree	45	9.7
Somewhat agree	186	40.2
Agree	157	33.9
Strongly agree	30	6.5
Total	15.375 pt	100
Loss aversion – D6		
	Frequency (*f*)	**Percentage (%)**
Strongly disagree	31	6.7
Disagree	81	17.5
Somewhat disagree	111	24.0
Somewhat agree	144	31.1
Agree	80	17.3
Strongly agree	16	3.5
Total	463	100
Regret aversion – D7		
	Frequency (*f*)	**Percentage (%)**
Strongly disagree	65	14.0
Disagree	91	19.7
Somewhat disagree	89	19.2
Somewhat agree	122	26.3
Agree	81	17.5
Strongly agree	15	3.2
Total	463	100

(Contd...)

Table 7: *(Continued)*

Mental accounting – D8		
	Frequency (*f*)	**Percentage (%)**
Strongly disagree	19	4.1
Disagree	34	7.3
Somewhat disagree	73	15.8
Somewhat agree	178	38.4
Agree	134	28.9
Strongly agree	25	5.4
Total	463	100
Self-control – D9		
	Frequency (*f*)	**Percentage (%)**
Strongly disagree	11	2.4
Disagree	14	3.0
Somewhat disagree	33	7.1
Somewhat agree	134	28.9
Agree	207	44.7
Strongly agree	64	13.8
Total	463	100

specified that they somewhat agree that their investment decisions are driven by this behavioural finance bias. However, only 16 out of the 463 participants, which represent the minority of the sample (3.5%), specified that they strongly agree that their investment decisions are driven by this behavioural finance bias. Also, the majority of the sample (26.3%) indicated that they somewhat agree that their investment decisions are driven by the regret aversion bias, while the minority of the sample (3.2%) indicated that they strongly agree that their investment decisions are driven by the regret aversion bias.

Concerning the mental accounting bias, 178 out of the 463 participants, representing the majority of the sample (38.4%), indicated that they somewhat agree that their investment decisions are driven by this behavioural finance bias. Only 19 out of the 463 participants, which is the minority of the sample (4.1%), indicated that they strongly disagree that their investment decisions are driven by the mental accounting bias. Lastly, the majority of the sample (44.7%), which is 207 out of the 463 participants, stated that they agree that their investment decisions are driven by the self-control bias. Only 11 out of the 463 participants, representing the minority of the sample (2.4%), stated that they strongly disagree that their investment decisions are driven by the self-control bias.

Derived from the above-mentioned discussion and results shown in Table 7, most individual investors specified that they somewhat agree that their investment decisions are driven by a particular behavioural finance bias. However, the contrary was true for the anchoring bias as most individual investors specified that they disagree that their investment decisions are driven by this behavioural finance bias, since they do not rely on a single piece of information (past or current information) to make investment decisions (Mazzoli and Marinelli, 2011). Thus, it can be inferred that the investment decisions of individual investors are driven to a rather great extent by the behavioural finance biases. Accordingly, the descriptive statistics for the behavioural finance biases are illustrated in Table 8.

As demonstrated in Table 8, the highest mean (mean = 4.52) was recorded by the self-control bias, indicating that the investment decisions of individual investors are driven to the greatest extent by this behavioural finance bias. This is followed by the availability bias (mean = 4.15), the representativeness bias (mean = 4.03), the mental accounting bias (mean = 3.97), the gambler's fallacy bias (mean = 3.77), the loss aversion bias (mean = 3.45), the overconfidence bias (mean = 3.27) and the regret aversion bias (mean = 3.23). However, the lowest mean (mean = 2.61) was recorded by the anchoring bias, indicating that the investment decisions of individual investors are to the smallest extent driven by this behavioural finance bias. The regret aversion bias recorded the highest standard deviation (Std. Dev. = 1.40), which indicates a greater dispersion in the responses to items in this behavioural finance bias.

4.2. The Relationship Between the Behavioural Finance Biases and Individual Investor Risk Tolerance

Correlation analysis was conducted to establish the relationship between the behavioural finance biases and individual investor risk tolerance. Non-parametric Spearman's rho correlation was applied to determine the strength and direction of the relationship between the behavioural finance biases and individual investor risk tolerance. The strength of the relationship is specified by the Spearman's rho correlation coefficient with values ranging from −1.0 to +1.0. A correlation value of −1.0 signifies a perfect negative relationship, a correlation value of 0 signifies no relationship and a correlation value of +1.0 signifies a perfect positive relationship. The direction of the relationship is signified by the positive correlation (as one variable increases, the other variable also increases) or negative correlation (as one variable increases, the other variable decreases) (Pallant, 2020; Statistic Solutions, 2020). The following guiding principles, as recommended by Cohen (1988), were used to determine the strength of the relationship between the behavioural finance biases and individual investor risk tolerance:

- r = 0.10–0.29 point towards a small/weak strength relationship
- r = 0.30–0.49 point towards a medium strength relationship and
- r = 0.50–1.00 point towards a large/strong strength relationship.

The following hypotheses were formulated to test the relationship between the behavioural finance biases and individual investor risk tolerance:

Null hypothesis ($H_0$1): There is no relationship between the behavioural finance biases and individual investor risk tolerance.

Alternative hypothesis (H_a1): There is a relationship between the behavioural finance biases and individual investor risk tolerance.

Table 9 demonstrates the results of the correlation analysis performed to establish the relationship between the behavioural finance biases and individual investor risk tolerance.

Concerning the relationship between the representativeness bias and individual investor risk tolerance, Table 9 shows small, positive statistically significant relationships between

Table 8: Descriptive statistics for behavioural finance biases

Behavioural finance bias	Item	N	Minimum	Maximum	Mean	Standard deviation
Representativeness	D1	463	1.00	6.00	4.03	1.11
Overconfidence	D2	463	1.00	6.00	3.27	1.31
Anchoring	D3	463	1.00	6.00	2.61	1.12
Gambler's fallacy	D4	463	1.00	6.00	3.77	1.15
Availability bias	D5	463	1.00	6.00	4.15	1.09
Loss aversion	D6	463	1.00	6.00	3.45	1.25
Regret aversion	D7	463	1.00	6.00	3.23	1.40
Mental accounting	D8	463	1.00	6.00	3.97	1.15
Self-control	D9	463	1.00	6.00	4.52	1.07

the representativeness bias and high risk tolerance (rho = 0.157, $p = 0.001 < 0.05$), the representativeness bias and average risk tolerance (rho = 0.255, $p = 0.000 < 0.05$), as well as the representativeness bias and low risk tolerance (rho = 0.236, $p = 0.000 < 0.05$). Therefore, the null hypothesis ($H_0 1$) can be rejected and the alternative hypothesis ($H_a 1$) can be concluded at the 5 per cent significance level. It can be inferred from the above-mentioned findings that individual investors who are subject to the representativeness bias have a propensity to take high, average and low risks. However, Pompian (2012) found that individual investors who are subject to the representativeness bias have a propensity to take high risks, whereas Dickason and Ferreira (2018a) found that individual investors who are subject to the representativeness bias have a propensity to take average risks.

Regarding the relationship between the overconfidence bias and individual investor risk tolerance, Table 9 illustrates medium, positive statistically significant relationships between the overconfidence bias and high risk tolerance (rho = 0.411, $p = 0.000 < 0.05$) and the overconfidence bias and average risk tolerance (rho = 0.328, $p = 0.000 < 0.05$). Accordingly, the null hypothesis ($H_0 1$) can be rejected and the alternative hypothesis ($H_a 1$) can be concluded at the 5 per cent significance level. Conversely, no statistically significant relationship was established between the overconfidence bias and low risk tolerance (rho = 0.029, $p = 0.535 > 0.05$). Consequently, for the relationship between the overconfidence bias and low risk tolerance, the null hypothesis ($H_0 1$) cannot be rejected at the 5% significance level. It can be concluded from the above-mentioned findings that individual investors who are subject to the overconfidence bias have a propensity to take high and average risks. However, Pompian (2012) found that individual investors who are subject to the overconfidence bias have a propensity to take high risks, while Dickason and Ferreira (2018a. p. 10) found that individual investors who are subject to the overconfidence bias have a propensity to take average risks.

Pertaining to the relationship between the anchoring bias and individual investor risk tolerance, Table 9 exhibits small, positive statistically significant relationships between the anchoring bias and high risk tolerance (rho = 0.166, $p = 0.000 < 0.05$), as well as the anchoring bias and low risk tolerance (rho = 0.235, $p = 0.000 < 0.05$). As a result, the null hypothesis ($H_0 1$) can be rejected and the alternative hypothesis ($H_a 1$) can be concluded at the 5% significance level. On the other hand, no statistically significant relationship was established between the anchoring bias and average risk tolerance (rho = 0.075, $p = 0.107 > 0.05$). Therefore, for the relationship between the anchoring bias and average risk tolerance, the null hypothesis ($H_0 1$) cannot be rejected at the 5% significance level. It can be construed from the above-mentioned findings that individual investors who are subject to the anchoring bias have a propensity to take high and low risks. Nonetheless, Pompian (2012), as well as Dickason and Ferreira (2018a) found that individual investors who are subject to the anchoring bias have a propensity to take low risks.

Relating to the relationship between the gambler's fallacy bias and individual investor risk tolerance, Table 9 illustrates medium, positive statistically significant relationships between the gambler's fallacy bias and high risk tolerance (rho = 0.298, $p = 0.000 < 0.05$), and the gambler's fallacy bias and average risk tolerance (rho = 0.355, $p = 0.000 < 0.05$). There is also a small, positive statistically significant relationship between the gambler's fallacy bias and low risk tolerance (rho = 0.095, $p = 0.042 < 0.05$). Consequently, the null hypothesis ($H_0 1$) can be rejected and the alternative hypothesis ($H_a 1$) can be concluded at the 5% significance level. The above-mentioned findings indicate that individual investors who are subject to the gambler's fallacy bias have a propensity to take high, average and low risks. However, Dickason and Ferreira (2018a) found that individual investors who are subject to the gambler's fallacy bias have a propensity to take average risks.

Concerning the relationship between the availability bias and individual investor risk tolerance, Table 9 exhibits small, positive statistically significant relationships between the availability bias and high risk tolerance (rho = 0.101, $p = 0.030 < 0.05$), the availability bias and average risk tolerance (rho = 0.262, $p = 0.000 < 0.05$), as well as the availability bias and low risk tolerance (rho = 0.166, $p = 0.000 < 0.05$). Consequently, the null hypothesis ($H_0 1$) can be rejected and the alternative hypothesis ($H_a 1$) can be concluded at the 5% significance level. The above-mentioned findings signify that individual investors who are subject to the availability bias have a propensity to take high, average and low risks. Nonetheless, Pompian (2012) found that individual investors who are subject to the availability bias have a propensity to take high risks, whereas Dickason and Ferreira (2018a) found that individual investors who are subject to the availability bias have a propensity to take average risks.

Relating to the relationship between the loss aversion bias and individual investor risk tolerance, Table 9 shows a small, positive statistically significant relationship between the loss

Table 9: Relationship between the behavioural finance biases and individual investor risk tolerance

Risk tolerance behaviour category	Spearman's correlation	Representativeness	Overconfidence	Anchoring	Gambler's fallacy	Availability bias	Loss aversion	Regret aversion	Mental accounting	Self-control
High risk	Correlation coefficient	0.157**	0.411**	0.166**	0.298**	0.101*	0.084	0.184**	0.065	0.010
	Sig. (2-tailed)	0.001	0.000	0.000	0.000	0.030	0.071	0.000	0.163	0.825
	N	463	463	463	463	463	463	463	463	463
Average risk	Correlation coefficient	0.255**	0.328**	0.075	0.355**	0.262**	0.274**	0.126**	0.309**	0.262**
	Sig. (2-tailed)	0.000	0.000	0.107	0.000	0.000	0.000	0.006	0.000	0.000
	N	463	463	463	463	463	463	463	463	463
Low risk	Correlation coefficient	0.236**	0.029	0.235**	0.095*	0.166**	-0.020	0.189**	0.182**	0.030
	Sig. (2-tailed)	0.000	0.535	0.000	0.042	0.000	0.668	0.000	0.000	0.519
	N	463	463	463	463	463	463	463	463	463

* Correlation is significant at the 0.05 level (2-tailed)

**Correlation is significant at the 0.01 level (2-tailed)

aversion bias and average risk tolerance (rho = 0.274, $p = 0.000 < 0.05$). Accordingly, the null hypothesis ($H_0$1) can be rejected and the alternative hypothesis (H_a1) can be concluded at the 5% significance level. However, no statistically significant relationship was established between the loss aversion bias and high risk tolerance (rho = 0.084, $p = 0.071 > 0.05$) and between the loss aversion bias and low risk tolerance (rho = −0.020, $p = 0.668 > 0.05$). As a result, for the relationship between the loss aversion bias and high risk tolerance, as well as the loss aversion bias and low risk tolerance, the null hypothesis ($H_0$1) cannot be rejected at the 5% significance level. It can be construed from the above-mentioned findings that individual investors who are subject to the loss aversion bias have a propensity to take average risks. In contrast with this finding, Pompian (2012), as well as Dickason and Ferreira (2018a), found that individual investors who are subject to the loss aversion bias have a propensity to take low risks.

Regarding the relationship between the regret aversion bias and individual investor risk tolerance, Table 9 illustrates small, positive statistically significant relationships between the regret aversion bias and high risk tolerance (rho = 0.184, $p = 0.000 < 0.05$), the regret aversion bias and average risk tolerance (rho = 0.126, $p = 0.006 < 0.05$), as well as the regret aversion bias and low risk tolerance (rho = 0.189, $p = 0.000 < 0.05$). Consequently, the null hypothesis ($H_0$1) can be rejected and the alternative hypothesis (H_a1) can be concluded at the 5% significance level. The above-mentioned findings indicate that individual investors who are subject to the regret aversion bias have a propensity to take high, average and low risks. However, Pompian (2012), as well as Dickason and Ferreira (2018a), found that individual investors who are subject to the regret aversion bias have a propensity to take average risks.

Concerning the relationship between the mental accounting bias and individual investor risk tolerance, Table 9 shows a medium, positive statistically significant relationship between the mental accounting bias and average risk tolerance (rho = 0.309, $p = 0.000 < 0.05$). There is also a small, positive statistically significant relationship between the mental accounting bias and low risk tolerance (rho = 0.182, $p = 0.000 < 0.05$). As a result, the null hypothesis ($H_0$1) can be rejected and the alternative hypothesis (H_a1) can be concluded at the 5% significance level. However, no statistically significant relationship was established between the mental accounting bias and high risk tolerance (rho = 0.065, $p = 0.163 > 0.05$). Consequently, for the relationship between the mental accounting bias and high risk tolerance, the null hypothesis ($H_0$1) cannot be rejected at the 5% significance level. It can be concluded from the above-mentioned findings that individual investors who are subject to the mental accounting bias have a propensity to take average and low risks. Nonetheless, Pompian (2012), as well as Dickason and Ferreira (2018a), found that individual investors who are subject to the mental accounting bias have a propensity to take low risks.

With reference to the relationship between the self-control bias and individual investor risk tolerance, Table 9 illustrates a small, positive statistically significant relationship between the self-control bias and average risk tolerance (rho = 0.262, p = 0.000

< 0.05). Thus, the null hypothesis ($H_0$1) can be rejected and the alternative hypothesis (H_a1) can be concluded at the 5 per cent significance level. Conversely, no statistically significant relationship was established between the self-control bias and high risk tolerance (rho = 0.010, p = 0.825 > 0.05), as well as between the self-control bias and low risk tolerance (rho = 0.030, p = 0.519 > 0.05). Consequently, for the relationship between the self-control bias and high risk tolerance, as well as the self-control bias and low risk tolerance, the null hypothesis ($H_0$1) cannot be rejected at the 5% significance level. It can be construed from the above-mentioned findings that individual investors who are subject to the self-control bias have a propensity to take average risks. Contrary to this finding, Pompian (2012), as well as Dickason and Ferreira (2018a), found that individual investors who are subject to the self-control bias have a propensity to take high risks.

5. CONCLUSION

Behavioural finance is a fundamental component in the investment decision-making process of individual investors, as it largely influences investment performance. Individual investors' attitudes and behaviours are not constantly rational because their investment decisions are influenced by cognitive and psychological errors. In a behavioural finance context, individual investors should take into consideration their likely reaction towards known risks, and particularly unknown risks, to acquire a comprehensive depiction of their risk tolerance. If individual investors are able to comprehend and measure the risks they are taking, the results from their investment decisions can be accepted.

Firstly, this study aimed to identify the behavioural finance biases that drive individual investment decisions. The findings from the study indicated that most individual investors specified that they somewhat agree that their investment decisions are driven by a particular behavioural finance bias. However, the contrary was true for the anchoring bias, as most individual investors specified that they disagree that their investment decisions are driven by this behavioural finance bias. Thus, it can be inferred that the investment decisions of individual investors are driven to a rather great extent by the behavioural finance biases. It was also established that the investment decisions of individual investors are driven to the greatest extent by the self-control bias. This was followed by the availability bias, the representativeness bias, the mental accounting bias, the gambler's fallacy bias, the loss aversion bias, the overconfidence bias and the regret aversion bias. However, the investment decisions of individual investors are to the smallest extent driven by the anchoring bias.

Secondly, this study aimed to establish the relationship between the behavioural finance biases and individual investor risk tolerance. Table 10 provides a summary of the behavioural finance biases that individual investors are subject to based on their risk tolerance levels. Based on the findings in Table 9, the behavioural finance biases are ranked according to the strength of their relationship with the respective risk tolerance categories in Table 10.

In view of the high risk tolerance category, the strongest relationship was established between the overconfidence bias and high risk tolerance, which was followed by the gambler's fallacy bias, the regret aversion bias, the anchoring bias, the representativeness bias and the availability bias, respectively. Thus, high-risk tolerant individual investors are subject to the overconfidence bias, the gambler's fallacy bias, the regret aversion bias, the anchoring bias, the representativeness bias and the availability bias. With reference to the average risk tolerance category, the strongest relationship was established between the gambler's fallacy bias and average risk tolerance. This was followed by the overconfidence bias, the mental accounting bias, the loss aversion bias, the availability bias, the self-control bias, the representativeness bias and the regret aversion bias, respectively. Therefore, average-risk tolerant individual investors are subject to the gambler's fallacy bias, the overconfidence bias, the mental accounting bias, the loss aversion bias, the availability bias, the self-control bias, the representativeness bias and the regret aversion bias. Relating to the low risk tolerance category, the strongest relationship was established between the representativeness bias and low risk tolerance, which was followed by the anchoring bias, the regret aversion bias, the mental accounting bias, the availability bias and the gambler's fallacy bias, respectively. Hence, low-risk tolerant individual investors are subject to the representativeness bias, the anchoring bias, the regret aversion bias, the mental accounting bias, the availability bias and the gambler's fallacy bias. It can be concluded from the findings in the study that individual investors' attitudes and behaviours towards risk are not constantly rational as their investment decisions are influenced by behavioural finance biases.

Table 10: Individual investor risk tolerance from a behavioural finance perspective

Individual investor risk tolerance		
High risk	**Average risk**	**Low risk**
Behavioural finance biases		
Overconfidence	Gambler's fallacy	Representativeness
Gambler's fallacy	Overconfidence	Anchoring
Regret aversion	Mental accounting	Regret aversion
Anchoring	Loss aversion	Mental accounting
Representativeness	Availability	Availability
Availability	Self-control	Gambler's fallacy
	Representativeness	
	Regret aversion	

Given that the role of behavioural finance in the profiling of individual investors' risk tolerance are becoming more prominent, this study provides individual investors, financial planners and investment companies with better insights and comprehension regarding the behavioural finance biases that drive individual investment decisions and the behavioural finance biases that individual investors are subject to based on their risk tolerance levels. This study will also contribute to facilitate the more practical and accurate profiling of the risk tolerance of individual investors to ensure the successful implementation of investment strategies not only within South Africa, but also internationally. It can be recommended for future research endeavours to follow a mixed-methods research approach, by also incorporating qualitative interviews to examine the rationales as to why the investment decisions of individual investors are driven by behavioural finance biases and why individual investors are subject to certain behavioural finance biases based on their relevant risk tolerance categories.

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