Influence of risk propensity, behavioural biases and demographic factors on equity investors' risk perception

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Abstract

Purpose – Investor risk perception is a personalized judgement on the uncertainty of returns pertaining to a financial instrument. This study identifies key psychological and demographic factors that influence risk perception. It also unravels the complex relationship between demographic attributes and investor's risk attitude towards equity investment.

Design/methodology/approach – Exploratory factor analysis is used to identify factors that define investor risk perception. Multiple regression is used to assess the relationship between demographic traits and factor groups. Kruskal–Wallis test is used to ascertain whether the factors extracted differ across demographic categories. A risk perception framework based on these findings is developed to provide deeper insight.

Findings – There is evidence of the relationship and influence of demographic factors on risk propensity and behavioural bias. From this study, it is apparent that return expectation, time horizon and loss aversion, which define the risk propensity construct, vary significantly based on demographic traits. Familiarity, overconfidence, anchoring and experiential biases which define the behavioural bias construct differ across demographic categories. These factors influence the risk perception of an individual with respect to equity investments.

Research limitations/implications – The reference for the framework of this study is limited as there has been no precedence of similar work in academia.

Practical implications – This paper establishes that information seekers make rational decisions. The paper iterates the need for portfolio managers to develop and align investment strategies after evaluation of investors' risk by including these behavioural factors, this can particularly be advantageous during extreme volatility in markets that concedes the possibility of irrational decision making.

Social implications – This study highlights that regulators need to acknowledge the investor's affective, cognitive and demographic impact on equity markets and align risk control measures that are conducive to market evolution. It also creates awareness among market participants that psychological factors and behavioural biases can have an impact on investment decisions.

Originality/value – This is the only study that looks at a three-dimensional perspective of the investor risk perception framework. The study presents the relationship between risk propensity, behavioural bias and demographic factors in the backdrop of "information" being the mediating variable. This paper covers five characteristics of risk propensity and eight behavioural biases, such a vast coverage has not been attempted within the academic realm earlier with the aforesaid perspective.

Keywords Behavioural finance, Risk perception, Factor analysis, Risk propensity, Behavioural bias

Paper type Research paper

1. Introduction

The complex phenomenon called "investor risk perception" is affected by a multitude of factors that fall within the categories of demography (personality traits, age, gender), cognition (heuristics, biases), context (information access) and affection (attitudes, emotions). The study assesses the influence of the dynamics between demography, risk propensity and behavioural biases of the investors on risk perception within a controlled contextual backdrop. This study concurs with Starr's (1969) assumption that individuals carefully evaluate available information before rational decision making. Deconstruction and reconstruction are popular methods in social neuroscience and psychiatric research, they define the nuances pertaining to the theory of mind (Schaafsma et al., 2015). Within the realm of behavioural finance, there have been attempts to deconstruct the influence of psychology in investment decision making which has led to many factors being identified as possible influencers of risk perception. In this paper, the attempt is to conduct a complementary reconstruction of factors that influence investor psychology. This effort to reduce dimensions that have a telling influence on the investor's risk perception can help in profiling individuals in accordance with their risk better. By gaining a deeper understanding of behavioural finance vis-à-vis the risk appetite of the investor, the industry practitioners will be able to enhance their understanding of investor preferences and provide recommendations for investment strategies and products that are better aligned with the investor's risk appetite. This work complements the existing work within the realm of BFMI (Behavioural Finance Micro) that examines the behavioural biases and risk propensity that influence individual investors' decision making, this work identifies those factors which wavers them from being the rational investors as envisioned in classic investment theories (Pompian, 2016; Pompian, 2012).

Conventional wisdom in the stock market world coheres to the "Efficient Market Hypothesis", which stipulates that prevalent stock prices in the financial market incorporate all available information and are the best estimate of intrinsic value (Fama, 1970). Around the same time, "Prospect Theory" took the foreground challenging the expected utility theory and establishing the convexity of losses and prevalence of risk aversion around choices with uncertain outcomes (Kahneman and Tversky, 1979). This study was one of the pioneering efforts in behavioural finance. Bondt and Thaler (1985) evinced the presence of "overreaction", "irrationality" and "loss aversion" among investors; many aspects of their experiment remained inexplicable. Many economic theories are deeply ingrained with the "rationality" hypothesis, this causes severe strain in analysing real-world scenarios. Further, the concept of "rationality" of an individual is influenced by knowledge, market information, and the socio-cultural and economic environment (Arrow, 1986). While expectations of rational behaviour may be warranted during situations where outcomes are certain, the element of uncertainty in financial markets complicates the decision-making process.

According to Bernstein (1996), "risk" is the phenomenon that defines the difference between modern times and the past. However, risks are also viewed as "mental representations of threats" that possess the ability to generate "real losses" (Renn, 1998). The essence of every economic activity is risk and corresponding human reaction. The "theory of choice under risky conditions" cites that the chief problem in making a choice in risky conditions is the dynamism of components in the economic environment, hence the human reaction to vague and ever-changing dispositions is tough to comprehend (Arrow, 1951). Information has been a key catalyst in enabling investors to make rational investment decisions; however, it has been found that the significance of perceived risk is higher than that of actual risk during the decision-making process (Ricciardi, 2008). Studies indicate that investor personality and behaviour biases influence risk perception to a large extent (Sachse et al., 2012; Dickason and Ferreira, 2018).

Risk perception is a complex function of multiple factors that have cross-bearings among attitudes, personality attributes and heuristics. This study attempts to establish a

relationship between these facets and identify the factors which play a pivotal role in the formation of risk perception among stock market investors. The work identifies factors that contribute to the risk perception of investors under – cognitive, affective and demographic categories within the premise of contextual accessibility of relevant information. The factors extracted are grouped and assessed to evaluate their relationship with demographic traits. The risk perception framework is graphically represented based on the findings.

The study uses exploratory factor analysis to extract and group factors within the premise of risk propensity and behavioural bias. Multiple regression is applied to ascertain the statistical significance of the relationship between factor scores (extracted) and collective demographic traits. To gather insight on the possible difference between factor scores across the demographic category, Kruskal–Wallis H test is conducted. The findings iterate the complexity of human neural networks in investment decision making, this is evident from the overlapping of factors across different groups. Multiple regression establishes that there is at least one instance of a statistically significant relationship between factors extracted and collective demographic traits. Kruskal–Wallis H test offers a deeper understanding of the significance of the difference in factor scores across each demographic trait's categories.

The rest of the paper is organised as follows: Section 2 has two sub-sections, one that establishes a theoretical framework and prominent literary works in behavioural finance, and the other that discusses the literary evidence supporting the framework proposed for study, Section 3 outlines the research design and methodology, Section 4 highlights the findings and interpretations, Section 5 outlines the implications of this study and finally, Section 6 provides the conclusion and scope of future research of the study.

2. Literature review
2.1 Theoretical framework and prominent works in behavioural finance
There are various theories pertaining to risk perception within the behavioural finance realm, this is a phenomenon that has evolved and continues to evolve. Bounded rationality theory, proposed by Simon (1972), states that the rationality of individuals is limited by the information available. The other key limitations are the individual's cognitive ability and the response time for decision making. The work by Weber and Milliman (1997) establishes the mediating role of information in decision making under risky situations. The study involved the assessment of risk perception of individuals towards two risky propositions wherein the information was presented differently. From a series of experiments conducted, the work concluded that "informational and cognitive interventions" could help in the creation of realistic risk perception among investors. Risk homeostasis theory proposed by Wilde (1998) observes that risk attitude is influenced not only by macro-economic factors but also by social, cultural and psychological factors. An individual is likely to assume a higher risk if they feel a greater sense of security. This potentially explains the fact that an individual who has planned adequately for his/her financial goals is willing to undertake higher risks on his/her investments that are not mapped to his financial milestones (Bhattacharjee *et al.*, 2021). Shefrin and Statman (2000) proposed the behavioural portfolio theory (BPT) in contrast to modern portfolio theory (MPT). This paper establishes that investment decisions are based on perceived value, emotions, attitudes and behavioural traits. This theory draws inspiration from Maslow's hierarchy of needs theory. Within the BPT framework, individuals make their choice of investment by considering expected returns, downside protection and aspirations. The risk attitudes transform and individuals are willing to infuse additional funds into risky assets as they move up the hierarchy in the financial pyramid. Security-Potential and Aspiration Theory by LLopes and Oden (1999) proposes that individuals align their investment decisions on these criteria. This dual criterion model uses logic and psychological criteria to assess individual investment decision making in risky situations. The study

conducts a series of experiments and juxtaposes its results against cumulative prospect theory and establishes that an individual's risk perception is driven by a combination of logic and behavioural considerations. Dual-system theory, a concept developed by Samson and Voyer (2014) who established that decision making could be affect-based which is carried out automatically and fast, this is often driven by prior experience or familiarity of the individual with the given situation. These types of decisions could also be driven by emotions and behavioural biases pre-dominantly. On the other hand, decisions could be controlled and well-thought if the individual has enough time and information at hand to reflect and analyse before arriving at a decision. This when extended to stock market investing explains the bouts of market inefficiency and irrational decision making among investors. The influence of gender on investor risk perception can be attributed to the gender schema theory of cognitive development, the theory indicates how individuals develop gender-specific characteristics early-on in life, which influences their behaviour and attitude throughout their lifespan. The confluence of socio-demographic factors and rational decision theory has been studied extensively leading to the establishment of the influence of socio-demographic factors on rational decision making (Goll and Rasheed, 2005; Mathanika et al., 2018). Savage (1992) studied the demographic influences on risk perception; the psychometric attitudes towards risk were assessed based on three factors: dread or fear, known risk and personal exposure to risk. The study evaluated the relationship between demographic factors (age, education, gender, race and income) and perception of risky situations. It concluded that women, young people with lower education levels, lower income and blacks were more fearful, as they were less informed about hazardous situations and thus, their tolerance levels towards hazardous situations were considerably low.

These theories have inspired numerous works in the behavioural finance area, there is increased interest among academicians to gain insight into the factors which influence risk perception and risk attitudes of investors.

A study was conducted by Grable (2000), which examined the influence of demography, socio-economic status and attitudes of individuals on financial risk tolerance. Results from the discriminant analysis indicated that domain knowledge, personality traits and socio-economic status had a telling impact on the level of risk tolerance and financial success. Another study conducted to evaluate the effect of salience on men and women, based on scenarios/options concluded that men were more affected by salience. As compared to women, men changed their choices of investment to riskier avenues when the possibility of higher returns was made more apparent. Interestingly, it also concluded that part of the risk difference in gender could be manipulated by orchestrated information (Booth and Nolen, 2012). Survey data that gathered investment risk perceptions from both professional portfolio managers and their clients indicated that there was a high correlation between risk attributes and perceived risk. The prominent factors which influenced risk attributes were potential for downside, lower than targeted returns, investor's ability to control the losses and domain expertise (Olsen, 2014). In an experimental study, individuals' risk perception, information assimilation and stock selection were examined under a series of contrasting financial outcomes. The results indicated that while risk preference is a constant personal disposition, risk perception varied as a consequence to change in situational attributes. To achieve realistic risk perception among investors, information dissemination and other cognitive interventions should be administered. The work mentioned that factors that cause changes in risk perception should be investigated (Weber and Milliman, 1997).

A sample size of 536 was used to study the influence of demographic traits such as gender, age, marital status and behavioural biases (representativeness, availability, anchoring, overconfidence, risk aversion and herding) on financial risk tolerance. It was found that single individuals, young respondents and men preferred investing in risky assets (results concurring with other literary works). Among behavioural biases, representativeness and

overconfidence have a statistically significant impact on the level of financial risk tolerance. The study concluded that financial risk tolerance was influenced by demographic traits and psychological biases (Kübilay and Bayrakdaroğ, 2016). As per the study conducted by Lazányi *et al.* (2017) to ascertain socio-demographic factors influencing risk perception, risk elimination and risk-taking behaviour across 1,141 respondents concluded that gender and age played a significant role in risk attitudes. While men were more willing to take risks as compared to women and young respondents were risk-takers compared to older participants. A study was conducted with the intent of identifying key factors affecting stock market risk perception in the economically backward region of India. By aligning risk perception theories and using confirmatory factor analysis – information screening, investment education, fear psychosis, fundamental expertise, technical expertise, familiarity bias, information asymmetry and understanding of the market, were identified as key factors influencing risk perception (Singh and Bhattacharjee, 2019).

A systematic review by Kumar and Goyal (2018) across three decades concluded that there was a need to study the role of behavioural biases in equity and related markets in a holistic manner. Further, the contributions of credible research from emerging markets were inadequate. A majority of studies in this area were empirical and drew evidence from secondary data. This review indicates that no literature tries to encompass cross-cultural differences concerning behavioural biases. Another recent literature review indicates key limitations in existing studies such as inadequate sample size, studies limited to single/very few biases, work restricted to studying a single demographic trait (particularly gender) and its impact on investment decision making. Out of the 17 behavioural biases listed; a majority of the studies were around only four of the behavioural biases (Zahera and Bansal, 2018).

Based on the above literature review, it is evident that there is scope for conducting a study encompassing a multitude of demographic traits, behavioural biases and aligning them with the risk propensity of individuals to assess the overall influence of various factors on risk perception towards equity and related investments. It is apparent that there is limited work encompassing multiple angles to the investor risk perception problem. This study tries to bring a three-dimensional perspective by analysing the impact of risk propensity of the investor alongside behavioural biases on investment decision making among retail investors given their demographic traits.

2.2 Risk propensity and behavioural biases

As per Oxford Learner's Dictionary (2021), "risk" is defined as "the possibility of something bad happening at some time in the future". Risk propensity in common parlance is the attitude of an individual towards variability in outcomes. According to Hung and Tangpong (2010), risk propensity is a characteristic that influences the individual to take or avoid risks. This is not a static phenomenon, it is constantly evolving and changes with the experiences of the investor. Sitkin and Weingart (1995) indicate that there is a need to place risk perception and risk propensity in a pivotal role in frameworks that involve "risky decision-making". While risk perception referred to the individual's probabilistic estimate of the degree of uncertainty in a situation, risk propensity is the attitude of the individual towards risk appetite. They concluded that risk perception and risk propensity had a direct and mediating impact on the investor's decision. It has been established by numerous academic works that risk propensity is an indicator of individuals' decision making attitude under risky situations (Pablo, 1997; Ghosh and Ray, 1997). While the statistical measure "variance" is used to measure market risk, risk propensity is a far more complex phenomenon to measure.

Risk propensity has been evaluated, in this paper, as a function of five key aspects which define the risk-return objective of an investor. The five factors have been meticulously chosen, as they are inter-linked as evidenced by existing literature.

(1) Return expectations – Investor return expectations have shown a high correlation with past stock market returns, price-dividend ratio and fund infusions by investors into equity-related instruments. These represent the collective belief of expected market returns. Return expectations are related to the risk perception of individuals (Greenwood and Shleifer, 2014).

(2) Diversification/Investment style – In theory, informed and rational investors are required to hold an adequately diversified portfolio. Socio-demographic traits, cognitive bias and financial literacy are known to influence portfolio diversification (Mouna and Jarboui, 2015).

(3) Fund infusion – Investing according to portfolio strategy is important, however, cost averaging is a basic technique to reduce the portfolio risk considerably (Constantinides, 1979).

(4) Time horizon – While there is no empirical evidence in support of a longer time horizon leading to lower risk and enhanced return in equities, it has been evidenced in studies that investors' risk tolerance subjectively increases as the investment horizon lengthens (Jaggia and Thosar, 2010).

(5) Loss aversion – This refers to the investor's appetite for downside in the stock market. Loss aversion has a direct impact on risk perception and consequently on risk tolerance levels (Hoffmann et al., 2015).

Arrow (1951) indicates that "behaviour under uncertainty" is random and its convergence to optimal behaviour is impossible due to the ever-changing environment. However, awareness and conscious efforts can go a long way in rational decision making. Out of the 17 behavioural biases listed by Zahera and Bansal (2018), 8 have been methodically chosen. The nine biases that have been excluded are time-varying and have severe dependencies such as evaluation of key financial milestones (mental accounting), assessment of personality, belief system, immediate (past) metacognitive experiences (conservatism bias, self-attribution bias, regret aversion, recency, house money effect, representativeness). Hindsight bias was excluded from this study, due to its similarity with familiarity and experiential bias. Further, to fully understand hindsight bias, individuals' subjective experiences are critical. Since "information" was considered a mediating variable for this study, framing bias was excluded, the very essence of this bias is to study the influence of investor perception based on the presentation of the information (Grinblatt and Han, 2005; Sanna and Schwarz, 2007). These exclusions are important and have to be studied within a customised framework that tackles the dependencies and longitudinal aspects effectively. The eight biases have been chosen as they can be evaluated independently with a scenario-based questionnaire. The behavioural biases evaluated in this study are listed alongside existing literature.

(1) Overconfidence bias – This is a situation where the investor overestimates financial knowledge and underestimates risk. While doing so, critical information may be ignored which could lead to irrational behaviour (Zahera and Bansal, 2018).

(2) Disposition bias – Shefrin and Statman (1984), evidenced and theorised disposition bias where investors tend to sell winning stocks too early and hold on to losers. Multiple factors such as mental accounting, loss aversion, self-control and tax aspects contributed to such bias.

(3) Anchoring bias – In an experiment conducted by Kaustia et al. (2008) wherein finance professionals and students participated, information was manipulated to ascertain the anchoring bias among participants. The results indicate that the anchoring effect

was "statistically and economically" significant. Although professionals exhibited lower anchoring bias as compared to students.

(4) Experiential bias – Personal experience influences belief formation and decision-making disproportionately. This psychological trait seems to hold ground even in the case of asset pricing, risk perception and other macro-economic aspects (Collin-Dufresne *et al.*, 2016).

(5) Familiarity bias – Also known as home bias, is the tendency of an investor to prefer to invest in stocks or businesses which are local. Information asymmetry could be one of the proxies for such bias among investors (Seasholes and Zhu, 2010).

(6) Herding bias – Herding is often labelled as a "momentum strategy" among institutional investors, who tend to buy or sell stocks that have moved in the same direction in the past (Grinblatt *et al.*, 1995). Individual investors are likely to exhibit herding behaviour by following institutional investors and noise traders (Zahera and Bansal, 2018). This is not essentially backed by a clear exit strategy, often leading to losses when the institutional investors exit their holding.

(7) Loss–Aversion – This factor not only helps in the assessment of risk propensity but is also a behavioural bias that at times leads to irrational decision making among investors.

(8) Status quo bias – Psychology shows ample evidence that individuals stick to status quo disproportionately in a series of decision-making experiments (Samuelson and Zeckhauser, 1988). Investors have often tended to postpone their decision-making in situations involving uncertainty. It has also been observed that loss–aversion influences investors to maintain status quo (Kahneman *et al.*, 1991).

This work does not evaluate the impact of the belief system which influences the formation of these biases. There is scope for studying the influence of an individual's belief system on behavioural biases and risk perception. While there have been efforts to evaluate each of these latent variables independently, the overlapping of factors across risk propensity, and behavioural biases which influence risk perception is undeniable. It may be impossible at times to determine the exact factors which led the investor to take a certain decision in a particular situation. This is a key limitation across all studies related to behavioural finance.

3. Research design and methodology
This is a descriptive study to gain a deeper understanding of factors that influence risk perception in equity investors and the underlying relationship between these factors. The study used the non-probability, convenience sampling method. This method was chosen due to the socio-demographic dimensions associated with the participants in equity investing. This sampling method has also been used extensively in behavioural finance-related studies (Al-Tamimi and Kalli, 2018; Baker *et al.*, 2018). This method facilitates a fair representation of investors across gender, culture, belief systems, nationality and level of expertise. The sample not only represents complex and layered interactions between demographic, socio-cultural and behavioural factors, it also represents varied macro-economic ecosystems, diverse investment environments and regulatory frameworks. Convenience sampling has been found to help in achieving a range of attitudes, and perceptions which can be used for rigorous research. It remains one of the most sought-after sampling methods in social sciences, including literary works in the behavioural finance area (Jager *et al.*, 2017; Galloway, 2005). As per Ramsey and Hewitt (2005), a representative sample can be collected only if the data

quality objective is clearly defined. The data quality objective was defined based on the wide variety of investors participating in equity markets across emerging and developed markets. However, the sample so collected is limited by the time at which it was collected and the circumstances under which the participants responded. To understand the landscape of retail participants in the stock market, multiple reference points across major economies were studied. In the UK stock market, there has been a strong increase in retail investor activity on prominent trading platforms. It is estimated that ~25% of small-cap and mid-cap stocks listed on the London Stock Exchange (LSE) are owned by retail investors (ShareSoc, 2021). The US equity markets show a trading boom among individual investors who are reshaping the US stock markets. The trading activity in individual accounts has seen the highest spike in the past 10 years. In the first 6 months of 2021, the retail investors accounted for approximately 20% of market share volume in the US stock markets. As per Parker and Fry (2020), the individual investors in the US stock market had representation from age groups <35 years to 65+ years. The quantum of investment in equities was mostly proportional to the family income. The majority of households had equity investments, especially those which were headed by young adults (<35 years). Almost 88% of the families with over $100 K annual earnings had investments in the stock market (Osipovich, 2020). As per NSE (2021), the Indian markets are dominated by retail investors who represent ~45% of the volume in equity market share. There has been a paradigm shift in terms of market movers, the FIIs (Foreign Institutional Investors) and DMFs (Domestic Mutual Funds) that were once considered to create the extreme market volatility have taken a backseat. The retailers have become the new market movers. There has been a resurgence in the young investors in India, with a sharp rise in the age group of 18–36 years turning to stock markets for investments. With new-age tech platforms, the penetration into smaller towns, where individuals are predominantly self-employed has increased. The representation of women investors in equity markets, despite a reasonable increase, continued to be lower than their male counterparts (Kelkar, 2022; Dave and Mascarenhas, 2022). The criteria for participating in the survey were: Age> 18 years, good understanding of equity/related investments and/or an avid investor in equity/related investments. The sample is representative of the retail investor participants who trade in equities and aligns with the detailed market participant landscape study that was conducted across economies; it covers the age group of 18 years–66 years. Market participants include individuals with varied economic backgrounds (based on the source of income) and investment expertise (experience in equity investing). Respondents belong to a variety of employment backgrounds, suggestive of their income source. This study includes a variety of employment types such as student, salaried, self-employed (freelancer and business income), home-maker and others. The respondents varied across levels of investment expertise – beginners, intermediate and experts, with majority representation by investors at the beginner level (<2 years of equity investing experience) and intermediate level (2–10 years of equity investing) experience. To overcome the cultural/geographic bounds, the paper was circulated to emerging markets and developed markets alike. Country in the dataset refers to the location of residence of the respondent, it also refers to the local capital market easily accessible for equity investing. The sample was gathered from Asia (40%), Europe (42%) and other continents (America and Australia – 18%). Within Asia, respondents were from India, China, Korea, Malaysia, Pakistan, with a predominant representation from India (75% of Asian respondents). For Europe which formed 42%, the majority of the representation was from England (39.4%), the Netherlands (14.4%) and Germany (7%). The paper also attempts to bring to the forefront cross-cultural undercurrents by collating data from across developed and emerging economies. A total of 319 responses were received, 4 responses were excluded due to incomplete/incorrect demographic (age, expertise) information. Hence, a sample of 315 is considered for this study. The survey method was used to collect data via the face-to-face method, telephone and social media.

Secondary data from journals, books, official reports, etc. was used to substantiate the study. The data was collected over a two-month timeframe.

3.1 Demographic spread of sample
The total sample of 315 saw 42% representation by male respondents and 35% by females. Around 23% of respondents preferred not to disclose their gender. Almost 79% of the distribution represented the age group <35 years – 42% of the respondents were from Europe and 40% from Asia. 45% of the respondents were salaried and almost 38% chose their employment category as "others". A significant part of the sample was constituted by individuals who were either beginners (73% – equity/related investment experience of <2 years) or at an intermediate level (24% – equity/related investment experience of >2–10 years) concerning expertise in equity investing. Only a marginal 3% rated themselves as experts (equity/related investment experience of 10+ years) (see Figures 1–3).

The key limitations of this study were that the data was collected during the pandemic, and the stress on individuals and the economy was significantly high. The responses could have been influenced by such stress levels. The demographic representation is inequitable across geography, minority, ethnicity, urbanicity, etc. The authenticity of the respondents' claims (self-declaration) of being equity enthusiasts and their ability to understand the dynamics of markets was not verified/testified by any means.

3.2 Questionnaire preparation
A structured questionnaire with three parts – demographic details, investment objective (to ascertain risk propensity) and information assimilation (to assess behavioural biases), was
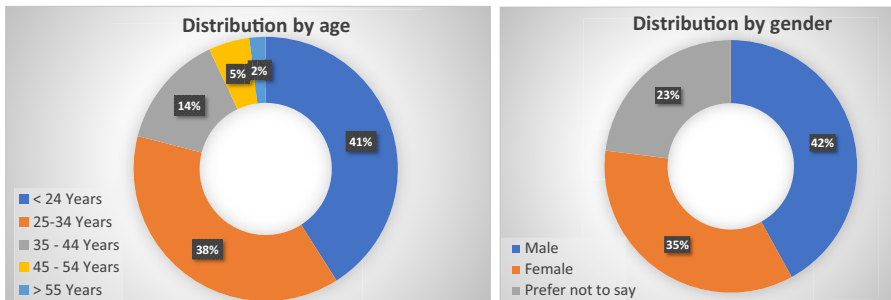

Figure 1.
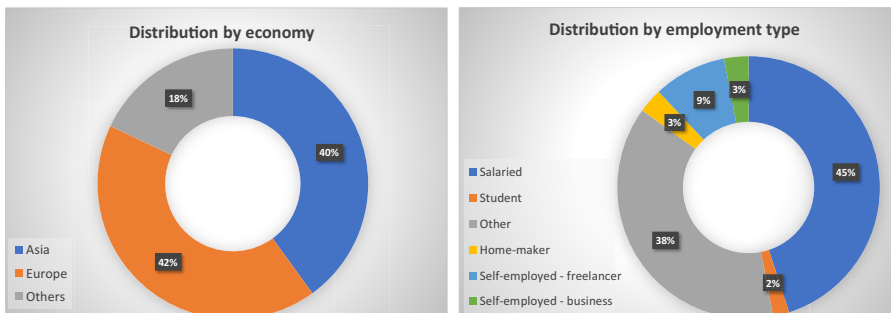Demographic
distribution by age and
gender

Figure 2.
Demographic
distribution by country
and employment type

prepared to collect information for the study. The questions were prepared after a rigorous study of existing literature which has used the questionnaire method to conduct studies relating to investment risk perception/risk attitudes. However, the questions were modified to align with the premise of the current research paper. It was observed that many existing works had questions that were verbose and laced with jargon. This questionnaire was simplified to be easily understood by a wide variety of audiences and the time spent on the questionnaire was minimised to encourage wider participation. An expert panel evaluated the questionnaire, based on feedback the questions were revised to eliminate jargon and any ambiguity. This questionnaire was pre-tested with a sample of 54 participants and based on the responses received, it was used for collecting additional samples for the study. Teijlingen and Hundley's (2002) article on "The importance of Pilot Study" was used as a reference point. Refer to the questionnaire in Appendix (see Figure 4).

3.3 Methodology

This study intends to use factor analysis, however, before extraction of constructs, there is a need to measure the depth of collinearity, sample adequacy and data suitability for factor analysis (Yong and Pearce, 2013; Taherdoost *et al.*, 2014; Burton and Mazerolle, 2011).

3.3.1 Determinant of correlation matrix. While interdependence among explanatory variables is expected in social analyses, multicollinearity can be a problem. The determinant of correlation matrix is a value between 0 and 1, if the determinant is greater than 0.00001, there is no multicollinearity. In such a case, factor analysis can be used for the dataset (Field, 2005; Rockwell, 1975).

3.3.2 Kaiser, Meyer, Olkin (KMO) measure of sampling adequacy (MSA). The sampling adequacy of the dataset can be assessed using KMO, the value ranges between 0 and 1, a value greater than 0.5 is considered conducive for factor analysis (Kaiser, 1970; Hair *et al.*, 2016).

3.3.3 Bartlett's test of sphericity. Bartlett's (1950) test of sphericity indicates that the correlation matrix of the dataset is not an identity matrix, the measure uses the chi-square output, the p-value <0.05 (significant) is suitable for factor analysis.

3.3.4 Exploratory factor analysis. Factor analysis is a statistical technique used to reduce a large set of variables into a smaller, meaningful set of variables – also called factors. There are two types of factor analysis – exploratory factor analysis and confirmatory factor analysis. Since there is no existing theoretical model against which the extracted factors can be validated, exploratory factor analysis is used. The number of factors that is likely to be extracted is tough to comprehend, the principal component method is applied for factor extraction. Williams *et al.* (2012) recommend using the principal component method in studies where a prior model, established theory does not exist. This method extricates maximum
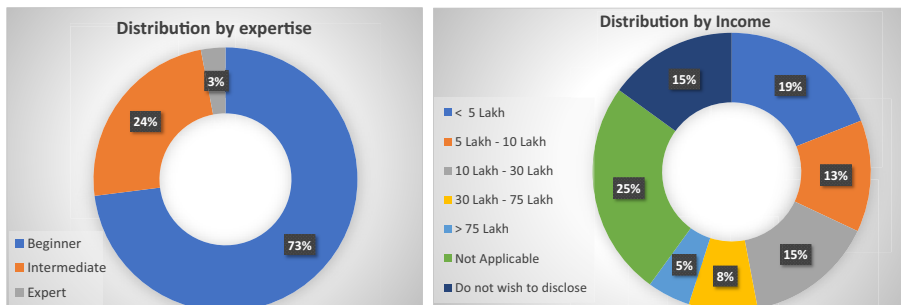
Figure 3.
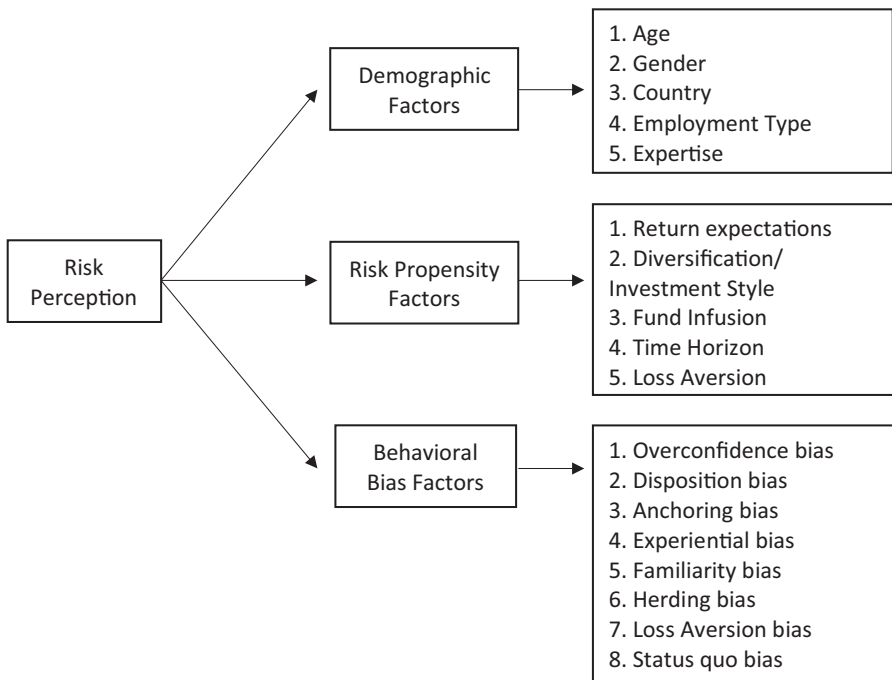Demographic distribution by expertise and income

Figure 4.
Questionnaire pattern

variance and assigns it to the first factor, repeats the process until all the variance is extracted and assigned to the last factor. The number of factors is then reduced based on the Kaiser criterion (eigen value ≥ 1) and Cattell's scree-plot (Yeomans and Golder, 2016; Cattell, 1966). It is important to include an orthogonal rotation technique to make the output more reliable and understandable. The study uses the varimax method, which reduces and groups the number of factors into those with higher factor loadings. This simplifies the interpretation of the extracted factors.

3.3.5 Multiple regression analysis. Multiple regression (MR) is a statistical tool to understand the relationship between a single dependent variable and a group of independent variables.

Equation of MR is given as: $Y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_p x_{pi} + e_i$ Y_i refers to the dependent variable which can be predicted by a set of explanatory variables (independent variables). β_0 refers to the constant, also called intercept, which is the predicted value of Y when all the other explanatory variables are zero. If a model has "p" independent variables, each such independent variable is represented as "x_i" in the above equation which will have its β co-efficient, "e_i" is the error term (Tranmer *et al.*, 2020). In this paper, the purpose is limited to understanding the depth and direction of the relationship between the variables and identifying the demographic factors which have significant loading on the factors.

3.3.6 Kruskal–Wallis H *test.* This test ascertains the difference in average factor scores across demographic categories, it identifies whether the observations have been drawn from identical populations. It can be gathered from existing literature that this is yet another extensively used method of establishing that the factors extracted differ across specific demographic traits in studies dealing with risk perception/behavioural finance (Das, 2016;

Bahovec, 2015; Gultekin and Gultekin, 1983). Kruskal–Wallis *H* Test is the non-parametric equivalent of the one-way ANOVA test. The assumptions of the Kruskal–Wallis test include (Kruskal and Wallis, 1952; Ostertagová *et al.*, 2014) – The dependent variable is measured on an ordinal or continuous scale and the independent variable consists of two or more categorical groups. The sample should possess independence of observations and the distribution is non-normal.

4. Findings and interpretations

The determinant which is a measure of multi-collinearity for the available dataset is at 0.0781, which is higher than the threshold limit of 0.00001, thus making this dataset conducive for factor analysis. The KMO and Bartlett's test affirms that this sample qualifies for factor analysis. The overall MSA is 0.7 for KMO, which indicates the existence of correlation among the observed variables, thereby factor analysis is feasible. Bartlett tests the null hypothesis of a spherical matrix, the *p*-value < 0.05 indicates that there is enough evidence to reject the null hypothesis, hence, factor analysis can be applied to this dataset (see Table 1).

4.1 Factor analysis for risk propensity

Factor reduction is conducted using the principal component method with varimax rotation, the Kaiser criterion and scree plot is used to reduce factors. Factors are extracted for both factor-sets – Risk propensity and Behaviour bias separately (see Figure 5).

Based on the Kaiser criterion (Hair *et al.*, 2016), the eigen value ≥ 1 for the three factors extracted. The three factors explain 69% of the variance amongst themselves. There is no overlap of factors when the cut-off is set at 0.5 (Hair *et al.*, 2016) (see Table 2).

The correlation between the factor groups is negative. There is enough evidence to substantiate that these factors are inter-related. Factor 1 substantiates the linear relationship between fund infusion and investment style. In the case of institutional investors, it has been observed that fund size determines the fund performance, which is, in turn, a function of investment style. Additional fund infusion provided the window to actively manage a portfolio based on the information and achieve higher returns. It is evidenced that value and blend portfolio styles gained higher returns from such active portfolio management as compared to a conservative growth portfolio (Indro *et al.*, 1999).

In the case of factor 2 (Time horizon and Risk tolerance), according to Noussair and Wu (2006), there is a linear relationship between risk tolerance and time horizon, the longer the time period, the lower the loss aversion and hence, higher the risk tolerance level.

Return expectation is a function of multiple macro-economic forces and information (Chen *et al.*, 1986). This is evident from the significant and stand-alone factor loading on factor 3. This factor has been retained to enable further study in relation to macro-economic factors.

Determinant of the correlation matrix	
Determinant score	0.0781
Kaiser-Meyer-Olkin factor adequacy	
Overall Measure of Sampling Adequacy (MSA)	0.7
Bartlett's test of sphericity	
Chi-Squared (χ^2)	780.69
Degree of Freedom	210
p-value(<)	2.22E−16

Table 1.
Determinant, KMO and Bartlett's test

Risk Propensity – Factors
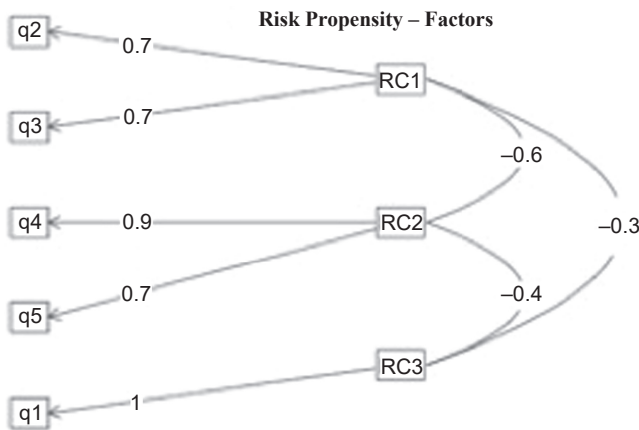
Figure 5.
Factor extraction for
risk propensity

Sl. No.	Question codes	Factors grouped
Factor 1	q2 and q3	Investment style and Fund infusion
Factor 2	q4 and q5	Time horizon and Risk tolerance
Factor 3	q1	Returns expectations
Note(s): *refer Appendix for complete questionnaire with codes		

Table 2.
Factor groups for risk
propensity

4.2 Factor analysis for behavioural bias

Based on the Kaiser criterion of eigen value ≥ 1; 4 factors were extracted. The cut-off was maintained at 0.5, the items were grouped under 4 factors without any overlap (Hair *et al.*, 2016). The 4 factors cumulatively explain 60% of the variance among themselves (see Table 3 and Figure 6).

The correlation between the factor groups is negative, essentially indicating that the increase in prominence of one set of biases (factor group) leads to the reduced presence of other behavioural biases (factor groups).

Overconfidence can be understood as the investor's ability to overestimate the chances of positive outcomes and the underestimation of any downside. Investors who exhibit overconfidence have shown the tendency to trade more often and also indulge in loss-making transactions. While rational theory indicates that investor experience is likely to reduce overconfidence bias, evidence indicates that negative experiences are offset by positive experiences which reinvigorate overconfidence (Manglik, 2006; Seppälä, 2009). Reduced confidence and lower experience often result in loss aversion in investors. Overconfidence bias is more common among experienced investors compared to loss aversion. Both overconfidence and loss aversion bias have a negative impact on stock performance. There is evidence of a relationship between overconfidence, loss aversion and hindsight bias or experiential bias, inline these variables are grouped under factor 1 in the current study (Bouteska and Regaieg, 2018).

Anchoring bias and experiential bias have been grouped under factor 2, these two personality traits could be extremely tough to distinguish since both of them indicate the tendency of individuals to fall back on existing information or experience (Jain *et al.*, 2020).

Experiential bias is also closely related to overconfidence bias, while anchoring bias also correlates strongly with disposition bias.

Disposition bias, herding and anchoring bias have been grouped under factor 3, disposition bias is the tendency of investors to let go of their profitable holdings and hold on to their loss-making stocks. Anchoring bias refers to a form of systematic bias where the forecasts anchor to prior information or previous arbitrary point. Herding refers to the tendency of investors to follow the most prevalent market practice which may or may not be rational. It is cited as a significant bias that causes brief periods of extreme volatility in markets. There is evidence that disposition and anchoring bias re-enforce each other and this triggers a positive sentiment in the market resulting in momentum profit. On the contrary, if both the biases offset each other, positive sentiment diminishes or disappears (Campbell and Sharpe, 2009; Hur and Singh, 2019; Spyrou, 2013).

Familiarity bias loaded on factor 4 on a stand-alone basis, this bias also called home bias has been studied extensively. It can be observed that familiarity bias is the next best alternative to the status quo bias. Familiarity bias could lead to under-diversification and lower potential returns. This could also skew the risk perception of the investors who "fear

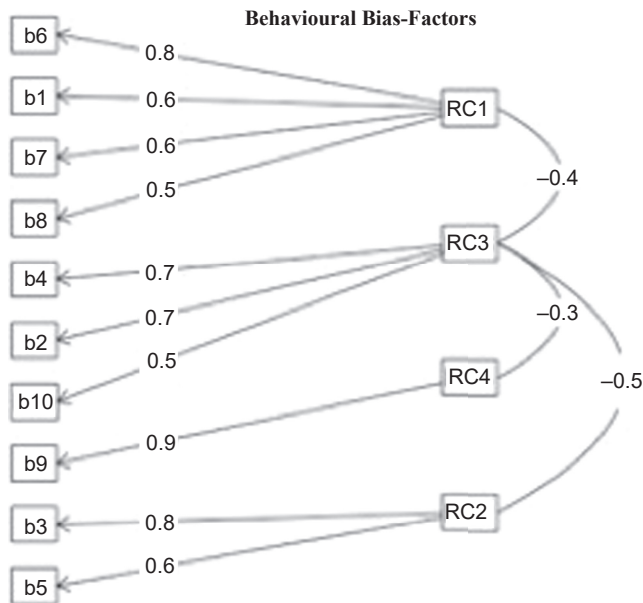| Sl. No.	Question codes*	Factors grouped
Factor 1	b1, b6, b7, b8	Overconfidence, disposition, experiential, loss aversion
Factor 2	b3, b5	Anchoring, experiential
Factor 3	b2, b4, b10	Overconfidence, disposition, anchoring, herding
Factor 4	b9	Familiarity
Note(s): *refer appendix for complete questionnaire with codes		

Table 3.
Factor groups for behavioural bias

Figure 6.
Factor extraction for behavioural bias

the unknown" (Cao *et al.*, 2009). The false sense of comfort in investing or holding on to stocks in the home turf could mean higher risk, if not backed by sound fundamental credentials.

In this study loss – aversion, status-quo and herding bias had lower factor loadings and hence, play a role of lower prominence in the creation of risk perception among investors. There were 1 or 2 items (questions) each that measured the latent variables, however, the correlation among them (items measuring the same bias) was lower as compared to the correlation of each of these items with another item measuring a different latent variable, primarily due to the mediating influencer "information" which was altered to portray favourable/unfavourable investment conditions. This led to an overlap of biases across the factor groups. It merely reiterates that multiple factors (knowledge, assimilation, positive/ negative connotation) influence information processing by investors. There is scope for further study on the implication of type of information on the investor decision-making process within the purview of behavioural finance.

4.3 Multiple regression analysis
The factor scores extracted are evaluated for establishing a relationship with a collection of independent factors. This facilitates the identification of demographic traits which have a statistically significant impact on factors extracted. The co-efficient is indicative of the change in the dependent variable with every unit of change in the explanatory variables. If the explanatory variables' co-efficient is positive, then an increase in the explanatory variable will result in a corresponding increase in the dependent variable. The *p*-value indicates the statistical significance of the co-efficient in reference to the predicted variable (Princeton University Library, 2021).

Table 4 summarises the readings of the demographic factors' influence on risk propensity factors. The *p*-value across Age, Gender, Country and Employment type indicates that the influence on Investment style – fund infusion, time horizon – loss aversion and return expectations remain statistically insignificant. Expertise, which represents the investment experience of investors in equities, is the only demographic trait that has a statistically significant influence on all risk propensity factors. There is enough literature to substantiate the results observed in the current study. Maheshwari and Mittal (2017) in their work observe that age does not have any impact on the financial decisions of the investor. It goes on to conclude that any variations in investment preferences and risk perception thereof can be attributed to varying levels of cognitive abilities. The financial goals, priorities and stage of life were also important variables that determined investment preferences. Another work by Korniotis and Kumar (2011) provides deeper insight that older (by age) investors do not apply investment knowledge effectively, their investment

| | Co-efficient for risk propensity factors | | | | | |
| | Investment style- Fund infusion | | Time horizon-Loss Aversion | | Return Expectations | |
Intercept and demographic trait	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Intercept	0.2635	0.3998	0.3881	0.2220	0.1653	0.6040
Age	(0.0021)	0.9716	(0.0670)	0.2733	0.0413	0.5008
Gender	0.0583	0.4258	(0.0672)	0.3655	0.0070	0.9254
Country	0.0632	0.4193	0.0736	0.3541	0.0956	0.2308
Employment Type	0.0524	0.1701	0.0594	0.1252	0.0234	0.5470
Expertise	(0.4381)	*0.0001*	(0.2873)	*0.0129*	(0.3314)	*0.0044*
Note(s): The values in italics are those that are statistically significant						

Table 4.
Co-efficient for multiple regression

skills are poor, especially if they lack the required expertise. The lower-income group, without relevant financial knowledge and expertise, may also make poor investment decisions. However, older investors' portfolio decisions reflect a higher level of financial knowledge and expertise especially if they have past investing experience. The demographic aspect of gender has been studied extensively, there are conflicting observations in this arena. However, there is enough evidence that substantiates that gender does not determine the quality of the portfolio. In their work, Mazzoli *et al.* (2017) indicate that although gender explains differences in decision making, risk perception and overall portfolio characteristics are primarily driven by differences in behaviour among men and women. The elaborate experiment did not evidence any difference in portfolio liquidity, investment style and return expectations which are primary determinants of portfolio quality. Another study that extended this perception of gender influence on style diversity and fund performance to fund managers, this study aligned with earlier literary works in observing that there were no significant differences in investing style, overall risk distribution and performance between funds managed by men and women (Babalos *et al.*, 2015). The impact of employment type on investing style, risk preferences and portfolio construction has been studied by Ramanujam and Chitradevi (2012) from an Indian context, the study spanned across salaried individuals and entrepreneurs, there was no conclusive evidence of varied investment styles across employment type, however, the study observed that higher income groups had a relatively higher preference to invest in stock markets. The paper also concluded that awareness, knowledge about equities and expertise of the investor influenced the investment preferences significantly. The current study's observation that country or geography does not have a significant impact on investment preferences and risk propensity aligns with a prominent work by Covrig *et al.* (2006). This study compared the stock preferences between domestic and foreign fund managers across 11 developed countries. The findings stated that both groups of fund managers preferred stocks that offered an optimal return on equity, low volatility and large turnover. The study observes that there was no significant difference in the stock preferences among American, European and Asian fund managers. This paper concludes by providing the significant insight that while the geographic location of fund managers did not influence their investment preferences, the mandate influenced the geographic allocations and hence, the stock preferences of the fund. As per Fillinger (2017), financial qualification, knowledge and experience in investing have a statistically significant impact on informed decision making by investors. The study evidenced that expert investors made conscious efforts to diversify and re-balance their portfolios in line with their risk-return profile. They also consider value investing and fundamental analysis as important investment strategies.

Table 5 summarises the readings of demographic factors' influence on behavioural biases. Behavioural bias factors are, influenced by multiple demographic traits. Gender influences overconfidence, disposition, experiential, anchoring, loss aversion and familiarity biases. In a study, by Barber and Odean (2001), a dataset from a large broking house with over 35,000 observations was analysed between the period 1991 and 1997. This research found that men traded 45% more than women, which aligned with the theory that men traded excessively as compared to women due to overconfidence. The findings from MR for overconfidence concur with this disparity in confidence levels among genders. The relationship between disposition effect and gender is a well-established behavioural irregularity, an experiment on stock purchase and sale, conducted across 54 men and 52 women, concluded that subject's gender had a statistically significant impact on this behavioural bias. This study speculates that the variation in disposition effect, among men and women, could be due to the difference in interpretation of changing reference points (Newton *et al.*, 2008). Experiential bias is a relatively less explored behavioural bias, the effect of gender on experiential bias within the investment framework has not been directly evidenced in the past. However, the work by

Madan *et al.* (2017) subtly touches upon this aspect by studying an individual's risk preferences based on described probabilities vis-à-vis experience. The paper finds that extreme outcomes are systematically overweighted in the memory of individual. Depending on the type of extreme outcomes the investor has experienced, the risk preferences could vary. Thus, indicating that experience could play a significant role in investment and risk preferences. Further, there is enough evidence to indicate that investment experience is critical for confidence levels and gender dictates confidence levels, by using this premise and the findings from the present study, it can be gathered that gender impacts experiential bias. The studies in the field of psychology/medicine are indicative of the difference in the manner experience is handled by men and women (Mishra and Metilda, 2015; Barsky *et al.*, 2001). Lee *et al.* (2013) surveyed 84 subjects with finance and accounting educational backgrounds to assess the behavioural biases exhibited by men and women whilst engaging in investment decision making. The work involved studying the stock selection process and portfolio performance of men and women. The findings of the study stated that there was a statistically significant difference among gender in anchoring bias and loss aversion. Both these biases were significantly higher in the case of female participants. Another study that aligns well with the findings of this study is the one by Elizabeth *et al.* (2020) where they observe that gender has a statistically significant influence on overconfidence, age on disposition effect, however, the aforesaid study contradicted the study by Banerjee *et al.* (2018) which concluded that demographic factors (age, gender, occupation, expertise, etc.,) did not have a statistically significant impact on disposition effect. Familiarity bias has not been extensively explored from the perspective of equity investing, however, a study analysing familiarity bias with respect to house price movements indicated that demographic characteristics including gender, age, marital status and education have a statistically significant impact (Seiler *et al.*, 2013). Banerjee *et al.* (2018) observed in their work that age was the only major influencer in many of the behavioural biases including overconfidence and familiarity bias. Inline, our study also observes that age has been an influencer across many behavioural biases including overconfidence, disposition, anchoring, herding and familiarity biases. In addition, the study conducted by Saxena (2020), indicated that age was one of the important influencers of overconfidence and loss aversion bias. Investors above the age of 26 years were more prone to overconfidence and that confidence, in general, was directly proportional to age. Loss aversion was found to increase as one ages, the paper concluded that the investors aged 26 years and above made better investment decisions. Age is not a proxy for investor expertise, hence, many studies have not been carried out with age as a sole determinant of investor's behaviour bias. However, studies have indicated that a combination

Intercept and demographic trait	Overconfidence/ disposition-experiential-loss aversion		Anchoring-experiential		Overconfidence/ disposition-anchoring-herding		Familiarity	
	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Intercept	0.084	0.789	(1.072)	*0.001*	0.405	0.199	0.569	0.070
Age	(0.093)	0.121	0.101	0.091	(0.122)	*0.045*	(0.150)	*0.013*
Gender	0.284	*0.000*	0.279	*0.000*	0.078	0.292	0.064	0.382
Country	(0.093)	0.233	0.073	0.342	(0.153)	0.053	(0.032)	0.686
Employment type	(0.066)	0.081	(0.093)	*0.014*	0.068	0.078	0.029	0.447
Expertise	(0.113)	0.317	0.391	*0.001*	(0.224)	0.051	(0.332)	*0.004*

Note(s): The values in italics are those that are statistically significant

Table 5.
Co-efficient for multiple regression

of demographic factors has an impact on investors' behavioural biases (Oreng *et al.*, 2021). Employment type influences anchoring, experiential and familiarity biases. Research examining, a sample of 73,000 eligible salaried participants, the influence of behavioural biases on 401 k plan allocation concluded that higher salary translated to better decisions, the same study also concluded that women made more informed decisions. Essentially, a stable and high income indicated investment decisions that were free of undue biases (Agnew, 2006). Expertise or investment experience influences anchoring-experiential and familiarity bias. A survey conducted by Goyal *et al.* (2016) with 386 respondents to analyse the influence of behavioural biases on investment decision making. Empirical evidence was established that there was a statistically significant influence of behavioural biases at each stage of investment decision making. This research paper concluded that there were three stages of investment decision making, identifying investment avenues based on their ability to increase their overall wealth, seeking information from public sources and past experiences, make the choice of investment based on an evaluation of the options. Hence concluding that experience is an essential part of investment decision making and can trigger anchoring, experiential, familiarity and other biases (see Table 6).

Multiple regression tests the statistical significance of the relationship between a dependent variable and a collection of independent variables. Interestingly, country was the only demographic trait that did not influence any of the factors.

H0. None of the collective independent variables have a statistically significant relationship with the dependent variable

H1. Collective independent variables have a statistically significant relationship with the dependent variable in at least one instance

F-test in multiple regression test indicates whether any of the independent variables are significant in defining the dependent variable. It establishes that there is at least one instance of a statistically significant relationship between the explanatory variable and dependent variable (Olive, 2017). Evidence indicates that there is at least one instance of a statistically significant relationship between the dependent variable and the collection of independent variables. The investment style-fund infusion variable has a *p*-value of <0.05, which indicates that there is enough evidence to reject null hypothesis. The time horizon – loss aversion variable has a *p*-value <0.05, which indicates that there is enough evidence to reject null

Factor	*F*-statistic	*p*-value	Adjusted R^2	Outcome
Investment style-Fund infusion	4.895	2.51E−04	0.05841	*p*-value<0.05, *enough evidence to reject null hypothesis*
Time horizon-Loss Aversion	2.993	0.01181	0.03075	*p*-value<0.05, *enough evidence to reject null hypothesis*
Return Expectations	2.479	0.03199	0.02301	*p*-value<0.05, *enough evidence to reject null hypothesis*
Overconfidence/disposition-experiential-loss aversion biases	5.283	0.0001131	0.06385	*p*-value<0.05, *enough evidence to reject null hypothesis*
Anchoring-experiential biases	6.622	7.11E−06	0.08217	*p*-value<0.05, *enough evidence to reject null hypothesis*
Overconfidence/disposition-anchoring-herding biases	4.001	0.001565	0.04561	*p*-value<0.05, *enough evidence to reject null hypothesis*
Familiarity biases	4.747	0.000341	0.05631	*p*-value<0.05, *enough evidence to reject null hypothesis*

Table 6.
Multiple
regression test

hypothesis. Return expectations also have a p-value <0.05, thus providing enough evidence to reject null hypothesis. From the earlier tables, it can be gathered that only expertise has a statistically significant influence on these dependent variables. The p-value < 0.05 across overconfidence, disposition, experiential, loss aversion, anchoring, herding and familiarity biases indicates that there is at least one instance of a statistically significant relationship between dependent factors studied and independent variables. The adjusted R^2 which is a measure of the explanatory power of the independent variable, in this study is <10% considering that only a few of the independent factors explain the dependent factors studied. As per Abelson (1985) in social and behavioural sciences, it is quite the norm to see lower R^2, even a minuscule R^2 is considered meaningful if the effect being studied is likely to subsist over the long haul. In the context of psychometrics or prediction of behaviour using attitude measures, the process of variables operating in the real world remains more significant. The lower percentage variance explanation need not be scorned provided the values are above zero and the extent of potential cumulation is significant. Since model fitting is beyond the scope of this paper, there have been no attempts to improve the fit scores. Developing a predictive model using multiple regression tests with the classification of risk profiles can be considered a future research area to explore.

4.4 Kruskal–Wallis test

The factor scores extracted from factor analysis are now evaluated to ascertain if the samples come from a population with the same distribution using the Kruskal–Wallis H Test. They evaluate the difference in mean factor ranks across various demographic categories (see Table 7).

H0. No statistically significant difference exists in factor scores across demographic trait.

H1. Statistically significant difference exists in factor scores across demographic trait.

4.4.1 Interpretation. The variation in time horizon and loss threshold across age groups is statistically significant. There is an evident disparity in investment style and fund infusion across gender, employment type and country. As one would expect investment style, fund infusion pattern, time horizon and loss threshold differ across varying categories of expertise, this is concurrent with the findings from multiple regression analysis. Employment type is the only factor that has a statistically significant impact on return expectations (see Table 8).

Interpretation: There is an evident disparity in all the biases across gender, except for loss aversion, there is considerable variation in all other biases in relation to expertise. Factor scores across all biases (except anchoring bias) differ based on the country of origin of the respondent. There is an evident disparity in familiarity, anchoring and experiential bias across employment type categories. The difference in factor scores due to age was seen only in familiarity bias. The results from Kruskal–Wallis H test mostly validates the findings of multiple regression analysis that risk propensity and behavioural biases vary depending on the demographic personality of individuals. However, the factor scores of investment style, fund infusion and multiple biases differed based on country.

The findings in this paper are restricted due to the scientific limitations of the convenience sampling method. There is a need to apply this risk perception framework to varied demographic samples to assess and generalise the findings.

4.5 Risk perception framework

Based on the findings above, below is a graphical representation of the depth of the relationship between factor groups and demographic traits; their confluence in the creation of investor risk perception (see Figure 7).

Factors	Demographic trait	KW statistic	p-value	Outcome
Investment style-Fund infusion	Age	8.9192	0.06315	p-value> 0.05, not enough evidence to reject null hypothesis
Time horizon-Loss Aversion	Age	34.566	5.70E−07	p-value<0.05, *enough evidence to reject null hypothesis*
Return Expectations	Age	4.7189	0.3174	p-value> 0.05, not enough evidence to reject null hypothesis
Investment style-Fund infusion	Gender	8.2138	0.01646	p-value<0.05, *enough evidence to reject null hypothesis*
Time horizon-Loss Aversion	Gender	3.6381	0.1622	p-value> 0.05, not enough evidence to reject null hypothesis
Return Expectations	Gender	1.0111	0.6032	p-value> 0.05, not enough evidence to reject null hypothesis
Investment style-Fund infusion	Country	22.474	1.32E−05	p-value<0.05, *enough evidence to reject null hypothesis*
Time horizon-Loss Aversion	Country	2.7437	0.2536	p-value> 0.05, not enough evidence to reject null hypothesis
Return Expectations	Country	1.6863	0.4304	p-value> 0.05, not enough evidence to reject null hypothesis
Investment style-Fund infusion	Employment type	14.689	0.01178	p-value<0.05, *enough evidence to reject null hypothesis*
Time horizon-Loss Aversion	Employment type	7.1286	0.2113	p-value> 0.05, not enough evidence to reject null hypothesis
Return Expectations	Employment type	13.603	0.01834	p-value<0.05, *enough evidence to reject null hypothesis*
Investment style-Fund infusion	Expertise	22.97	1.03E−05	p-value<0.05, *enough evidence to reject null hypothesis*
Time horizon-Loss Aversion	Expertise	9.4937	0.008679	p-value<0.05, *enough evidence to reject null hypothesis*
Return Expectations	Expertise	2.167	0.3384	p-value> 0.05, not enough evidence to reject null hypothesis

Table 7.
Kruskal–Wallis test on risk propensity factors

5. Implications

This study evidences the neural complexity of investor risk perception. Certain cognitive, affective and demographic factors have a significantly higher influence as compared to others. Behavioural biases are impacted more notably by demographic factors as compared to risk propensity. However, there is no meaningful correlation identified amongst the factor groups, which indicates the possibility of the dominance of one set of factors in a particular situation.

Among the risk propensity factors – return expectations, time horizon and loss aversion have a higher influence on the formation of investor risk perception (higher factor loadings). Familiarity, overconfidence, experiential and anchoring biases (higher factor loadings) are dominant behavioural biases, they have an imperative and overlapping influence on investor risk perception.

There is a statistically significant relationship between the variables studied, they are critical in the formation of risk perception among equity enthusiasts. Information can be a harbinger in influencing rational decisions among investors. The proliferation of information for equitable consumption among investors can reduce the influence of behavioural biases leading to reduced irrational behaviour. Individual investors should evaluate their heuristics and biases to ensure that these play a minimal role in influencing their decisions. They should also become information seekers to be able to make rational and well-informed decisions.

Factors	Demographic trait	KW statistic	*p*-value	Outcome
Overconfidence/disposition-experiential-loss aversion bias	Age	7.1364	0.1289	*p*-value> 0.05, not enough evidence to reject null hypothesis
Anchoring-experiential bias	Age	8.3211	0.0805	*p*-value> 0.05, not enough evidence to reject null hypothesis
Overconfidence/disposition-anchoring-herding bias	Age	6.905	0.141	*p*-value> 0.05, not enough evidence to reject null hypothesis
Familiarity bias	Age	17.078	0.001867	*p*-value<0.05, *enough evidence to reject null hypothesis*
Overconfidence/disposition-experiential-loss aversion bias	Gender	70.767	4.30E−16	*p*-value<0.05, *enough evidence to reject null hypothesis*
Anchoring-experiential bias	Gender	17.118	0.0001918	*p*-value<0.05, *enough evidence to reject null hypothesis*
Overconfidence/disposition-anchoring-herding bias	Gender	7.338	0.0255	*p*-value<0.05, *enough evidence to reject null hypothesis*
Familiarity bias	Gender	17.279	0.000177	*p*-value<0.05, *enough evidence to reject null hypothesis*
Overconfidence/disposition-experiential-loss aversion bias	Country	12.094	0.002365	*p*-value<0.05, *enough evidence to reject null hypothesis*
Anchoring-experiential bias	Country	1.1148	0.5727	*p*-value> 0.05, not enough evidence to reject null hypothesis
Overconfidence/disposition-anchoring-herding bias	Country	8.3589	0.01531	*p*-value<0.05, *enough evidence to reject null hypothesis*
Familiarity bias	Country	17.271	0.0001776	*p*-value<0.05, *enough evidence to reject null hypothesis*
Overconfidence/disposition-experiential-loss aversion bias	Employment type	3.8387	0.5729	*p*-value> 0.05, not enough evidence to reject null hypothesis
Anchoring-experiential bias	Employment type	13.722	0.01748	*p*-value<0.05, *enough evidence to reject null hypothesis*
Overconfidence/disposition-anchoring-herding bias	Employment type	7.9756	0.1576	*p*-value> 0.05, not enough evidence to reject null hypothesis
Familiarity bias	Employment type	21.425	0.0006731	*p*-value<0.05, *enough evidence to reject null hypothesis*
Overconfidence/disposition-experiential-loss aversion bias	Expertise	5.8953	0.05246	*p*-value> 0.05, not enough evidence to reject null hypothesis
Anchoring-experiential bias	Expertise	8.5974	0.01359	*p*-value<0.05, *enough evidence to reject null hypothesis*
Overconfidence/disposition-anchoring-herding bias	Expertise	8.2721	0.01599	*p*-value<0.05, *enough evidence to reject null hypothesis*
Familiarity bias	Expertise	12.334	0.002098	*p*-value<0.05, *enough evidence to reject null hypothesis*

Table 8.
Kruskal–Wallis test on
behavioural bias
factors

This research work provides deeper insight into the cognitive aspects of decision making
which when aligned to classical economics bestows an enhanced understanding of the
systematic biases which occur in the course of decision making. It provides deeper insight
into the behavioural input variables which need to be considered to build a comprehensive
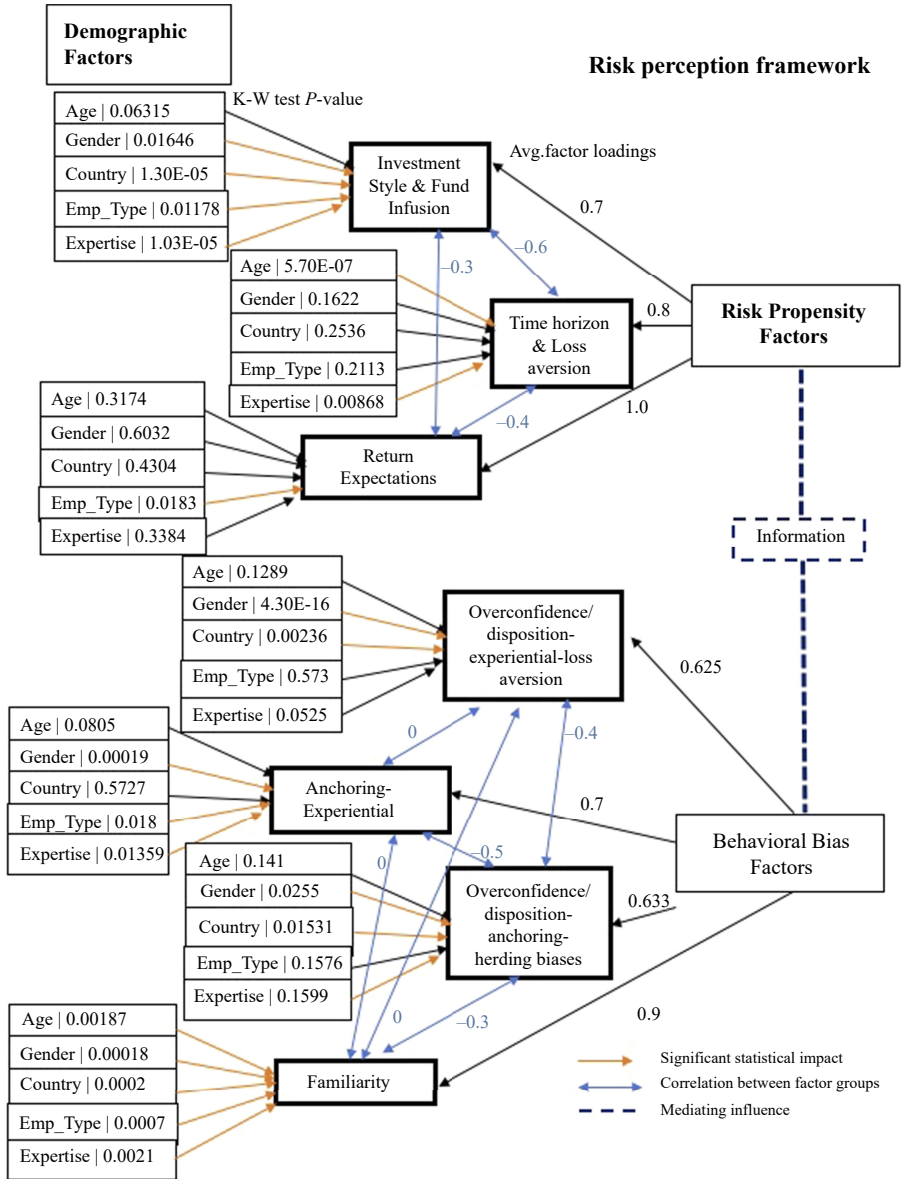
Figure 7.
Risk perception
framework

financial modelling framework for asset pricing. This study becomes even more relevant given the backdrop of data analytics which now has the ability to incorporate and quantify abstractions such as market sentiment and behavioural dynamics. The incorporation of behavioural factors within the asset pricing framework will lead to realistic representation and optimal accuracy. This study emphasizes the need for developing inclusive risk management strategies by investment managers, the ones which evaluate and incorporate

the affective, cognitive and demographic factors which influence the market trend. There is a necessity for governing bodies to acknowledge these factors and take efforts in creating awareness among investors about the influence of heuristics and biases. The onus of equitable and centralised information dissemination also falls upon these governing bodies. The current regulatory market risk controls need to be aligned with the "human element".

6. Conclusion
This framework studies the factors that fall within the purview of cognitive, contextual and affective categories in conjunction with the demographic factors. This three-dimensional study is a unique approach to the behavioural finance realm within the equity markets. The reference for the framework of this study is limited as there has been no precedence of similar work in academia. It also lays the foreground for further exploration by including other behavioural biases and environmental factors. It can also serve as a stepping stone to attaining a meaningful quantitative model which achieves holistic risk management protocols.

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Appendix

To evaluate the risk propensity, five questions were framed to evaluate the objective on various parameters, the responses were designed to align with a 3-point Likert scale (measures: High (+1)-medium (0)-low (−1)).

Question	Options	Latent variable	Question inspired from
q1. What is the primary motive of your investment?	a) Moderately fair returns at minimal risk b) Achieve high returns c) No capital loss, prefer low equity exposure	Return expectations	Risk-return is a time-honoured relationship, investors expecting higher returns are willing to assume higher risk (Malkiel and Xu, 1997)
q2. Which of these statements is more agreeable to you?	a) Buy stocks with a high dividend yield b) Buy different stocks to gain momentum across market cycles c) Strike a balance between opt a) and b)	Investment. Style	Investment style is one of the key detriments of risk-adjusted performance (Lobosco, 1999). Choice of style will determine the quantum of risk an investor is willing to assume
q3. Regarding incremental investment in equity – Which statement best describes your plans?	a) Increase according to portfolio strategy and comfort level b) Only funds which are not required for needs/goals will be invested c) Periodic infusion of additional funds	Fund Infusion	BPT indicates that investors are willing to infuse additional funds into risky assets after taking care of their financial goals (Shefrin and Statman, 2000). Essentially, if they are planning their financial goals using the equity route, they may choose to keep the exposure minimal
q4. You will not access your equity investments for the next 10 years. Do you agree?	a) Fully agree b) Somewhat agree c) Do not agree	Time horizon	Risk tolerance tends to increase as the investment horizon increases. From a portfolio management perspective, long-term is defined as 5–10 years (Hoffmann *et al.*, 2015; Fulton *et al.*, 2012)
q5. If the equity investment took a sharp hit by 20%, what would you prefer to do?	a) Buy more to average the cost b) Ignore or move funds to safer avenues – bonds, bank deposits c) Move funds from risky stocks to less risky stocks	Risk tolerance	The traditional definition of a bear market is a condition where securities fall by 20% or more amidst negative investor sentiment. Downside risk appetite is a key determinant of risk propensity (Quail and Belluz, 2012)

Source(s): Compiled by authors by consulting various sources

Table A1.
Risk propensity questions mapped to the latent variable

For appraising behavioural bias, ten scenario-based questions were framed, and the responses were designed to align with a 5-point Likert scale (measures: Strongly agree to Strongly disagree). The response indicating high rationality was marked 5 and low rationality was marked 1. Every question in this section had a status-quo element which was labelled "Neutral". While some of the latent variables were evaluated with multiple items by altering the mediating influencer "information" which could either be favourable or negative, there were other biases that could be evaluated without multiple items.

Question	Options	Latent variable	Question inspired from
b1. Stock 'A' fell by 25% based on negative news, your investment is in deep red. You continue to hold the stock, in the hope that it will bounce back	a) Strongly Agree b) Agree c) Neutral d) Disagree e) Strongly disagree	Disposition bias/ Overconfidence bias	As per Kaustia (2018), a propensity to sell a stock remains constant over a wide range of losses. This is in line with prospect theory's prediction that propensity to sell a stock reduces as the price moves away from the purchase price in either direction
b2. Your stock 'B' was bought with the intent of gaining x% returns. You have hit the target and happily exit your holding, despite favourable news around the stock	a) Strongly Agree b) Agree c) Neutral d) Disagree e) Strongly disagree	Disposition bias/ Overconfidence bias	
b3. There is negative news around stock 'A', which was bought after intense research. You ignore the news since you have complete faith in your research	a) Strongly Agree b) Agree c) Neutral d) Disagree e) Strongly disagree	Anchoring bias	Psychology states that individual's judgement relies heavily on information to which they have been previously exposed. Investor's often based their future investment decisions on preceding price information (Robin and Angelina, 2020)
b4. You have assessed stock 'B' to be undesirable for your portfolio, however, a trusted source indicates that the stock could see a sharp upside. You have faith in your research, you ignore the news	a) Strongly Agree b) Agree c) Neutral d) Disagree e) Strongly disagree	Anchoring bias	
b5. If the 2008 market crash were to repeat, you would not panic and continue to hold your stocks. You believe markets will rebound like in previous times	a) Strongly Agree b) Agree c) Neutral d) Disagree e) Strongly disagree	Experiential bias	The theory of experiential learning states that future choices are influenced by past experiences. Individuals tend to reinforce past choices with positive rewards and discount past options with negative rewards (March, 1996)
b6. The market correction during the current pandemic was similar to the market crash in 2008 and 1992. Do you agree?	a) Strongly Agree b) Agree c) Neutral d) Disagree e) Strongly disagree	Experiential bias	

Table A2.
Behavioural bias questions mapped to the latent variable

(*continued*)

Question	Options	Latent variable	Question inspired from
b7. Markets are scaling new highs and are overvalued, one could expect a sharp correction in the near future. Do you agree?	a) Strongly Agree b) Agree c) Neutral d) Disagree e) Strongly disagree	Loss aversion bias	Psychologically losses are two times more influential in decision making than gains. There is no standard definition of loss aversion, hence leading to multiple interpretations (Abdellaoui *et al.*, 2007; Ainia and Lutfi, 2018)
b8. Midcap stocks can be rewarding, but there are chances of losing capital as well. Do you agree?	a) Strongly Agree b) Agree c) Neutral d) Disagree e) Strongly disagree	Loss aversion bias	
b9. I would rather invest in the bigger names in the industry – TATA, Reliance, Tier I IT companies etc., than invest in unknown names. To what extent do you agree?	a) Strongly Agree b) Agree c) Neutral d) Disagree e) Strongly disagree	Familiarity bias/ Experiential bias	Individuals on an average have more confidence in home-grown and familiar stocks than unknown/ foreign stocks. Competence and expertise may be a trait that influences this bias (Kilka and Weber, 2010)
b10. Sources seem to indicate that 'Y' sector is likely to flourish in near future. It only makes sense to buy 'Y' sector	a) Strongly Agree b) Agree c) Neutral d) Disagree e) Strongly disagree	Herding	A more realistic risk perception is attributed to less herding behaviour and lower loss aversion. Herding also has a mediating effect on the confidence level of investors (Lin, 2012)

Source(s): Compiled by authors by consulting various sources

Table A2.

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