Elucidating The Behavioral Factors Influencing Investors' Intuitive Decision Making In Pakistan

BY

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DEDICATION

This dissertation is dedicated to My Family, especially to my Parents and Wife, who always believed in me and inspired me to aim higher and succeed.

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MUHAMMAD HAROON RASHEED

ABSTRACT

The study aims to establish a framework for understanding stock market behavior in Pakistan. By deriving on the theories of behavioral finance, a model is established. The study contributes to the existing literature by providing a comprehensive framework regarding individual and stock market behavior and the link between them. The study explores personality traits that make an investor rely on behavioral biases leading towards irrational/intuitive behavior, which then spread to stock markets making them predictable and inefficient.

So in first part of the study, the study established the impact of behavioral factors on stock market return. Behavior of Pakistan's stock market is explored with respect to investor's sentiments and behavioral factors including biases, heuristics and framing effect. The study utilized socionomic theory that considers market sentiments to be a manifestation of individual investors' biased behavior causing predictability. The study used secondary data of the daily return of KSE-100 index from 2008 till 2019 and by applying threshold regression for investor sentiments, overconfidence, availability heuristic, representative heuristic, and disposition effect, it has concluded that investors' sentiments do cause stock market predictability. It is further established that in absence of behavioral biases this predictability fails to exist and market follows a random walk. This empirical evidence established behavioral biases as a significant determinant of return predictability in Pakistan stock market. Making individual investors behavior vital to study for understanding underlying reasons of such behavior. The policymakers can utilize this knowledge to understand the underlying reasons for the stock markets' inefficiency.

The second part of the study focuses on dynamics of individual investor's behavior and established a link between personality traits, behavioral biases, and decision-making style of investors. Utilizing an adopted instrument, primary data from 426 investors in Karachi, Lahore, and Islamabad is considered for final analysis. The results obtained through partial least square based structural equation modelling (PLS-SEM) supported the study's hypothesis main hypothesis and partial support for mediation analysis is established. The findings supported that behavioral biases lead investment decision-making towards irrationality and personality traits can be used to identify the degree of behavioral biases associated with individual investors. This knowledge provided stakeholders with a cause and effect mechanism. Individual investors and brokers can utilize this knowledge to access inclination towards biased behavior and better equip to make a rational decision. Whereas policy makers can utilize this knowledge to protect investors and better market regulations.

Lastly, the study also considered the impact of the demography of investors on their decision-making style. The analysis established support for significant difference among various groups based on marital status, age, investment experience, qualification, and specialization, but support for gender and location can't be established. These findings provided a better contextual understanding of the results and identified groups of investors which are more prone towards intuitive decision making.

Conclusively, this study has both theoretical and practical significance for all the stakeholders. Theoretically, this study provided a comprehensive framework of stock market functioning and practically at individual investor level, this research provided insight into the behavioral factors that affect an investor's rational decision-making process by making it intuitive. This knowledge will also help to understand the decision-making process in a much better way with empirical evidence.

Keywords: Stock Market Behavior, Investor's Decision Making, Behavioral Factors, Personality Traits

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List of Abbreviation

PSX	Pakistan Stock Exchange
KSE	Karachi Stock Exchange
MSCI	Morgan Stanley Capital International
U.S/U.S.A	United States of America
BFMA	Behavioral Finance Macro
BFMI	Behavioral Finance Micro
EMH	Efficient Market Hypothesis
NUML	National University of Modern Languages
BC	Before Christ
UK	United Kingdom
EU	European Union
NYSE	New York Stock Exchange
AMEX	American Stock Exchange
NASDAQ	National Association of Securities Dealers Automated Quotations
CAPM	Capital Asset Pricing Model
CEO	Chief Executive Officer
IPO	Initial Public Offerings
MBTI	Myers-Briggs Type Indicator
NCCPL	National Clearing Company of Pakistan Limited
SPSS	Statistical Package for Social Sciences
AIC	Akaike Information Criterion
JIT	Joint Investigation Report
N/A	Not Applicable

R	Return
V	Volume
OLS	Ordinary Least Square
BLUE	Best Linear Unbiased Estimator
AR	Autoregression
MA	Moving Average
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
VAR	Vector Autoregression
ARCH	Autoregressive Conditional Heteroscedasticity
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
TAR	Threshold Autoregression
EAR	Exponential Autoregression
SETAR	Self-Exiting Threshold Autoregression
SIC	Schwarz Information Criterion
IBM	International Business Machines
SEM	Structural Equation Modeling
ANOVA	Analysis of Variance
AMOS	Analysis of Moments Structure
WHO	World Health Organization
E	Extraversion
A	Agreeableness
O	Openness to Experience
OC	Overconfidence Bias
AB	Availability Bias

RB	Representativeness Bias
DE	Disposition Effect
DM/IDM	Decision Making/Intuitive Decision Making
ADF	Augmented Dickey-Fuller
CBSR	Creative Business and Social Research
AVE	Average Variance Extracted
CR	Composite Reliability
HTMT	Heterograft Monotrait
GoF	Global fit Index
SRMR	Standardized Root Mean Residual
NFI	Normed Fit Index
VIF	Variance Inflation Factor
BCA	Bias Corrected and accelerated

List of Publications:

1- Rasheed, M.H., Rafique, A., Zahid, T. and Akhtar, M.W. (2018), "Factors influencing investor's decision making in Pakistan: Moderating the role of locus of control," *Review of Behavioral Finance*, Vol. 10 No. 1, pp. 70-87. https://doi.org/10.1108/RBF-05-2016-0028

2- Rasheed, M. H., Gul, F., Akhtar, M. W., & Tariq, S. (2020). Dynamics of Overconfidence among Stock Market Investors in Pakistan. *International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies, 11*(4), 11A04T:1-11. https://tuengr.com/V11/11A04T.pdf

3- Rasheed, M., Gul, F., Hashmi, A., Mumtaz, Z. (In Press). Predictability of Return in Pakistan Stock Market through the application of the Threshold Quantile Autoregressive Models. *Iranian Economic Review*. https://dx.doi.org/10.22059/ier.2020.76527

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1. Introduction

The stock market is a place where buyers and sellers of financial assets are aggregated to trade equity and debt instruments of publicly held companies. The role of stock market in an economy is to acts as a financing source for business organizations. Stock markets also play several other functions within an economy (Samuel, 1996). Stock market also promote investments and employment through business and economic growth and are considered a gauge for strength and development of an economy. Therefore, the movement of stock market index or market trend represents an economy's economic health. The increase in share price is said to be a sign linked with an improvement in investment environment and considered as a positive sign for the economy, which act as a driver to achieve enhanced growth of companies and eventually leads to sustainable economic growth (Jaswani, 2008). For investors stock market provide a liquid mode of investment and a source for earning profits by taking appropriate risk. Investors of stock market benefits from capital gains and dividend income. Therefore study of the stock market remained a point of vital significance in finance. Throughout literature identification of the factors associated with stock market movement remained a core consideration in the world of finance. Financial theory states that stock markets are efficient but in real world this isn't the case and exists predictability. In their work, Boudoukh, Richardson and Whitelaw (1994) summarized the different school of thoughts existed on the stock market behavior. There are three school of thoughts on the matter. The first school of thought advocated in the studies of Lo and MacKinlay (1990) and Scholes and Williams (1977) also known as loyalists tend to attribute this return autocorrelation to the market frictions. The second school of thought or the revisionist including Fama and French (1988) and Conrad and Kaul (1988) believed this return autocorrelation is due to the variation in the risk factors and the time fluctuating economic risk premiums.

The third school and the view adopted by the current study states that the reason behind autocorrelation in return is due to the psychological factors and the fact that the investors are not perfectly rational. The predictability of returns exit since market participants either over or under-react to the available and often irrelevant information (Xue & Zhang, 2017). There are many biases reported in the prior research that significantly impact the investors' behavior including overconfidence, availability, representativeness, and framing effects etc. (Kudryavtsev, Cohen, & Hon-Snir, 2013; Tversky & Kahneman, 1974; Waweru, Munyoki, & Uliana, 2008). By deriving on to the prospect theory by Kahneman and Tversky (1979) that states that investors behave differently to good and bad news, Veronesi (1999) established that investors are inclined to overact to the adverse information during the period of market flourishing and underreact to the same in the periods of depression. This under-reaction and overreaction to the news lead to the return autocorrelation in the stock market (Bondt & Thaler, 1985). They also believed and attributed the positive autocorrelation to the overreaction in the market, whereas because of the market adjustment to the overreaction, the negative autocorrelation is caused. Herding behavior caused through social interactions causes this autocorrelation to be higher in the stock markets (Amini et al., 2013). This linkage of overreaction and the existence of autocorrelation in stock returns is confirmed by Lewellen, (2002) and Baur, Dimpfl and Jung (2012). Based on the discussion, the current study is focused on investors' sentiments caused by behavioral factors to be considered as a reason for stock market autocorrelation. The behavioral approach is particularly significant to understand because even in a perfectly efficient conditions, investors will still be irrational attributing to their inclination towards behavioral biases.

1.1. Contextual Background

The current study is focused on Pakistan, and so the history of the stock market in Pakistan will be elaborated first, there were initially three stock exchanges of which the

premier was the Karachi stock exchange established in 1949, second-largest exchange was Lahore stock exchange, which came into being in 1970. The last one was in Islamabad, which was established in 1989 (Chakraborty, 2006). These markets continue to trade separately until recently; on 11th January 2016, all these three markets merged to form one market and started operating as Pakistan stock exchange limited (PSX) with KSE 100 as an index.

Pakistan is one of the emerging economies. As reported in Bloomberg, the stock market in Pakistan is the fifth-best performing market globally (Mangi, 2015) and the best performing market in Asia in 2016. Pakistan stock market lately declared to reclaim its status as an emerging market by MSCI (Mangi, 2016), hence is an indicator that Pakistan stock market has rapid accomplishments in improving its overall efficiency and effectiveness (Chakraborty, 2006) and especially when investors around the globe are aiming for such stock markets that are less pretentious by U.S interest rate cycle and to the financial decline in China (Mangi, 2015). For them, Pakistan is an excellent avenue to invest. Pakistan was also among the top five economies for infrastructure investment in 2017 (The News, 2018), offering tremendous opportunities to the investors in the stock market (Morin, 2018) and as investors globally are eyeing Pakistan stock market as their future venture, this study may be extremely relevant for them.

The study of the Pakistan stock market is also essential because most of the prior research focused primarily on individualistic cultures. There are very few studies on the stock market in collectivist cultures like Pakistan, where members are taught to value harmony and solidarity with others (Markus & Kitayama, 1991), and their values, norms, traditions, and family may have more impact on investors as compared to individualistic western cultures and in a much more integrated society like Pakistan. The impact of behavioral factors as dictated by the socionomic theory through social interaction is expected to be much more

than an individualistic culture. Demographically the general level of education, awareness, gender diversity among market participants can also provide unique and useful insights.

1.2. Theoretical Background

In the traditional financial theory of stock market behavior, Fama (1970) classified the stock markets into three forms: weak-form efficient market, semi-strong form efficient market, and strong form efficient market. A weak state of the efficient market reflects all the historical information making the stock completely unpredictable from past prices (Xue & Zhang, 2017). In other words, in a weak-form efficient market, the stock returns follow the random walk hypothesis. The future value of the stock is unpredictable (Chakraborty, 2006). As stated by the theories of conventional finance, investors in stock markets are perfectly rational and wealth maximizer in financial decisions and will prefer the minimum level of risk at any given level of return or will prefer the optimal level of recovery at a given level of risk (Markowitz, 1952). The prices will remain at their intrinsic value but in real-world market efficiency fails to hold due to many factors like market frictions such as transaction cost and limited dissemination of information (Campbell et al., 1997; Cohen et al., 1986; Keim & Stambaugh, 1986) and stock markets movements fail to follow a random walk, resulting in stock market predictability. Researchers from the past four decades are trying to identify those factors which cause such deviation from the standard (Kahneman & Tversky, 1979). The field of behavioral finance attributes this deviation from stock market efficiency and irrationality in investors' decision-making to be caused by behavioral biases. Behavioral finance is classified into two categories behavioral finance macro, which focuses on the overall stock market behavior (BFMA) and behavioral finance micro (BFMI), which study individual investor's behavior. The current study focused on both of these aspects and applied a mixed approach by establishing the impact of behavioral factors on the stock market and then further analyzing individual investors' behavior through a detailed framework.

According to Hong, Torous and Valkanov (2007) and Rapach, Strauss, and Zhou (2013), the frictions of information is an essential factor on the matter of stock market inefficiency, but apart from that, behavioral factors including biases, heuristics, and sentiments which also play their role in stock market predictability by effecting investors decisions (Barber & Odean, 2008; De Bondt & Thaler, 1995; Kahneman & Riepe, 1998; Tversky & Kahneman, 1974) and the prospect theory by Kahneman and Tversky (1979) established that investors do follow a pattern which is not aligned with traditional rational view, exhibiting overconfidence, herding behavior, and other psychological factors. All these factors led investors to inadequate response or overreaction to the available information, resulting in stock predictability from the past data (Xue & Zhang, 2017). As a result, it is evident that the investors do behave irrationally, and their decisions deviate from the way explained by the conventional theories of finance. Behavioral finance explores such behavior and factors and their antecedents causing such deviations from the standard finance theories. It states that investors are prone to several biases, errors, and illusions while making decisions due to a lack of capabilities in processing the complete information available to them (Shefrin, 2007). Shefrin (2007) categorized all these behavioral factors into three categories: biases, heuristics, and framing effects that influence investor's decisions and cause them to deviate from traditional financial theories that eventually manifest themselves in the stock market's movement.

Why these behavioral factors influence investor decisions? According to Feng and Seasholes (2005), investors' prospect towards gain and loss differs from static alterations across investors. Psyche of an investor also has a strong influence on financial decision making in stock markets while deciding a capital investment. That’s why they act in an irrational manner (Zaidi & Tauni, 2012). Sentiments and mind are significant aspects that cause biases in the judgement of investors. Biases can be explained as a predisposition towards mistake (Shefrin, 2007). Investors are inclined towards several biases, mistakes, and delusions while making decisions owing to a absence of capabilities in dispensation of the comprehensive and relevant information available

(Shefrin, 2009). Overconfidence is one of these behavioral factors, and according to Michailova (2010), the most significant and experimented factor among all the factors is focused on the current research. These errors also resulted from mental shortcuts in their judgment, and these shortcuts are also called heuristics (Slugoski et al., 1993). "A heuristic is a strategy that ignores part of the information to make the decision, more quickly, frugally or accurately than more complex methods" (Gigerenzer & Gaissmaier, 2011). Heuristics are the rule of thumbs or shortcuts created in investor conscious that aid investors decide without undertaking the probabilities assessment and then predicting values affiliated with a decision. In general, heuristics are very useful for investors. Still, these can also lead an stockholder to severe and systematic faults in their judgements (Tversky & Kahneman, 1974), triggering them to act irrationally. The reason to consider heuristics for current study is that the effect of these heuristics is not restricted to the laymen only but also the proficient investors (Tversky & Kahneman, 1974). Our main focus in the study is on the availability and representativeness heuristic, which are the most frequently used heuristic in their judgements. Although it's not astonishing if investors use these heuristics in their judgements (Tversky & Kahneman, 1974), what's odd is that the individuals having vast knowledge and lifelong experience also fail to apply their understanding and experience in application of basic statistical techniques for rational judgement and rely on these heuristics for their judgements. Lastly the study also focused on framing effects that include those biases that cause error in decision due to the way the information is presented to them. Investors value losses and gains differently which is the basis of prospect theory presented by Tversky and Kahneman (1974). It is one of the major contribution in the field behavior finance to understand behavior of investors in real world, which defines the behavior biases with the consequence of disposition and also the risk and return paradox (Kahneman & Tversky, 1979). According to this theory risk taking and aversion concerns vary from stock to stock. It elucidates the actions of investor as risk averse when the prior return was above the estimated level of return and risk hunter in case of prior loss (Jegers, 1991). These

individual behavioral factors are then disseminated across stock market as proposed by Robert Prechter through theory of social mood.

After exploring and establishing the influence of behavioral aspects on investor judgement style, this study will also explore personality traits that make an individual prone to using these behavioral factors in decision making, which previous studies failed to be focused on. Investors are influenced by these behavioral factors, as concluded by Kudryavtsev, Cohen, and Hon-Snir (2013). Personality traits are among most significant factors in determining an individual's behavior, which plays a significant role in determining how individuals respond to any information (Sadi et al., 2011). "Personality is the quality or collection of qualities which makes a person a distinctive individual; the distinctive personal or individual character of a person, especially of a marked or unusual kind." This study proposed a model to identify the antecedents of biased behavior by drawing on the personality's disposition approach. Every person has a different situation and desires and differs in personality traits (Nandan & Saurabh, 2016). According to the disposition approach, personality traits of a person shapes their behavioral outcomes/decisions, and financial behavior will also be impacted by the personality traits (Bashir et al., 2013) and there is a substantial link found amongst personality of an investor and behavioral biases in previous studies (Lin, 2011). Earlier studies mainly fixated on the impact of personality traits on their stock market choices (Nandan & Saurabh, 2016) and their intentions. It was suggested by Simon, Houghton, and Aquino (2000) that other factors and settings should be tested that can directly or indirectly affect investor's judgements. There are minimal studies exploring personality traits leading to biased behavior. Hence the purpose of this study is to identify the impact of behavioral factors on the stock market in Pakistan as a whole and to analyze further the impact of behavioral factors, namely overconfidence bias, availability heuristic, representativeness heuristic, and framing effects on investment decision-making

style of investors operating at the stock market in Pakistan and then to link the biased behavior and decision-making behavior style with investors personality traits. The current study's focus is only on the traits that make them prone to irrational or intuitive decision-making style, while also analyzing the impact of demographic variables to obtain a comprehensive and generalizable profile of investor's behavior during investment decision making and its antecedents.

1.3. Research Gap

A well-defined research gap is pivotal for a well-articulated research project. In order to identify research gap for this research study, a literature review of existing and most recent literature is conducted on behavioral biases and its influence on stock market behavior. By exploring the literature it is observed that vast gap exists regarding stock market and individual investor's behavior, especially in context of Pakistan. The table 1-1 below elaborates the most relevant research and their findings. Later the research gaps identified in these studies are discussed in detail.

Table 1-1- Recent Research on Behavioral Finance

Author	Sample	Methodology	Results
Waweru et al. (2008)	All 40 Institutional Investors Operating at NSE	Factor Analysis	The study established that behavioral factors affect the decisions of the institutional investors operating at the Nairobi Stock Exchange.
Kudryavtsev et al. (2013)	41 Portfolio Managers and 305 Investors and Professionals at Tel Aviv Stock Exchange	Correlation Analysis	This study determine active capital market investors exhibit moderate degrees of behavioral biases. The correlation coefficients between the biases are higher for more experienced and male investors.

Zaidi & Tauni (2012)	200 Investors at Lahore Stock Exchange	Correlation Analysis	There is a relationship between overconfidence bias and Personality traits and there is an association between investment experience and bias behavior.
Bashir et al. (2013)	225 Investors, Professionals and Students from several cities of Pakistan	Structure Equation Modeling	The results show that personality traits have a significant relationship with overconfidence, herding behavior and risk taking
Kumar & Goyal (2015)	117 articles from 1980 till 2013 on behavioral biases and investment decision making	Systematic Literature Review	The results show that limited research exist in context to the emerging economies and there is a lack of empirical research.
Nandan & Saurabh (2016)	313 students from India	Regression Analysis	The results established that personality traits are significant determinants of investment intentions.
Xue & Zhang, (2017)	Stock Market Data of Shanghai stock market from 2005 till 2014	Threshold quantile autoregressive model	The results indicate that predictability of stock market in China is determined through investors' sentiments.
Khan et al. (2017)	160 investors in Pakistan and 140 investors from Malaysia	Descriptive and Regression Analysis	The study establish that the heuristics biases influence stock buying behavior of investors in Pakistan and Malaysia
Shah et al. (2018)	143 Investors trading at Pakistan Stock Exchange	Regression Analysis	The study establish that there is a negative influence of overconfidence and heuristics on investors' decision making and perceived market efficiency.
Rahim et al. (2020)	462 stock market investors in Pakistan	Logistic Regression Analysis	The study established that in the post Covid-19 period overconfidence behavior increased in Pakistan stock exchange.
Pokharel (2020)	120 stock market investors in Nepal Stock Exchange	Correlation Analysis	The study established that the behavioral factors influence markets but do not influence investment performance.

Kumar and Goyal (2015), in their study, explored the literature of the past 30 years on the topic. They concluded in their study that in emerging economies like Pakistan the

research in behavioral finance is minimal. Hence, firstly, this study is a step towards filling this disparity in the existing research. They also concluded that most of the empirical research in behavioral research is based on secondary data. This study will also address this aspect, and a comprehensive framework based on the primary mode of investigation is incorporated for understanding individual investor's decision-making. Methodologically all of the studies on the topic focused on either used preliminary data or secondary data. The current study will also address this research gap and is based on a mixed approach regarding data analysis and utilized both primary and secondary data for analysis. The present study has used SMART-PLS based SEM and threshold regression for analysis, and none of the studies on the topic utilized these techniques for analysis. Most of the prior studies relied on non-probability statistical techniques; this study also filled this research gap using a probability sampling technique for sample selection. Qualitatively there is a lack of a comprehensive framework regarding investor's decision-making and stock market behavior. This study filled this gap by proposing a market mechanism initiating from an individual level. The existing literature on the topic is of exploratory nature with focusing on only one aspect of behavioral biases namely biases, heuristics or framing effects with an aim of establishing influence of behavioral factors; this study added to the existing literature by proposing a causal model for individual investors' behavior by including behavioral factors from each category. Lastly, in the existing literature, only the influence of personality traits is reported; this study filled this research gap by proposing and incorporating personality traits as the antecedent of investors' behavior, including biased behavior and decision making. The impact of demographic variables is also vital to contextually understand the findings and their generalizability in other settings and contexts. Most of the studies ignored this fact especially in context of Pakistan, so address this research gap a comprehensive set of demographical characteristics is also incorporated.

1.4. Problem Statement

Given the recent performance of the Pakistani stock market, investors from around the globe are eyeing Pakistan stock market as their future venture, apart from that there is a direct linkage of a stock market with an economy. This link also makes its behavior vital to understand and as it is known that the behavior of stock markets is the direct manifestation of investors' behavior and primarily individual investors' behavior. That's why it's vital to explore and study individual investor behavior alongside stock market, in order to establish a comprehensive understanding of real life stock market behavior. Thus, studying behavioral factors that impact investors' decision-making style at the stock market in Pakistan can provide useful insight for a better understanding of investors and stock market behavior. By deriving from behavioral finance that accepts the role of behavioral factors contrary to the assumption of conventional finance, which considers the action of the investors to be rational and uniform under efficient market hypothesis; the current study focuses on the behavioral and contextual factors and their antecedents that are directly impacting intuitive decision-making of an investor and stock exchange by formulating a study.

1.5. Research Questions

During the study of the literature following questions are raised, which are enlisted below, and the current research is conducted to empirically answer these questions empirically.

1. Are the behavioral biases significant determinants of stock return predictability?
2. Do behavioral biases affect individual investor's intuitive decision-making at the Pakistan stock exchange?
3. Do personality traits of individual investors have an impact on intuitive decision making?

4. Do personality traits of an investor have an impact on the behavioral biases of investor at the Pakistan stock exchange?
5. Do behavioral biases mediate the relationship between personality traits of individual investors and their intuitive decision making?
6. Do demographic variables play a significant role in individual investors' intuitive decision-making at the Pakistan stock exchange?

1.6. Objectives of the Study

In a more explicit statement, based on the problem statement and research questions, this research will focus on achieving the following objectives,

1- To determine the impact of behavioral factors on predictability of the stock market.
2- To examine the relationship between behavioral biases and intuitive decision-making of investors.
3- To examine the relationship between personality traits and the intuitive decision-making of investors.
4- To examine the relationship between personality traits and behavioral biases.
5- To examine the mediating role of behavioral biases between personality traits of individual investors and their intuitive decision making.
6- To analyze the impact of demographic variables on the intuitive decision making of investors.

1.7. Significance of the Study

This study has practical significance for all the investors, managers, financial planners, investment consultants, and policymakers in Pakistan. This study provides a comprehensive framework of stock market functioning. This knowledge provided stakeholders with a cause and effect mechanism. The policymakers can utilize this

knowledge to understand the underlying reasons for the stock markets' inefficient working. The findings of the study related to financial literacy are also useful at a policy level. A higher level of financial literacy is associated with less biased decisions and a stable stock market.

This research provides insight into the behavioral factors that affect an investor's rational decision-making process by making it intuitive. This knowledge will help to understand the decision-making process in a much better way with empirical evidence. These findings will also help investors understand and overcome the irrational behavior and make financial decisions more efficient and rational, hence getting maximum value out of a financial decision. Financial advisors and planners can also use these findings to evaluate investors' type and the investment best suited for them. By analyzing the biasness profile of an investor, they will be better positioned to guide individual investors and make strategies by keeping in view these underlying biases.

The research also focused on personality antecedents that lead to biased behavior and influence the rational decision-making process. The results indicated that personality traits are a significant determinant of biased behavior and irrational decision making. These findings also have implications for all stakeholders. By identifying the personality traits associated with such behavior, policymakers can devise policies based on this framework to safeguard and protect investors' interests and ensure the smooth functioning of the Pakistan stock exchange (PSX). The professional consultants and analysts can use this knowledge to identify the types of investors based on their personality traits and their shortcomings in their decision-making. The individual investors can utilize this knowledge to overcome the irrational behavior based on the personality traits and de-bias there decision making.

As far as the theoretical contribution is concerned, in Pakistan's stock market investors, behavioral finance is a relatively new field. Only a few studies are conducted about the factors impacting investors using behavioral finance. As per the best of our knowledge, none of the previous studies conducted in Pakistan tested the effect of behavioral factors on investment decision making in such a comprehensive manner. Previous studies like studies by Zaidi and Tauni (2012), Bashir, Azam, Butt, Javed, and Tanvir (2013), Sarwar, Mansoor and Butt (2014), and Rasheed et al. (2018) were mainly focused on change on just one aspect of behavior, without linking it to the stock market. The study extended beyond this relationship and also included the personality antecedents that causes such behavior. The comprehensive nature of the framework is novel in its nature, especially in context of Pakistan and further need to be affirmed and tested.

With an increased focus on contextualized studies, culture's impact cannot be neglected while decision-making, especially in developing countries. In collectivist cultures like Pakistan, members are taught to value harmony and solidarity with others compared to European countries where they prefer individual interests (Markus & Kitayama, 1991). Values, norms, traditions, and family can also cause to deviate investors from rational decisions. How investors make decisions changes in collectivist cultures as compared to individualistic culture because the programming of the mind is different in each type of culture (Hofstede, 2006) hence it is important to study collectivist cultures like Pakistan where power distance is also high (Soares et al., 2007), to understand the difference in behavior across different cultures. Prior researchers conducted studies on the impact of behavioral factors on investment decisions primarily conducted in individualistic dominated cultures and the cultures where the power gap was low. This study will also fill this contextual gap in prior studies by exploring the differences among various groups of investors based on demographical characteristics.

1.8. Thesis Structure

The thesis will lead as per the following structure. Followed by the introduction, the next chapter will be the literature review. The next chapter will include a critical study of the stock market's history and behavior and the history of stock markets in Pakistan investment decision making, biases, and personality traits. The study's hypothesis will also be included in this portion of the survey, along with the theoretical framework. Later in the next chapter will be of the research methodology, which provides detail about sample selection, questionnaire, and proxies for the variables and statistical technique which are going to be used for analysis. Chapter four will include the pretesting of the instrument of the study for the survey. The survey results will be reported in chapter five, under the heading empirical analysis and findings. Chapter six will report along with the discussion and interpretation of the results. The ending branch of the study will have conclusions, limitations, and suggestions for future research. After which reference and appendix section will be reported.

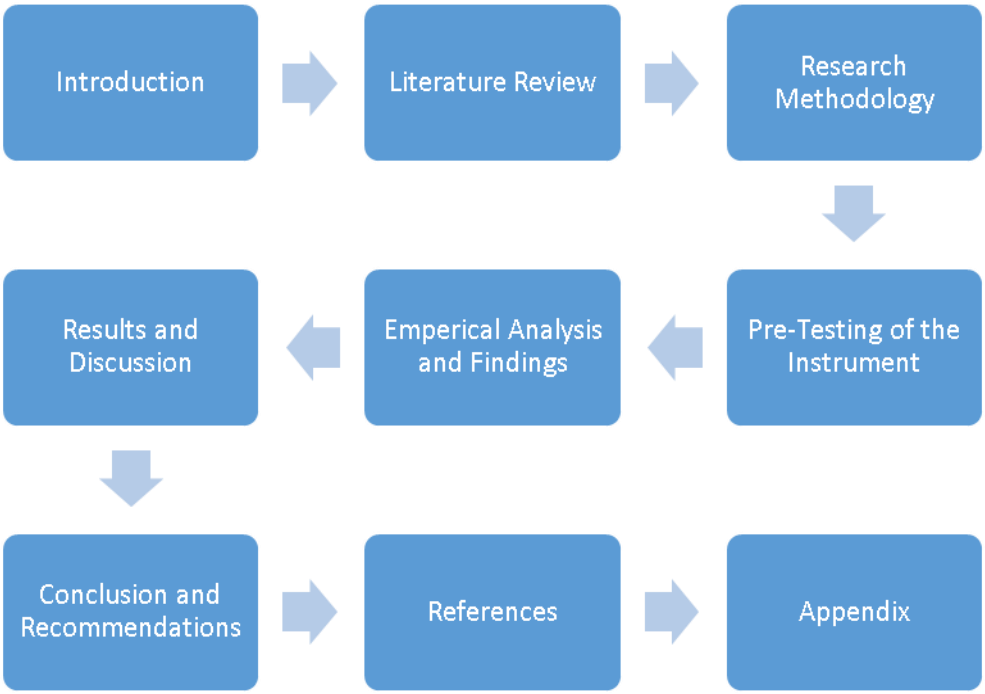

Figure 1-1-Thesis Structure

2. Literature Review

This chapter aims to review the available literature by keeping in view the scope of the study. The chapter will start with selecting underlying theories based on which the study's theoretical framework is established. A detailed conceptual framework is established by deriving these theories and critically examining the relevant existing literature.

2.1. Theoretical Underpinning

The term literature covers all the available data sources relevant to a particular topic, and the literature review is a scientific and systematic search of existing knowledge on a subject (Collis & Hussey, 2013). The literature on a topic is vital in justifying the study objectives and research questions and theoretical and conceptual underpinning on that topic (Bryman & Bell, 2015). The literature review of a specific study also keeps a researcher away from reinventing the wheel by analyzing what is already known about the area of interest, including any research gaps that need to be addressed and then selecting the appropriate and relevant underlying theories (Blumberg et al., 2005; Collis & Hussey, 2013).

According to Gregor (2002), underpinning theories refer to theories that help understand a study's context. The underpinning theory acts as a lens for any survey (Mkhomazi & Iyamu, 2013). The focus of these theories is to express how and why things happen in a particular pattern. Underpinning theories help explain the dependence and relationships existing among different factors and provide direction for data interpretation; hence, underlying theories are critical for data analysis (Mkhomazi & Iyamu, 2013). Although these theories don’t predict the outcome of the study, it only enhances the understanding and helps explain the relationships under study. This particular study relies on the Socionomic theory of finance, prospect theory, and trait theory to infer a theoretical framework in line with its research objectives.

2.1.1. Socionomic Theory of Finance

Socionomic theory refers to studying the social mood in a society and its impact on actions and attitudes. The theory of Socionomic is first to posit by Robert R. Preacher in the 1970s (Nofsinger, 2005). This theory develops a model for the causality of social actions. His theory believes that economics and finance are two separate fields. Since its inception, financial economics followed modern economics as a branch of physical sciences like physics and mathematics, but financial economics cannot isolate complete systems, unlike the physical sciences. Most of the finance is based on Robinson Crusoe Economic, which alienates it from the social network (Nofsinger, 2005). The basis of rationality theory considers the agents as rational entities who decide by keeping in view their own best interest.

This theory is embedded deeply in the field of finance. It acts as a foundation of all other financial theories (Olson, 2006). Similarly, the conventional economic paradigm of stock markets is that securities are rationally evaluated under the efficient market hypothesis (EMH) and remain at equilibrium (Fama, 1970). Still, this theory fails to hold due to many anomalies in the stock market like a mean reversion, excess volatility, and season and other calendrer effects (Prechter & Parker, 2007). This efficient market hypothesis (EMH) theory is further extended to theories like the random walk hypothesis, which states that the stock prices are independent and are entirely random, making it impossible to predict the future. Still, Lo and MacKinlay (2011) pointed out that there is significant evidence that the stock price movement is non-random and prone to deviations and volatilities. The vast overloaded information causes this, the impact of emotions and other behavioral factors, leading to suboptimal or irrational financial decisions. hence it is argued by Lo (2002) that the financial system is not a physical system; instead, it's a social system, which got influenced by social interactions with others, and these interactions lead towards an aggregate social mood in the

society that produces waves of pessimism and optimism. Prechter (2016) is of the view that this social mood is neither conscious nor rational. Traditionally, in socioeconomics, it was believed that social events determine social mood, but the socionomic of finance considers it to be the opposite of that traditional causality. It posits that social events are determined by social mood and not the other way around. The theory of socionomic is based on the paradigm of human interaction. Humans can interact with each other, and because of these interpersonal communication skills, human beings as a race having the ability to respond collectively (Shiller, 1995).

Technology aids its impact by enhancing and improving ways of communication. This human interaction through communication allows the sharing of information and opinions. Persuasive information and opinions influence actions (Nofsinger, 2005). Stock markets also got influenced by interaction, as brokers communicate with investors and other brokers. Financial analysts and fund managers communicate with managers and executives. Institutional and individual investors also form groups and interact with each other, and are influenced by other social actors about investing (Shiller & Pound, 1989). More social people are more likely to get influenced by human interactions (Hong et al., 2004). The impact of behavioral factors alongside social interaction leads to a shared emotional or mental state known as social mood. The economy as a whole is the sum of these social interactions (Nofsinger, 2005). The collective optimism or pessimism in society also acts as the mood for stock markets, and as most of the investment decisions deal in financial predictions. This overall mood impacts these predictions. An optimistic mood leads to overestimating the financial predictions and vice versa.

Similarly, when a change in mood begins among investors in the stock markets, it shifts to all investors through interaction and causes an overall shift in the social mood (Nofsinger, 2005). Unlike the economy, which requires ample time to indicate the impact of social mood, stock

markets can reflect this social mood immediately. Hence according to the socionomic theory of finance, social mood can predict stock market movements. The socionomic theory of finance posits that the stock market works in waves fluctuating from optimistic to pessimistic social mood according to a wave pattern identified by Ralph Nelson Elliott in his Elliot waves principle (Frost et al., 1999). The stock market wave follows limited variations and five specific forms, divided into two categories or phases known as impulse phase and corrective phase; due to the existence of this pattern, these waves are probabilistically predictable and hence also making these social trends in the stock market prices predictable as opposed to the traditional random walk hypothesis. Based on the scoionomic theory of finance, it is stated that the stock market doesn't follow a random walk and can be predicted from past data. This predictability is caused by overall social mood derived from an individual's emotions and behavioral factors.

2.1.2. Prospect Theory

Prospect theory is among the pioneer theories in the arena of behavioral financial management. The idea of prospect theory was first presented by Kahneman and Tversky (1979). This theory attempts to explain how individuals make judgements under the conditions of risk and uncertainty (Miles, 2012). Traditionally it was assumed in finance that investors are sensible and base their judgements on economic principles set under utility theory by considering the risk and return of various available options (Prechter & Parker, 2007). This neoclassical approach to economics has also provided the basis for the efficient market hypothesis (EMH).

In their study, Friedman and Savage (1948) adopted the assumption of rationality as established under Von Neumann and Morgenstern's (1947) study. Still, they concluded that the individuals behave in a manner inconsistent with this assumption of rationality. The

traditional economist considers these violations of rational behavior as anomalies and challenging to make their models valid. Such assumptions completely ignore the chances of irrational exuberance by the investors (Welty, 1971). The prospect theory is of the view that investors are irrational.

The decisions under uncertainty and risk depend upon beliefs regarding the occurrence of an event. These beliefs are expressed in the form of probabilities and outcomes, making them subjective to an individual. Prospect theory attributes these forecasts to using some mental shortcuts or heuristics that make the complex tasks simple. The judgments based upon the evaluations deriving from this heuristic-based analysis are irrational (Kahneman & Tversky, 1979). Markowitz (1952) reported that decisional outcomes could seem like choices among potential losses and gains. Tversky & Kahneman (1974) made this statement basis for their prospect theory. They categorized prospect theory into four, first among which is that when people need to make decisions between different prospects, they evaluate it based on gains and loss regarding some anchoring point (Miles, 2012).

While making decisions, if the prospect is higher than the reference point, it will be considered positive and vice versa. The same prospect of a decision can be positive in some individuals and negative for others, depending on their subjective reference point. The way the information is presented also influence the decisions. If information is presented positively, that results in decreasing its probability to seem like a neutral prospect. Still, if a piece of information is presented negatively, it increases its probability of being considered a neutral prospect (Highhouse & Paese, 1996). This change in decisions based on the way the information is presented is particularly interesting as, under the assumptions of conventional finance, a rational person should consider the impact on their total wealth rather than its comparison with some reference point, and also theoretically, they should be indifferent in their perception of risk to the way information is presented but according to prospect theory

this is the case (Mercer, 2005). The second aspect of the theory is the value function associated with judgement (Kahneman & Tversky, 1979). Prospect theory posits that a decision option is associated with its subjective reference point. The reference point difference is the deviation of that option that can be expressed as positive for gains and negative for losses (Miles, 2012). The curve for losses and gain against reference points is s-shaped and concave in positive deviations/ gains and convex in negative deviations/ losses. The value function is sharper for losses outweighing profits indicating that individuals/investors behave differently to the gain and losses. The third component of the prospect model is risk aversion in possible profits and risk-seeking while facing losses (Kahneman & Tversky, 1979). Investors, if faced with a loss situation, prefer probable loss over a certain loss. The fourth and last component of the prospect theory is investors' tendencies to overweight the outcomes with lower probabilities and vice versa (Rieger & Wang, 2006; Wakker & Tversky, 1993). This contributes to investing in insurance, gambling, and lotteries, where probabilities of a positive outcome are very low, and the principle of rationality dictates otherwise (Kahneman & Tversky, 1979). Hence the prospect theory provided robust quantities evidence that real-life financial decision making does not follow the principle of rationality (Kahneman & Tversky, 1979; Tversky & Kahneman, 1973, 1974; Wakker & Tversky, 1993). Following the prospect theory, Kudryavtsev et al. (2013) and Tversky and Kahneman (1974) concluded that investors operating at stock markets are intuitive, and cognitive and behavioral factors influence their decisions.

2.1.3. Trait Theory

According to personality theories, every individual has some innate preferences under which their actions are determined (Pittenger, 1993). “Personality is the quality or collection of qualities which makes a person a distinctive individual; the distinctive personal or individual character of a person, especially of a marked or unusual kind.” Theories of

personality, including psychodynamic theories, humanistic theories, learning theories, and dispositional theories, attributed an individual's personality to different factors (Phares, 1988). The psychodynamic theories are based on Sigmund Freud's work and attribute an individual's personality to the unconscious and the views, approaches, wishes, and memories in the unconscious when expressed from personality (Freud & Strachey, 1964). The humanistic approach to personality is based on Maslow's (1981) work, which attributed the personality to be motivated by need and suggests that the individuals are evolving with time towards self-actualization. The behaviorism or learning theories approach towards personality is based on Skinner's (1963) work and attributes an individual's personality to determined and void of free will. He argued that genetics and environmental stimuli are the tools that determine and explain the personality. Lastly, the personality trait theory can be traced back to Allport (1937), also named dispositional theories. Researchers of trait theories are interested in the dimension of personality that influences the behavior of a person. The focus of trait theories is on the existence of a difference between individuals based on which they behave differently. These differences or dispositions form the personality of an individual. This theory is a major theoretical area in the field of personality research. The disposition or trait theory of personality is a superficial theory compared to the previous approaches and tries to explain personality straightforwardly. Instead of focusing on clinical observation methods, it focuses on empirical research (Ewen, 2014). Hence the trait theory is compatible and following the scope of the study as compared to other approaches. According to trait theory, personality is a force that determines an individual's behavior, which later transforms into traits (Allport, 1937). Allport (1961) explored the English dictionary comprehensively, and after thorough study and analysis of almost eighteen thousand personality-related words, he concluded with above four thousand adjectives explaining different personality traits. These almost frothy five hundred traits were categorized into three categories, namely cardinal, central, and secondary traits. Still, these extensive traits were way too complicated

and were based on clinical observations. Later, Cattell & Gibbons (1968) used factor analysis to identify the traits of an individual. Cattell's theory, by utilizing factor analysis, identified sixteen different traits of an individual. Still, the said theory was also based on vast research and complex terminology; hence it fails to land significant impact in the field. Still, Cattell's approach based factor analysis were welcomed by the researchers as a much more objective approach to studying personality, which led to Eysenck (1968) contributions on the matter who sought to make trait theory more explanatory by attributing traits to physiological and social variables and concluded with three traits but further studies utilizing factor analysis indicated that five traits constantly emerge in results of the analysis (Ewen, 2014; Phares, 1988). Fiske (1949) was among the pioneers to study Cattell's approach-based factor analysis and concluded with a five-factor solution but fails to interpret the results significantly (Digman, 1990). Later Norman (1963) replicated the study with the five-factor model and concluded that the five-factor classification is adequate for personality traits. Norman further explored the five personality traits and refined the theory. Still, whatever the results are, personality theorists believed that personality traits have a linkage with an individual's behavior. The consistent emergence of five factors in various studies lead them to be called as big five. These big five were the result of forty years of research on personality (Digman, 1990). Although researchers had their opinions regarding the interpretation of these five dimensions of personality, a consensus existed among researchers regarding the big five's explanatory power for an individual's personality. The most studied and explored big five models is first established by Costa and McCrae (1992), which consisted of five dimensions: extraversion, openness to experience, neuroticism, agreeableness, and consciousness. Extrovert refers to individuals' behavior toward others. Such individuals have a habit of developing relationships and tend to be assertive, outgoing, and friendly. The extrovert individual is firm and likes to move with people. The agreeableness trait describes the way individuals respond to information received and is a trait that refers to the propensity of an

individual to comply with others. Highly agreeable people are warm, cooperative, and trusting, lastly, openness to experience is a trait in which an individual has a fascination towards new ideas. Conscientiousness refers to individuals that are persistent, organized, and dependable whereas neuroticism refers to emotional stability and ability of a person to withstand stress (Robbins, 2008) This big five model is most widely used model in social sciences for measuring the personality of an individual is big five personality traits by Costa and McCrae (1992). According to some researchers, all personality traits should be characterized by the big five models (Hogan et al., 1996). As one's personality traits determine its overall behavior, the current study will focus on the big five traits by Costa & McCrae (1992) to examine and determine the investors' biased behavior and behavior at the stock market.

2.1.4. Theoretical Framework

Based on the theories mentioned above, the following frameworks are established to be explored further according to the study's scope.

Figure 2-1-Socionomic Theory

Figure 2-2-Prospect Theory

Figure 2-3-Trait Theory

2.2. Conceptual Underpinning

Conceptual refers to ideas and concepts in mind. Conceptual underpinning utilizes concepts as building blocks for a detailed model based on the theoretical framework considered for the study. There no standardized conceptual framework in a field that can be applied to every study. Each study requires a framework that is derived from established academic disciplines or based on the prior studies having similar scope (Holcomb & Nightingale, 2003); hence it can be inferred that the conceptual models are not discovered; instead, they are created based on the existing literature, and the primary literature sources for the relationships considered under the study consists of articles and books on the field on behavioral finance.

The current research will explore literature by relying on resources available at the National University of Modern Languages and the University of Sargodha and by utilizing different search engines like google scholar and relevant reputed local and international journals of behavioral finance, as these resources are considered more reliable as compared to open sources like Wikipedia. The study will systematically explore the literature by utilizing the funnel approach, starting from an overview and introduction of the field of interest, and then defining the study's direction towards a particular hypothesis (Collis & Hussey, 2013). Initially, the goal was to explore the stock market behavior, but it was such a vast field that the aim was then narrowed down to the influence of behavioral factors.

Similarly, initially, the study aims to explore the impact of personality on the investor’s behavior but later the aim was limited to the personality traits that are theoretically making investors prone to behavioral biases and finally, the most relevant, recent and credible literature to the topic is chosen and reported in the study.

2.2.1. History of the Stock Market

A stock market is where the acquisition and sale of stock are made (Zuravicky, 2005). Going back and tracing the history of financial markets, it is evident that financial events relating to the stock market have also existed in ancient times. The Romans turn out to be the pioneers in this regard by founding corporative establishments in the course of history first of which is known as the forum, which was used not only to raise capital by selling shares to the public but also forbidding government contracts and other cash transactions, The history of which dates back to second century B.C. (Smith, 2004; Sobel, 2000) and by the time of 1000, there is evidence of the existence of markets resembling old Roman markets in Europe also, but as soon as we entered the fifteenth century, these markets refined further. The concept of brokers was introduced in those markets. The commercial revolution that spans from sixteen to eighteen century was the driving force for the boom that resulted in numerous stock markets worldwide (Sobel, 2000). The first active stock market was established in the sixteenth century at Antwerp in Belgium and later in Amsterdam's capital. In the USA, such a market existed for the trading of slaves and corn, established by traders in 1752, an official market was established in the broad street and Fraunces Tavern (Sobel, 2000). In the context of England, the London stock exchange was established by brokers and dealers in 1801. (Smith, 2004). The rapid expansion in stock markets first occurred from 1871 to 1914. By the end of World War 1, there existed eighty-nine stock markets around the globe, of which more than half existed across Europe, and the remaining spread crossed the settlements of European countries. These markets were the hub for almost 20 million investors (Chambers & Dimson, 2016). The recent expansion in the stock markets started after the abolishment of Bretton Woods's agreement in 1973. This trend further accelerated after 1989, and in 2015 there were 189 stock markets existent around the world as reported by the World Federation

of Exchanges, and comparing to their role and significance in the past, the role and significance of stock markets increased multiple folds (Chambers & Dimson, 2016).

2.2.2. Stock Markets in Today's World

In today's world, these stock markets are categorized into three kinds, namely developed, which includes the US, U.K, and EU, etc. These emerging markets include Mexico, India, Pakistan, etc., and lastly, the frontier or pre-emerging markets such as Vietnam and Kenya, etc. These categories are established based on a single criterion: markets' quality (Phuoc Luong and Thi Thu Ha, 2011). Among countries worldwide, the USA is the most influential and powerful economy impacting economies around the globe. Pakistan is one of the emerging economies with the stock market operating as the Pakistan stock market (PSX). In general, Tajaddini, Ahmad, and Masron (2009) found out that stock markets in Asia incline to get influenced by the New York index's control on a daily basis. Whereas, it is also evident from empirical evidence that the major stock markets globally, including the UK, the US, and the EU, are uniting at least over the extended term period, even though the UK and the US marketplaces appear to be less significantly linked to a common trend (Fraser & Oyefeso, 2005).

In other words, the influence and the dependence of stock markets on others are relatively high. Therefore, global issues such as terrorist movements, energy crises, and natural calamities have had a more significant influence on the volatility of all security markets worldwide, specifically in the USA, the UK, and Japan (Fernandez, 2006). From an internal perspective, In a country's economy, along with acting as a source for financing investment, stock markets also have several other functions, including acting as a signaling mechanism to managers regarding investment decisions and a catalyst for corporate governance (Samuel, 1996) but aside from these stock markets are best recognized for being

the best effective source to raise investment for a company (Zuravicky, 2005). The stock market is also considered as the measure for economic forte and expansion. Thus, the movement of the stock market or its trend represents the financial well-being of an economy. The increase in share price tends to be related with the increase in investors trust in the economy, which is indicative of the higher growth rate of a company in specific and an economy in general (Jaswani, 2008). Therefore understanding the stock market's behavior remained a prime focus of research in financial theory. Since the financial crisis that originated in the USA, investors around the globe are considering for stock markets that are less pretentious by the U.S interest rate cycle and the financial slowdown in China; for such investors, Pakistan is an excellent spot to invest (Mangi, 2015), as reported in Bloomberg, Pakistan stock market is the best market in Asia in 2016 and fifth-best performing market globally. Pakistan stock market just recently announced to regain its emerging market status by MSCI. (Mangi, 2016), due to which investors across the globe eyeing Pakistan as their future venture, hence it is of vital significance to study and understand the behavior of investors at the Pakistan stock market and the factors influencing their investment behavior

2.2.3. Stock Market Behavior

According to Fama (1970), stock predictability is not possible based on the historical return in an efficient market. Still, the researchers widely criticized this traditional finance model because there is an apparent autocorrelation and predictability of stock return, as found in the previous research (Amini et al., 2013). In some empirical research on return autocorrelation, Conrad and Kaul (1988) and Poterba and Summers (1988) find that the stock's returns are positively autocorrelated in a short time horizon. MacKinlay (1997) also finds significant autocorrelation of daily, weekly, monthly stock indices in NYSE, AMEX, and NASDAQ.

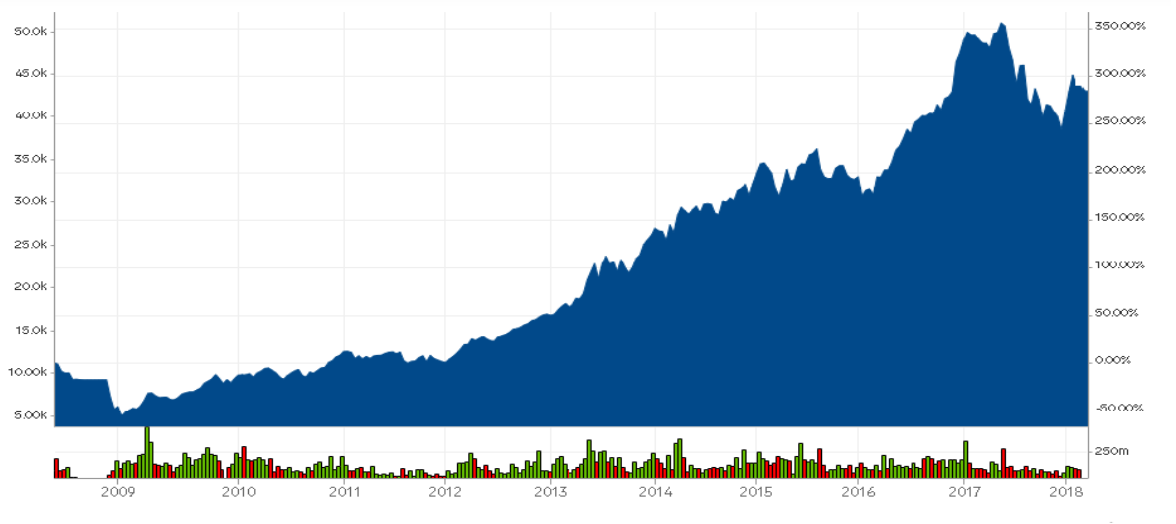

Figure 2-4-KSE 100 Index

The existence of this autocorrelation in stock returns leads to stock return predictability. Kim, Shamsuddin, and Lim (2011) tested this predictability empirically in Dow Jones industrial average index from 1900 to 2009 and finds that this predictability is statistically significant. The predictability of stock exists even during the periods of low autocorrelation (Hudson, 2010). Kinnunen (2013) conducted a similar study and concluded that return autocorrelation is one predictor of market return in Russia. Therefore the return autocorrelation reflects predictability of return (Xue & Zhang, 2017). In the Pakistan stock market (PSX), the likes of Khilji and Nabi (1993), along with Khan and Ahmad (2017), studied the stock return using linear regression models and concluded that return correlation exists in the market. In the research on the comparison of return autocorrelation among developing and developed countries, Harvey (1995) reported that the return correlation and predictability in emerging stock markets like Pakistan is even higher than the developed countries and one school of thought regarding the presence of the said autocorrelation is of the view that the reason behind autocorrelation in return is because of the psychological factors and the fact that the investors are not entirely rational. The predictability of returns exists because investors either over or under-react to the market information due to the influence of cognitive biases (Xue & Zhang, 2017). There are numerous biases identified in

the literature that lead to a systematic pattern causing irrationality in decision-making, which eventually leads to autocorrelation in the stock market.

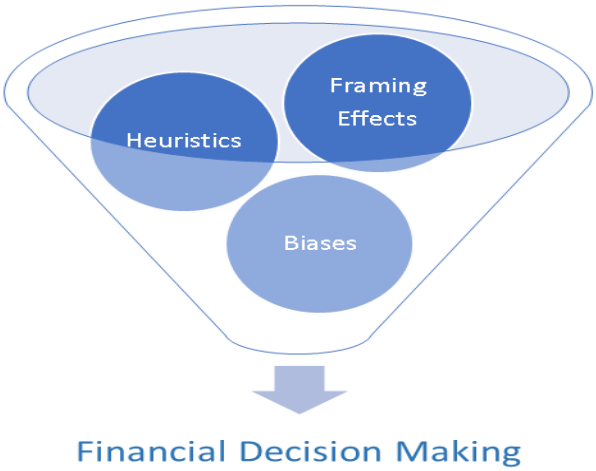

Figure 2-5-Behavioral Factors Categorization (Shefrin)

According to the theory of social mood, human interaction among investors leads towards persuasion of one another. These interactions as a human being also affect the investment decision making under uncertainty by transmitting different emotions based on behavioral factors, which eventually leads to a shared emotion or social mood across the market; hence the collective level of optimism or pessimism in the stock market is derived from these behavioral factors that impact investors decisions (Nofsinger, 2005). According to Kudryavtsev et al. (2013), all the behavioral factors are highly correlated. The presence of one factor implies the existence of all other factors also. There are many behavioral factors reported in the prior researches that established significant impact on the investor's behavior, including overconfidence, availability, representativeness, framing effects, and self-attribution bias, etc. (Tversky & Kahneman, 1974; Waweru, Munyoki, & Uliana, 2008; Kudryavtsev, Cohen, & Hon-Snir, 2013). By deriving on to the prospect theory by Kahneman and Tversky (1979) that states that investors behave differently to good and bad news, Veronesi (1999) established that investors tend to overact to the bad news and underreact to the good news. This underreaction and overreaction to the news lead to the return autocorrelation in the stock market (Bondt & Thaler, 1985). The study by Daniel, Hirshleifer,

and Subrahmanyam (1998) that this autocorrelation is attributed to the overconfidence and self-attribution bias. They believed that positive autocorrelation is due to the overreaction in the market. The negative autocorrelation is caused by the market adjusting to the overreaction, and this autocorrelation is expected to be higher in the presence of another behavioral factor, namely herding (Amini et al., 2013). Which is also a consequence of human interaction as predicted by socionomic theory of finance. This relation between overreaction and return autocorrelation is confirmed in stock markets by Lewellen (2002) and Baur, Dimpfl, and Jung (2012). In their study Khan et al. (2017) analyzed the impact of heuristic biases on investors choices in Malaysia and Pakistan and concluded that these heuristic do impact investors choices. The study Abdin et al. (2017) also identified that investors do rely on heuristics in their decision making. Whereas the studies of Barberis and Xiong (2009) and Dhar & Zhu (2006) focused on analyzing the impact of disposition effect on investors and concluded that disposition effect influence the individual investors trading.

Based on the above discussion, in the current study, firstly our focus will be on verifying the effect of investor sentiments as a proxy for behavioral factors on stock markets predictability or autocorrelation and then by deriving from the findings of the prior literature like the study of Cheng et al. (2021) who concluded that behavioral factors i.e. overconfidence among individuals transmit in their social groups i.e. investors in the stock market and the study of Daniel, Hirshleifer, and Subrahmanyam (1998), who attributed return autocorrelation to behavioral biases i.e. overconfidence, Therefore this study will further analyze the impact of biases on overall stock market as an indication of social mood under the current study's consideration. Hence it is proposed that;

H_1: Behavioral factors are significant determinants of return predictability in the Pakistan stock market.

H_{1a}: Overconfidence driven behavior is a significant determinant of return predictability in the Pakistan stock market.

H_{1b}: Heuristics driven behavior a significant determinant of return predictability in the Pakistan stock market.

H_{1c}: Disposition effect driven behavior is a significant determinant of return predictability in the Pakistan stock market.

2.2.4. Investment Decisions in the Stock Market

Investment is a process of investing money with the hope of getting future benefits. Every investor wants to get maximized returns from investment and to make an optimal investment decision. Sharpe (1964) explained the highest risk level for a specific return level to compare the benchmark decision.

Conventional theories of finance like the efficient market hypothesis (EMH) and capital asset pricing model (CAPM) state that an individual is perfectly rational and a wealth maximizer in their financial choices that include investment decision making (Markowitz, 1952). Thus, standard finance is the knowledge that stands on the pillars like the principles of arbitrage by Miller and Modigliani, the principles of Markowitz about portfolio selection, the capital asset pricing model of Sharpe, Lintner and Black for equity evaluation or the option-pricing theory of Black, Scholes, and Merton (Statman, 1999). Standard finance describes how an investor should behave rather than behavior in the real-world (Zaidi & Tauni, 2012). Conventional finance theories state that when individuals receive some new information, they update their knowledge and rationally choose. Still, when we observe the decision-making in the real world, this is not the case. To understand real-life financial behavior, it is essential to consider some models that consider participants irrational (Barberis & Thaler, 2003).

In real life, the investors do behave irrationally, and their decisions deviate them from the way explained by the conventional theories of finance. In the financial market, managers and individual investors' investment behavior isn't the same as access to the information differs. Managers have superior information than individual investors because investors interpret external factors while making investment decisions. Instead, managers are aware of internal and external as well (Myers and Majluf, 1984).

In past few decades, some researcher was of the view that optimal and rational decision must depend on the knowledge of finance (Merton, 1987) and the concept of bounded rationality prevailed, which states that investment decision can be irrational from the perspective of researcher but can be rational from the investor in their given circumstances and available information (Harrison and Harrell, 1993) but other than that psychological description of investor's mental processes can also play a vital role in decision making (Jaros et al., 1993) and based on this behavioral aspect, another school of thought emerged in 1980's known as behavioral finance in which researchers tried to explain real-life financial behavior by merging theories from psychology and finance (Zaidi & Tauni, 2012), so to answer that, why investors make irrational decisions (Phung, 2010). Comparing the conventional finance theories in which participants are considered rational, behavioral finance assumed them to be expected. Investors are considered to be affected by their psychology and bound to fall to framing effects in their decisions and risk assessment (Statman, 1999). Behavioral finance explained the various factors that influence the rational decision-making process, including cognitive and emotional factors (M. Simon et al., 2000).

Researchers have identified factors that influence the investment process, including returns from previous investments, whether investors' decision influences the firm's policy in which they are going to invest (David et al., 1998), cost of investment, and benefit from the investment. Apart from that, an investor's deviation from the rational decision is also

intended to get higher returns (Cascio et al., 1997). Researchers from the last two decades highlighted some behavioral phenomena of investors' psyche. They defined them as "cognitive unconscious," which is having perceptions, memories, and thoughts without awareness, which is used to describe why sane investors make an error in investment decisions (Hilton, 2001). Investors' thinking and feelings can also significantly impact changing the decision from rational to irrational (Baker and Nofsinger, 2002).

Although decisions based on the availability of information are somewhat reliable, the researchers found that partial or incomplete information can also mislead the investors (MacGregor et al., 2000). Investment preferences and decisions can also be influenced by the nature of securities they want to invest in, whether risk-free or risky (Sanders and Carpenter, 2003). Researchers have also identified that investors react differently when investing in stock options or equity ownership (Certo et al., 2003). Hence, there is no evidence of the unanimous rational behavior as predicted by conventional financial theories. There is a need to study and understand investors' real-life decision-making. According to Shefrin (2009), all these behavioral differences are three factors or behaviors that cause investors to deviate from the rational and to rely on their intuition, which he categorized into biases, heuristics, and framing effects. Although numerous studies like of Kudryavtsev et al. (2013), Tversky and Kahneman (1974) and Waweru, Munyoki, and Uliana (2008) established that investors are influenced by behavioral factors and their reliance on these factors leads to the employment of intuitive decision-making instead of the rational of decision making (Kudryavtsev et al., 2013). Investor are said to be intuitive if they rely on their feelings and sixth sense for making decision, instead of relying on rational analysis of all the relevant information. All the prior studies indicate that investors are not rational instead they rely on their intuition to make financial decision like investments but still, as evident from the prior studies, none of prior

work attempted to empirically link the intuitive decision-making with these factors, which is fundamental to understand this relationship further.

Hence, in the current study, our focus is only on investor's intuitive decision-making, and the aim is to explore the factors that led investors to rely on intuition instead of rational decision-making based on the complete analysis of all the available relevant information hence based on the preceding discussion it is proposed.

H_2: Behavioral biases are significantly and positively associated with the investor's intuitive decision-making.

2.2.4.1. Biases and Investment Decisions

Biases can be defined as a tendency of a person towards the error in judgment. Shefrin (2009) categorized biases into four categories: excessive optimism, overconfidence, confirmation bias, and the illusion of control. Biases are behavioral pitfalls that hamper investor's way of optimal decision making. These are innate attributes of an individual that varies from personality to personality. Each individual will have a different degree to which he will rely on these biases, and these biases generally result in the false calibration of one's abilities and result in investors sticking to their preference and choices instead of a rational one by just simply ignoring the information against their viewpoint or considering their intuition of the market to be superior (Burks et al., 2010). In this study, our focus will be on the impact of overconfidence bias as it is one of the most significantly impacting biases on investors.

According to Skala (2008), overconfidence is under researchers' consideration since the 1960s in psychology. The negative impact of this bias on investors also cannot be denied, as witnessed during the technological bubble of the 1990s in which the investors invested too much in the technological stocks due to their overconfidence that they will have super return

from having concentrated stocks but at the end when the bubble burst, losses incurred (Pompian, 2006). According to Sultana and Pardhasaradhi (2012), these biases' study is crucial as these factors impact investment choices. Evidence suggests that investors are prone to overconfidence bias resulting in excessive confidence in their abilities. Overconfidence will lead to ignoring the risk associated with their portfolio and will result in trading excessively and eventually, that overconfidence will lead investors to have an undiversified portfolio. Investors, due to the impact of overconfidence, overestimate their ability to control the events and their knowledge, resulting in undermining the risk associated with their decisions (H. K. Baker & Nofsinger, 2002). Hence it is of paramount importance to study the impact of overconfidence on the decision making of investors to analyze its impact and its nature through empirical evidence. Overconfidence bias is among the psychological factors that caught the researchers' attention after introducing behavioral finance in 1980 and has a vital role in investors' mental process (Jaros et al., 1993). The researchers in the financial theory focused and incorporated behavioral factors, including overconfidence, in their studies starting from Tversky & Kahneman (1973) and Tversky & Kahneman (1974). Later researchers like Allen & Evans (2005), Bhandari & Deaves (2006), Burks et al. (2010), Gul & Akhtar (2016), Michailova (2010), J. Scott et al. (2003), and Skala (2008) among numerous others focused on the influence of overconfidence in the field of finance particularly on investors and stock market behavior establishing the overconfidence as a cause of suboptimal decision making but this remains a growing avenue and a lot need to be explored in this respected and hence the study of these biases is particularly of significance.

According to Shefrin (2007), overconfidence is a bias that leads people to believe to be better than their actual abilities. The overconfident investors believe to know more than they know. Overconfidence bias is further categorized into two categories, prediction overconfidence, which leads investors to have a very high confidence interval and certainty

overconfidence leads investors to have a very certain judgment (Pompian, 2006). There is a consensus in the existing literature about the negative impact of all the behavioral biases, including overconfidence bias and investment decision-making. Investors with this bias believe themselves to be better than others. Hence, they tend to be overconfident in choosing stocks, leading them to trade excessively. The investors that trade excessively receive lower returns than the average (Gervais & Odean, 2001) hence having suboptimal or irrational decisions. In the case of market trends, investors also overestimate their abilities leading them to suboptimal or even faulty forecasts (Shefrin, 2002). According to Scott, Stumpp, and Xu (2003), overconfidence bias is one of the psychological reasons why securities are not traded on fundamental or value calculated using rational analysis. Studies also concluded that investors indulge in excessive risk-taking behavior and decisions. Hence it is proposed that;

H_{2a}: Overconfidence bias is significantly and positively associated with the investor's intuitive decision-making.

2.2.4.2. Heuristics and Investment Decisions

Heuristics are the rule of thumb that investors develop with time and previous experience. The biases caused by the use of these heuristics are known as heuristic biases. Heuristics are behavioral biases caused by the use of mental shortcuts or rule of thumbs, which make the decision-making process convenient and fast, especially in complex and uncertain circumstances (Ritter, 2003), with reducing the complex process of estimating probabilities and predicting values for simpler judgment (Tversky & Kahneman, 1974). Heuristics are very useful and widely used in decision-making, particularly when limited (Waweru et al., 2008). Still, in investment, heuristics' use leads the investors to select a suboptimal alternative. Investors don't incorporate all the available and relevant information, and decide using shortcuts, making the decision irrational (Ritter, 2003; Tversky &

Kahneman, 1974). Tversky and Kahneman are the first who study these heuristics, namely representativeness, availability, and anchoring. Different types of heuristics were also identified by different researchers like Waweru et al. (2008) and others. In the current study, our focus will be on the use of availability and representativeness heuristics, which, according to Tversky and Kahneman (1974), is among the most widely used psychological factors in decision making. Decisions based on heuristics are often suboptimal. This is because investors use mental shortcuts and the rule of thumb to make an investment decision in a company only based on its characteristics, including the type of management, historical returns, popularity, etc. Still, this pattern recognition can be weak due to the neglecting of supporting evidence.

Availability heuristic in which decision-makers rely upon the knowledge that is readily available rather than examines other alternatives and procedures. That is why it causes decisions to be irrational (Folkes, 1988). It can be observed in investors when they prefer to invest in local companies with which investor is more familiar, or the information about them can be easily obtained (Waweru et al., 2008). The information also influences decision-makers in the capital market. They give more weight to the people-oriented information (Haley & Stumpf, 1989). Investors also alter or change their investment preferences and choices by keeping in mind their cost of capital (Modigliani & Miller, 1958) and another effect of availability bias that it can cause an investor to wrongly believe that a stock perceived to have good return will have low risk and securities perceived as bad will be judged to be of high risk and low return (Ganzach, 2000) leading toward suboptimal decisions.

Researchers from the late 20th century investigate important factors that may cause availability bias. Depending on just a chunk of information, Investors changed their investment decisions based on information about the executives and management of firms or

after the appointment of the new CEO of the company in which investors are interested in purchasing securities (Lubatkin et al., 1989). Investors sometimes decide without considering the correct and relevant information due to firms' and stock reputation (Scharfstein & Stein, 1990). In case of a financial market crisis also, investors have to suffer more than of market due to their reaction based on availability bias (Marcus & Goodman, 1991) because investors react negatively when they hear the announcement about the securities and layoff (Worrell et al., 1991) and resulted in overreaction by investors leading to irrational decisions.

Sometimes investors change the decision by keenly observing just the actions and news leaked by the stock exchange representative (Stearns & Mizruchi, 1993). The nature of investment decisions makes investors conscious of whether available information should consider more or omit it (Simons et al., 1999), resulting in overweighing or underweighting it. Investors also tend to choose only those stocks that have recently caught their attention from news, the stock having abnormal trading or extreme returns (Barber & Odean, 2008). Collectivism and individualism impact the psyche. These biases vary from culture to culture and personality to personality. Every investor's efficiency in a different culture is not alike (Mitchell et al., 2000). So the same information will be weighted differently by investors from different cultures and on their decisions hence the effect of availability bias may be deviate for same information across cultures.

Information about Stock exchange gain/losses and macroeconomic influence investors' decisions (Bulmash, 2001).How information report in the financial market and intermediaries' role play a vital role in altering investment decisions and greatly influences investor’s decisions (Healy & Palepu, 2001). Investors' preferences change according to available information (Harris & Raviv, 2005). As a result, information leads to a particular leading pattern, and sometimes even irrelevant information also influences investment decisions (Kirchler et al., 2005). Based on investors' recently available information, risk-

taking behavior about particular security changes (Grable et al., 2004), and so are their decisions.

Since a few years ago to recent years, studies reveal some facts that investors feel comfortable in making a decision based on if they feel they have superior information (M. Wang et al., 2011) When a firm in financial market reveal misconduct, the investor of that particular firm's stock get negative signal quickly and jump on to the conclusion based on that (Paruchuri & Misangyi,2012). Investor compares the performance of the firm with the performance of the peer. They react just on the wave of information of the performance of securities (Brauer & Wiersema, 2012) These Information that changes the portfolio selection of investor become a liability instead of becoming an asset and beneficial for the investor (C. Wang et al., 2014) as instead of accessing and evaluating all the information, investors use only most recent or available information. Competition among investors compels investors to react quickly about available information instead of making a rational judgment (Bowers et al., 2014). Another effect of heuristics is that it can cause an investor to wrongly believe that a stock perceived to have good return will have low risk and securities perceived as bad will be judged to be of high risk and low return (Ganzach, 2000). Studies of Chen et al. (2017) and Shah et al. (2018) also explored the impact of availability heuristic on investors decisions and found the heuristic to leading toward suboptimal decisions hence based on the above discussion it is proposed that;

*H_{2b}**:** Availability heuristic is significantly and positively associated with investors' intuitive decision-making.*

Representativeness heuristic can be explained as the degree of similarity that an event has with its parent population (DeBondt & Thaler, 1995). This heuristic can be observed when a person is willing to generalize about a person or phenomenon, including stocks based

on only a few attributes (Bazerman & Moore, 2012; Nisbett & Ross, 1980). This is because investors use mental shortcuts and the rule of thumb to make an investment decision in a company only based on its characteristics. This can include the type of management, historical returns, popularity, etc. Pattern recognition can be weak due to neglecting supporting evidence. Investors prone to representativeness may have biased decisions as such as people put too much weight on recent experience and ignore the average long-term rate (Ritter, 2003). Representativeness can cause investors to infer the company's long-term growth rate from some recent increases (Waweru et al., 2008). Representativeness can also lead investors towards irrational decisions by making them overreact. It's when Investors try to buy "hot" stock instead of poorly performed ones (DeBondt & Thaler, 1995). Since mid of the 20th century, with the emergence of behavioral finance, the researcher provided some ways to make an investment decision based on facts, not on probability. Ideally, investors have to calculate financial ratios to calculate future expected returns from the investment, but they consider the probability of an outcome based on their previous experience (Gold & Kraus, 1964). Good quality and rational decisions based on information search are the concern of the actions that can make the investment decision rational (Fredrickson, 1985). Large firms and firms with a previous high level of returns are expected to generate high returns too in the future (Jacobson, 1994). Complex decision making in high uncertainty often based on intuition, and intuition role is crucial in most of the financial decisions (Kahneman & Riepe, 1998) but based on intuition are often irrational and biased decisions because they are not based on complete analysis of all the information instead are based on gut feelings and heuristics (H. A. Simon, 1987).

The rational investor should act as an investor and not as a speculator. After all, investors are not one who tells the future because most of the investors believe their previous experience and decision were mostly correct. Based on prior experience, they will make

rational decisions in the future (Rosman et al., 1994). They are stuck on the same pattern repeatedly; they do not have a vigilant eye on the current scenario (Prechter Jr, 2001). Investors mostly seem passive, and they do not easily change investment planning (Benartzi & Thaler, 2007). Still, rational and well aware investors know rigorous analysis before investment decision making is necessary, but the tendency of relying on experience is alarming in financial markets (Shimizu, 2007). Investors in the capital market act normally; rather, they should act rationally without considering their previous experience (Filbeck et al., 2005).

In the last few years, Researchers are trying to highlight some factors of the investor's representativeness behavior and how they cause them to decide irrationally. Investors of the modern era are greatly tempted by their reputation and celebrity effect (Pfarrer et al., 2010). Most repeatedly, phenomena are they usually look backward instead of looking forward. Still, the future outcome can vary from past experiences (Arrfelt et al., 2013). In most of the cases, the financial status of investor impact on their psyche, Investors with strong financial status are less concerned with expected loss, that is why they analyze the probability of desired return carelessly based on too few samples (Ma et al., 2013) and also due to firm's reputation in which investors are going to invest sometime leads the investor to decide based on prior performance of the firm (Petkova et al., 2014). All of these phenomena are caused by representativeness heuristics and often lead investors to select a suboptimal alternative.

At the Macro level also, in the case of investment in foreign capital investment, investors make a probability on the previous performance of foreign stock and macro-economic factors (Bell et al., 2014). More recently studies including Khan et al. (2017) and Shah et al. (2018) studied investors behavior in different settings regarding impact of representativeness and concluded that it leads to suboptimal and irrational decision making cause market inefficiency. Hence it's being proposed that;

H_{2c}: Representative heuristic is significantly and positively associated with Investor's intuitive decision-making.

2.2.4.3. Framing Effect and Investment Decisions

Framing effects include those biases that cause an error in the decision due to how the information is presented. According to Shefrin (2007), the frame is a substitute for description; therefore, the decision frame infers to the decision task's description. The current study is an investment decision style study. According to the framing effect, investor's decisions vary following the presentation of the information. Shefrin (2009) categorized the framing effect into two categories loss aversion. The investor retains the effect of a loss for a longer period than a gain, and aversion to a sure loss describes the behavior of investors who take unnecessary risk to avoid a sure loss. Both of these behaviors cause irrational or suboptimal decisions on the part of investors, and the bias that originates out of this behavior is termed as disposition effect. Disposition impact is a phenomenon in which investors' display an inclination to understand the gains. Simultaneously, hesitant to acknowledge losses (Statman, 1999), this term was first introduced by Shefrin and Statman (1985) in which they explained by attributing it to loss aversion and mental accounting. Hence for our current study, the disposition effect is better suited as it incorporates both the aspects of framing effects. Shefrin and Statman (1985) developed a structure and formally investigated the disposition impact, and The prospect theory by Kahneman and Tversky (1979) is based on these framing effects. Prospect theory expresses that individuals turn out to be more risk-averse after encountering gains while risk searchers in the wake of anguish from the losses. Explaining it further, it can be said each security of the investor's portfolio has its separate account in investor's minds, and investors try to maximize the value of each account separately, which according to Kahneman & Tversky (1979), follows a concave curve for gains and convex curve for losses. Barber and Odean (1999) examined the 10,000 clients'

records from across the nation markdown and experimentally upheld prospect theory's implication. Various researches have upheld the presence of disposition impact (Barber et al., 2007; Grinblatt & Keloharju, 2000; Jordan & Diltz, 2004; Shapira & Venezia, 2001; Weber & Camerer, 1998). Lakonishok and Smidt (1986) focused on the stock market by analyzing the past prices and concluded that the winners have a higher and abnormal volume of trading than loser stocks. Studies of Bremer and Kato (1996), Ferris et al. (1988), and Huddart et al. (2005) also studied disposition effect by utilizing various reference points and concluded the same and even in cases of IPO's the stocks trading below the offer price, which was considered as the reference point for the investor, resulted in decreased trading and comparison if IPO's were trading above offer price the trading volume increased. Hair and Graziano (2003) dissected the mutual funds and examined the choices of investors. They found proof that investors offer those funds which have acknowledged positive returns and are hesitant to sell the loss-making reserves. Moreover, Shapira and Venezia (2001) reported that individual investors are more inclined to disposition impact than professional investors. Hence, an individual investor's decisions while investing in the stock market can be significantly different and more irrational than corporate investors based on the disposition effect. Dhar & Zhu (2006) and Odean (1998) conducted studies on individual investors by considering security's purchase price as a reference point and concluded that investors displayed the significant presence of disposition effect. The results indicated a significant inclination in investors to sell the stocks that increased in value recently and tend to hold stocks that are losing value. This presence is particularly high in low income and less experienced investors. It is also documented in the study of Shapira and Venezia (2001) that the disposition effect impacts all classes of investors, although their degree varies among groups. Levine et al. (2018) and Weber and Camerer (1998) also conducted studies on this framing effect by utilizing experimental study design and found out that the individual subjects resulted in deciding to hold the securities when the price of the securities fall in

general and also to trade less when the price fall below the purchase price, hence it is proposed that;

*H_{2d}**: Disposition effect is significantly and positively associated with Investor's intuitive Decision-Making*.

2.2.5. Personality Traits linkage with Decision Making

Psychological factors play an important role in understanding financial behavior. One of these psychological factors is an individual's personality, which plays a significant role in determining how individuals respond to any information (Sadi et al., 2011). "Personality is the quality or collection of qualities which makes a person a distinctive individual; the distinctive personal or individual character of a person, especially of a marked or unusual kind."

Trait theory can be traced back to Allport (1937), also named as dispositions. Researchers dealing with trait theories are interested in the measurement of traits that influence a person's behavior. According to theories, every individual has some innate preferences under which their actions are determined (Pittenger, 1993). Hence, the researcher is interested in exploring the role of individual traits in determining or causing biased behavior and understanding their linkage with individuals' decision-making behavior. There are different approaches to studying human personality, among which Barnewall (1987) categorized investors into two personality types: active investors who are willing to take a risk.

In contrast, passive investors don't risk their wealth, whereas another popular personality trait model is the Myers-Briggs Type Indicator (MBTI) instrument test. MBTI elaborated on different personality types based on certain aspects of human psychology (Pompian, 2006). The most widely used social sciences model for measuring an individual's personality is the

big five personality traits by Costa Jr and McCrae (1992). This model characterized individuals based on five factors: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. According to some researchers, all personality traits should be characterized by the big five models (Hogan et al., 1996). So in this study, a big five personality model will be used to analyze the relationship between an investor's decision-making styles and personality traits. The model's dimensions include Agreeableness, Extraversion, Conscientiousness, Openness to experience, and Neuroticism (S. P. Robbins, 2001).

Decision-making style is the outcome of various affective and cognitive traits (Olson, 2006). Personality traits impact the investors' understanding of the decision environment and lead to a difference in decision making among different personality traits (Nandan & Saurabh, 2016). There are numerous studies in the field of management sciences that study the impact of personality traits on different behavioral outcomes including satisfaction, commitment, and carrier preference and turnover decisions (Briggs & Little, 2008; Dole & Schroeder, 2001; Harren, 1979; Kuo et al., 2010; Rasheed, 2018; Warr & Pearce, 2004) and hence the link of decision-making behavior is already established in the field of general management but in the field of finance there exists a little literature and there is a lack of comprehensive models for investors behavior explanation, most of the prior studies like Filbeck et al. (2005) and Kudryavtsev et al. (2013) focuses on establishing the difference in behavior among investors and others like Filbeck et al. (2005) and Nandan and Saurabh (2016) focused factors that lead towards difference in decision making i.e risk perception and intentions, hence the current focus on establishing a comprehensive framework by directly linking the personality traits with decision making styles.

As the focus of the study is only on one aspect of decision making namely intuition, the personality traits in focus are extroversion, openness to experience, and agreeableness,

where extrovert refers to the behavior of individuals towards others such individuals have a habit to develop relationships and tend to be assertive, outgoing, and friendly. The extrovert individual is firm and likes to move with people. The agreeableness trait describes the way individuals respond to information received and is a trait that refers to the propensity of an individual to comply with others. Highly agreeable people are warm, cooperative, and trusting. Lastly, openness to experience is a trait in which an individual fascinates new ideas (P. Robbins, 2008). Hence, an investor with personality traits of agreeableness, openness to experience, and extrovert will rely more on social interactions and interact with other investors. His decisions will be based on his interaction with society. That will make him influenced by their emotions and overall social mood, which will result in an intuitive decision-making style instead of a calculated and rational one. Whereas conscientiousness refers to persistent, organized, and dependable individuals, whereas Neuroticism refers to emotional stability and ability of a person to withstand stress (Robbins, 2008) and presence of these traits will reduce social interaction, and their decisions will be more calculated and rational.

In contrast, the current study's focus is the traits that make them prone to irrational or intuitive decision-making style; hence the traits of conscientiousness and neuroticism do not fall in the current study's scope. In earlier studies, these personality traits significantly impact financial behavior (Zaidi & Tauni, 2012). Pompian and Longo (2004), in their study, found out that the personality traits of an individual are linked with biased behavior in financial decision making. They suggested that investors consider the type of personality to develop investment programs that should minimize these biases. Literature indicates that different personality types are linked differently with risk (Bashir et al., 2013). Personality traits are more likely to impact the situation that is uncertain, ill-defined, novel, complex, stressful, or challenging (Briggs & Little, 2008). All of which can easily be associated with the financial

decision that an investor has to take at the stock market. In their study, Byrne et al. (2015) argued that individuals take effective and optimal decisions under low pressure and in high-pressure conditions like at the stock market where investors have to react immediately to capitalize on the market situation, decisions can be suboptimal or intuitive. Personality traits can be used to predict behavior in such conditions (Tett & Guterman, 2000). Based on the discussion, the current study believes that the personality traits of agreeableness, extraversion, and openness to experience lead investors towards suboptimal decision making. Hence it is proposed that,

H_3: Personality traits are significantly and positively associated with Intuitive Decision-Making.

H_{3a}: Agreeableness is significantly and positively associated with Intuitive Decision-Making.

H_{3b}: Extroversion is significantly and positively associated with Intuitive Decision-Making.

H_{3c}: Openness to experience *is significantly and positively associated with the Intuitive Decision-Making.*

2.2.6. Personality Traits linkage with Biased Behavior

As discussed earlier that according to personality theories of psychology, every individual has some innate preferences under which their actions are determined (Pittenger, 1993) and hence the researcher is interested in exploring the role of individual traits in determining or causing the biased behavior and as poor decision making that leads towards long run hazardous or suboptimal outcomes is of the prime focus of the current study (Davis et al., 2007). Hence, only one aspect of decision-making, namely intuition or irrationality, is considered. The personality traits in focus are extroversion, openness to experience, and agreeableness, which are assumed to cause biased behavior, leading to irrational decisions. In

his study, Lin (2011) concluded that personality traits are linked with investors' biased behavior, and differences in personality traits cause differences in the financial behavior, which eventually leads to variance in financial decision-making, instead of a similar and rational one. Therefore leading to the inference that based on one's personality traits, one can determine the type of biases the investor will fall prey to. Other studies that analyzed the impact of personality traits and behavioral biases in different settings include Bashir et al. (2013), Schaefer et al. (2004), Sharma and Vasakarla (2013), and Zaidi and Tauni (2012). These studies focused on different behavioral biases and approaches to personality traits. They concluded a relationship, but none of the prior studies comprehensively covered the behavioral biases classification, neither had they established the causal relationship as the current study. Sadi et al. (2011) also concluded that four out of five personality traits except for agreeableness are linked to biased behavior. Still, none of the prior studies was focused on all these categorizations of behavioral factors. Hence incorporating all these differences are particularly important to study. As we have already discussed, those personality traits of agreeableness, extrovert, and openness to experience indicate how much a person prefers his intuition instead of a complete analysis of the available information. These personality traits also result in having greater interaction with the society and get influenced by the external, often irrelevant information the society provides, resulting in ignoring basic financial principles. Pompian & Longo (2004) suggested that investment programs should be created by focusing on investors' personality traits to minimize behavioral biases. Sadi et al. (2011) find a correlation between investors' behavioral biases and personality traits at the Tehran stock market. In their study, Durand et al. (2013) concluded that personality traits are linked with overconfident behavior, hence based on all the above discussion, it is proposed that,

H_4: Personality traits are significantly associated with Investors' biased behavior.

H_{4a}: Agreeableness is significantly and positively associated with investors' overconfidence behavior.

H_{4b}: Agreeableness is significantly and positively associated with Investors' availability heuristics.

H_{4c}: Agreeableness is significantly and positively associated with Investors' representativeness behavior.

H_{4d}: Agreeableness is significantly and positively associated with Investors' disposition behavior.

H_{4e}: Extroversion is significantly and positively associated with Investors' overconfidence behavior.

H_{4f}: Extroversion is significantly and positively associated with Investors' availability heuristics.

H_{7g}: Extroversion is significantly and positively associated with Investors' representativeness behavior.

H_{4h}: Extroversion is significantly and positively associated with Investors' disposition behavior.

H_{4i}: Openness to experience *is significantly and positively associated with Investors' overconfidence behavior.*

H_{4j}: Openness to experience *is significantly and positively associated with Investors' availability heuristics.*

H_{4k}: Openness to experience *is significantly and positively associated with Investors' representativeness behavior.*

H_{4l}: Openness to experience *is significantly and positively associated with Investors' disposition behavior*.

2.2.7. Mediating Role of Behavioral Biases

In the current study, we are also interested in analyzing behavioral factors' mediating role concerning personality traits with investors' intuitive decision-making. Two approaches are commonly used for mediation analysis. The first one is based on the rules set by Baron and Kenny (1986)**,** and the second is mediation through bootstrapping as proposed by Preacher and Hayes (2004). The latter approach allows in-depth analysis of the mediation effect by testing for partial and full mediation effects. Therefore, the latter will be used in the current study for testing mediation, but some prerequisites need to be fulfilled before proceeding to mediation analysis. Firstly there needs to be a direct linkage between independent variables (Personality traits) and dependent variables (Decision-making style), established in hypothesis 3. Secondly, there needs to be a direct link between the independent variable (Personality traits) and mediator (Behavioral Biases), established in hypothesis 4 of the study. Lastly, there should be a relationship between the mediator (Behavioral Biases) and dependent variable (Decision making style) which is inferred in the hypothesis 2.

Lin (2011) and some other researchers concluded in their studies that personality traits are linked with investors' biased behavior. As discussed earlier, the difference in personality traits causes differences in financial behavior, leading to variance in financial decision making instead of a similar and rational one (Filbeck et al., 2005). Lauriola and Levin (2001) suggested a significant relationship between personality traits and risky decisions because of behavioral biases. Therefore, based on one's personality traits, one can determine the type of biases the investor will fall prey to. Based on personality traits, one can determine his decision-making style. Hence it can be concluded that the behavioral factors mediate the

relationship between investor's decision-making style and personality traits, so the following hypothesis is proposed;

H_5: Investor's biased behavior mediates the relationship between Personality traits (Agreeableness, Extroversion and openness to experience) and Investor's intuitive decision-making.

H_{5a}: Overconfidence mediates the relationship between Personality traits (Agreeableness, Extroversion and openness to experience) and Investor's intuitive decision-making.

H_{5b}: Availability mediates the relationship between Personality traits (Agreeableness, Extroversion and openness to experience) and Investor's intuitive decision-making.

H_{5c}: Representativeness mediates the relationship between Personality traits (Agreeableness, Extroversion and openness to experience) and Investor's intuitive decision-making.

H_{5d}: Disposition effect mediates the relationship between Personality traits (Agreeableness, Extroversion and openness to experience) and Investor's intuitive decision-making.

2.2.8. Impact of Demography on Investment decisions

Demography like gender, education, age, etc., also impacts the degree of biased behavior in an individual (Bashir et al., 2013). According to Pompian and Longo (2004), investors profiling should consider demographical differences to reduce behavioral biases. With the increased focus on contextualized studies and settings to better understand behavior, it is vital in modern research to consider demographic variables for increased validity and reliability of results. In behavioral finance, females are more affected by the biases as their decisions are more prone to emotions and feelings. Experienced investors are more prone to biased and suboptimal decision-making (Kudryavtsev et al., 2013).

Similarly, the higher the age and education level, the less the impact of behavioral biases. With the increase in age and after retirement, people become less interested in improving their financial position and want a stable income, and become risk-averse compared to the young investors. Apart from profession or occupation also affect the decisions an investor made. Investors with expertise in economics and finance are expected to be more successful than others (Gumus & Dayioglu, 2015). Hence in the present study, these additional aspects are also going to be analyzed.

For instance, Lin (2011) broke down those individual investors' types after the rational decision-making process to choose their investment items and inclined to different behavioral biases. Mathuraswamy and Rajendran (2015) found that family composition, gender, psychological factors, and individual investors' way of life influence investment rationality. Zaidi and Tauni (2012) indicated that both age and education don't significantly affect overconfidence bias. Besides, there is a significant relationship between investment experience and overconfidence. Using a survey of around 2,000 defined commitment annuity arrange individuals, Bhandari and Deaves (2006) found that men are more confident than women. Concerning the relationship between demographic attributes and disposition effect, Mayfield, Perdue, and Wooten (2008) recognized that males are more inclined to disposition effect than females. Dhar and Zhu (2006) observed that individuals in professional occupations and high-income workers have brought down the disposition effect.

Regarding the relationship between demographic attributes and herding inclination, Lin (2011) found that females are more involved in biased behavior than males. Besides, they recognized that young investors are more inclined to herd behavior than older ones. Based on the above discussion, it can be inferred that demography has a link with biased behavior and impact the decision-making process of investors; hence it is proposed;

H6: There is a significant difference in mean behavior of investors who are in different demographic groups.

H6a: There is a significant difference in mean behavior of investors who are in different marital status.

H6b: There is a significant difference in mean behavior of investors who are in different gender group.

H6c: There is a significant difference in mean behavior of investors who are in different age group

H6d: There is a significant difference in mean behavior of investors who are in different experience group.

H6e: There is a significant difference in mean behavior of investors who are in different qualification group.

H6f: There is a significant difference in mean behavior of investors who are in different field of specialization.

H6g: There is a significant difference in mean behavior of investors who are from different areas.

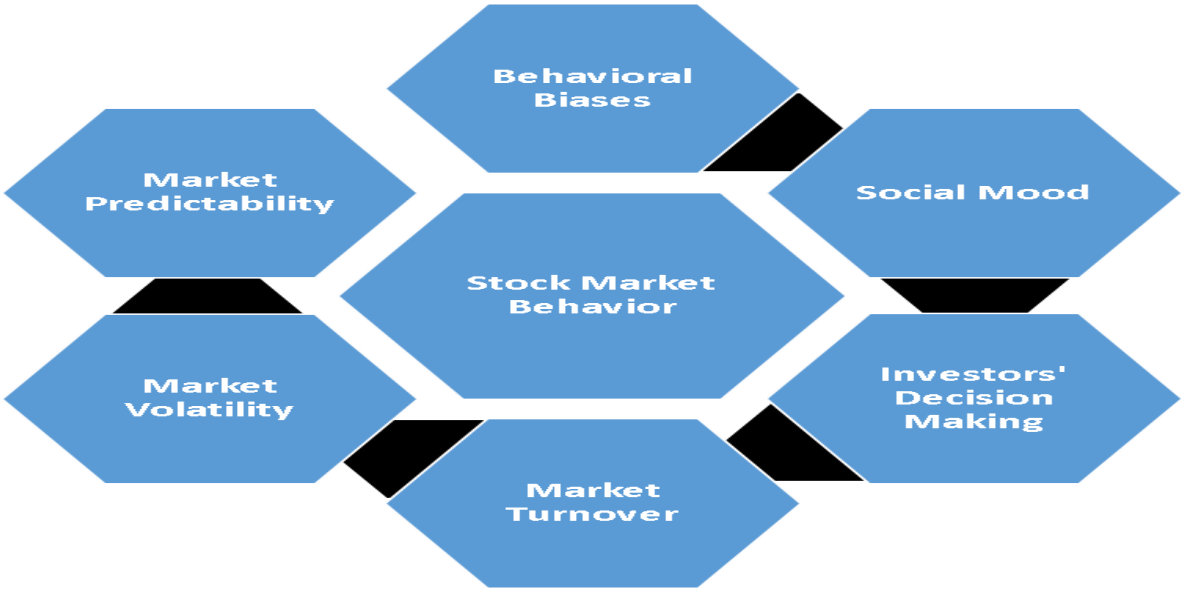

Figure 2-6-Proposed Market Mechanism

2.2.9. Conceptual Framework

Based on the preceding discussion, the following conceptual frameworks are derived

Figure 2-7- Secondary Data-Based Model

for analysis and testing.

$$y_t = \begin{cases} \mu_1 + \theta_1(y_{t-1}) + \cdots + \mu_{1t}\,, & if \quad S_{t-k} < \gamma \\ \mu_1 + \theta_2(y_{t-1}) + \cdots + \mu_{2t}\,, & if \quad S_{t-k} \geq \gamma \end{cases}$$

(Nofsinger, 2005; Xue & Zhang, 2017)

Equation 2-1: Secondary Data Model

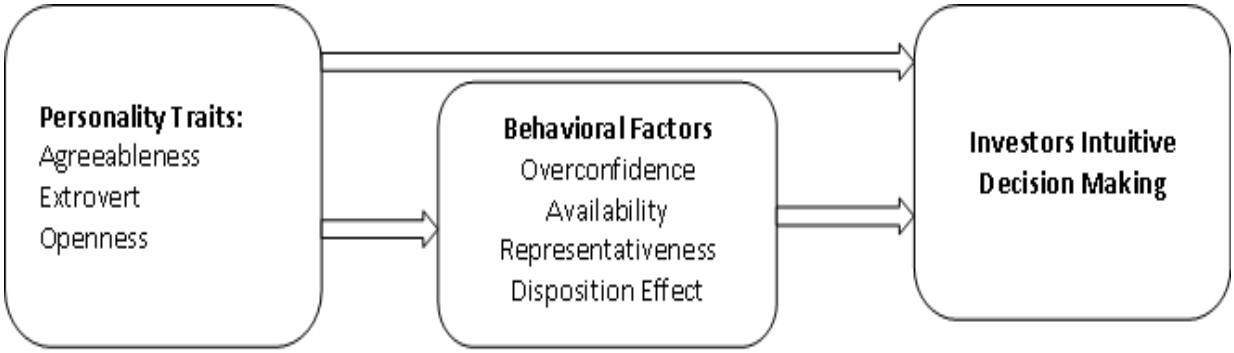

Figure 2-8-Primary Data-Based Models

(Kudryavtsev et al., 2013; Nandan & Saurabh, 2016; Waweru et al., 2008)

Figure 2-9- Demographic Analysis

(Bashir et al., 2013; Bhandari & Deaves, 2006; Kudryavtsev et al., 2013; Zaidi & Tauni, 2012)

Table 2-1-Study's Hypothesis

H_1	***H_1: Behavioral factors are significant determinants of return predictability in the Pakistan stock market.***
H_{1a}	*Overconfidence driven behavior is a significant determinant of return predictability in the Pakistan stock market.*
H_{1b}	*Heuristics driven behavior a significant determinant of return predictability in the Pakistan stock market.*
H_{1c}	*Disposition effect driven behavior is a significant determinant of return predictability in the Pakistan stock market.*
H_2	***Behavioral factors are significantly and positively associated with the investor's intuitive decision-making.***
H_{2a}	*Overconfidence is significantly and positively associated with the investors' intuitive decision-making.*
H_{2b}	*Availability heuristic is significantly and positively associated with Investors' intuitive decision-making.*
H_{2c}	*Representativeness heuristics is significantly and positively associated with Investors' intuitive Decision-Making.*
H_{2d}	*Disposition effect is significantly and positively associated with Investor's intuitive Decision-Making.*
H_3	***Personality traits are significantly and positively associated with the Intuitive Decision-Making.***
H_{3a}	*Agreeableness is significantly and positively associated with the Intuitive Decision-Making.*
H_{3b}	*Extroversion is significantly and positively associated with the Intuitive Decision-Making.*
H_{3c}	*Openness to experience is significantly and positively associated with the Intuitive Decision-Making.*
H_4	***Personality traits are significantly and positively associated with Investor's biased behavior.***
H_{4a}	*Agreeableness is significantly and positively associated with Investors' overconfidence behavior.*
H_{4b}	*Agreeableness is significantly and positively associated with Investors' availability heuristics.*
H_{4c}	*Agreeableness is significantly and positively associated with Investors' representativeness heuristic.*
H_{4d}	*Agreeableness is significantly and positively associated with Investors' disposition effect.*
H_4e	*Extroversion is significantly and positively associated with Investors' overconfidence behavior.*
H_4f	*Extroversion is significantly and positively associated with Investors' availability heuristic.*
H_4g	*Extroversion is significantly and positively associated with Investors' representativeness heuristic.*
H_4h	*Extroversion is significantly and positively associated with Investors' disposition effect.*
H_{4i}	*Openness to experience is significantly and positively associated with Investors' overconfidence behavior.*
H_{4j}	*Openness to experience is significantly and positively associated with Investors' availability heuristics.*
H_{4k}	*Openness to experience is significantly and positively associated with Investors' representativeness heuristic.*
H_{4l}	*Openness to experience is significantly and positively associated with Investors' disposition effect.*
H_5:	***Investor's biased behavior mediates the relationship between Personality traits (Agreeableness, Extroversion and openness to experience) and Investor's intuitive decision-making.***
H_{5a}	*Overconfidence mediates the relationship between Personality traits (Agreeableness, Extroversion and openness to experience) and Investor's intuitive decision-making.*
H_{5b}	*Availability mediates the relationship between Personality traits (Agreeableness,*

	Extroversion and openness to experience) and Investor's intuitive decision-making.
H_{5c}	*Representativeness mediates the relationship between Personality traits (Agreeableness, Extroversion and openness to experience) and Investor's intuitive decision-making.*
H_{5d}	*Disposition mediates the relationship between Personality traits (Agreeableness, Extroversion and openness to experience) and Investor's intuitive decision-making.*
H_6	***There is a significant difference in mean behavior of investors who are in different demographic groups.***
H6a	*There is a significant difference in mean behavior of investors who are in different marital status.*
H6b	*There is a significant difference in mean behavior of investors who are in different gender group.*
H6c	*There is a significant difference in mean behavior of investors who are in different age group*
H6d	*There is a significant difference in mean behavior of investors who are in different experience group.*
H6e	*There is a significant difference in mean behavior of investors who are in different qualification group.*
H6f	*There is a significant difference in mean behavior of investors who are in different field of specialization.*
H6g	*There is a significant difference in mean behavior of investors who are from different areas.*

3. Research Methodology

The research methodology consists of all the underlying assumptions that lead to the outcomes of the study. This section will focus on our underlying philosophical assumptions, research approach, research design, and methods adopted for the study. Underlying philosophical assumptions of the study will determine the way the study will view the world. Based on the philosophical assumptions, the research design will determine the study's purpose, type of investigation, the extent of interference, study setting, the study's time horizon, a suitable type of investigation method, and unit of analysis. In contrast, research methods consist of techniques and tools for data collection and analysis suitable for study design. This study's overall research methodology is derived from the research onion introduced as reported in Saunders et al. (2009).

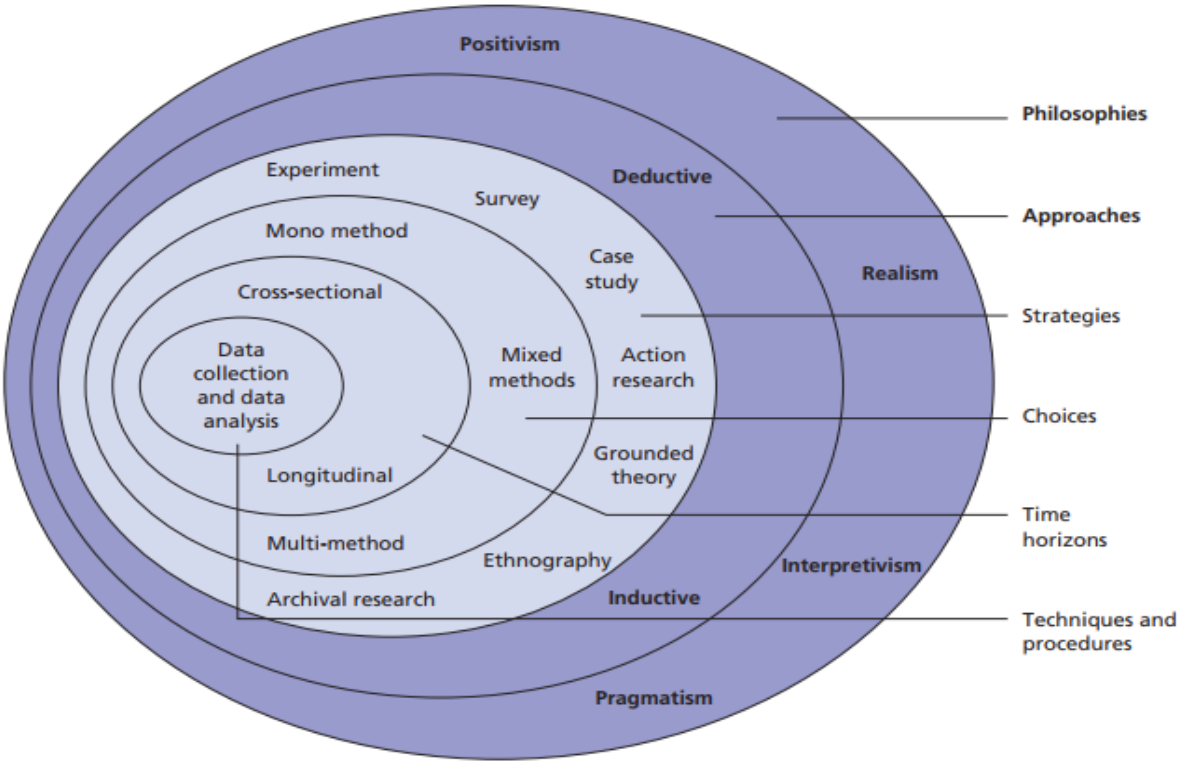

Figure 3-1-Research Onion

3.1. Philosophical Assumptions

The study's research philosophy strategy for pursuing your field of interest and the methods you adopt in the persuasion of that interest. The main factor that influences your choice of research philosophies is your view on the relationship under study and the process, which leads to that relationship (Saunders et al., 2009). When we consider research philosophies, there are three main aspects: ontology, epistemology, and axiology. Other factors include assumptions on human nature and methods.

3.1.1. Ontological Assumption

Objectivism and subjectivism are the two extremes ends of the ontological paradigm. Objectivism, also known as realism, considers the social entities that exist in reality. In contrast, subjectivism or nominalism considers social entities to be the product of social actors' perceptions and actions. The current study can be categorized as an objectivist study.

The study will consider that reality exists independently of the researcher's perceptions and independent existence even without the social actors (Bryman & Bell, 2015; Saunders et al., 2009). The paradigm of objectivism is selected because of its fit with the aim of the study. As the study is aimed at understanding stock market behavior as a direct outcome of the individual investors' behavior, which clearly is not influenced by the researcher's thoughts and exists regardless of the researcher's perceptions, as all the factors influencing investors' behavior are concrete and existent in the outside world. The study aims to explore and study them. All these factors are similarly existent worldwide; their aspects may vary, but the essence of their impact remains the same (Saunders et al., 2009).

3.1.2. Epistemological Assumption

Epistemology is concerned with what is acceptable knowledge in the study. Positivism and interpretivism are the two extremes regarding epistemology. Positivism refers to adopting the scientific mode of knowledge. It results in theories and laws that are generally applicable to every individual. In contrast, interpretivism refers to the knowledge to be behavior-oriented instead of scientific and tries to understand the differences in an individual's role as a social actor.

Regarding the epistemological assumption, the current study is in line with the positivist approach. As the aim of the study is to find and study the behavioral factors and their personality antecedents impacting investors operating at stock markets from a sample and to conclude with a general rule that should be applied to the whole population under study rather than trying to explain and interpret each investors decision making. Positivism is adopted from the natural sciences, and it utilizes scientific methods for analyzing social reality (Bryman & Bell, 2015). As this approach is aligned with natural sciences, so similar to them, it assumes that social reality exists objectively in the world. According to Saunders et

al. (2009), only by following scientific methods and deriving onto existing knowledge, can we learn about social sciences. This approach's main focus is to produce laws and theories regarding people's behavior in general (Fisher & Buglear, 2010), which is also in line with this study. By analyzing all these aspects, we can conclude that positivism is the best-suited approach for the current study.

3.1.3. Axiological Assumption

Axiology is a branch of philosophy that deals with value in the study. Regarding stand on axiology, the two extreme ends associated with it are value-free and value-laden. Value-free assumes that a researcher can research without the obligation of values. In contrast, the value-laden aspect assumes the first to be impossible to conduct a study without having values. The researchers' values play in the study are of great importance (Saunders et al., 2009). In the current study, which believes that knowledge is real and utilizes a scientific approach to study, the value-free approach aligns with the current study's scope. As a self-completion questionnaire having structured questions are used for the study. The survey is conducted in a very neutral manner, and the respondents weren't affected by the researchers and vice versa, which indicates a value-free research study.

3.1.4. Human Nature Assumption

Philosophy of human nature can be regarded as an approach to capture what a human being is in essence. Human nature consists of numerous characteristics, i.e., personality, feeling, acting, decisions, etc. The two extremes of philosophical discussion are determinism and voluntarism. Determinism attributes human characteristics to be derived from genes, situation, and environment, whereas the latter considers humans to be completely autonomous and have free will (Zikmund et al., 2003). The first approach is more appropriate and per the scope and aim of the study. As the aim of the current study to identify

and explore the individual factors that influence the investors and innate personality traits determined by the genes, situations, and environment that make them prone to rely on such cognitive biases. The determinism approach to human nature is also in line with our ontological, epistemological, and axiological assumptions of the study.

3.1.5. Methodical Assumption

Regarding the basic methodical assumptions of the study, the two contradicting approaches are idiographic and nomothetic. The idiographic approach of methodology focuses on direct, detailed, and in-depth observation of the society, and by inferring on this firsthand knowledge, one can gain true knowledge. Simultaneously, the nomothetic approach involves a scientific approach to the study of proposing and testing hypotheses based on quantifiable data utilizing standard tools (Bryman & Bell, 2015). Hence the idiographic approach is more suitable for qualitative studies. Still, this study is in line with the nomothetic approach. In this study, quantities data based on the existing theories will be utilized to systematically and scientifically analyze and interpret the results. This approach is also more suitable and in line with the continuing philosophical assumptions and standings.

3.2. Research Approach

The theory of a study can be built on two approaches, namely inductive and deductive. Each of these approaches is attributed to a different research philosophy (Saunders et al., 2009). When an inductive approach is utilized, the researcher makes observations and develops a theory based on the observations and then infers its implications. The deductive approach researcher initiates from the existing theory and by driving onto that existing theory builds relationships and then validates it through data. Hence the inductive approach is usually associated with interpretivism, and the deductive approach is associated with the philosophy of positivism. Which is the underlying philosophy for this study.

The current study is primarily focused on stock market behavior and influence and antecedents of behavioral factors, particularly all of these factors already existent in the world that need to explore and study. In this study, we infer these factors based on the existing literature instead of observing the stock market and then inferring from it. Then based on existing finding and literature, a model and hypothesis are proposed. Then the data is collected using a questionnaire and already existed secondary data of the stock market. All these steps are in line with the deductive approach of research, and according to Neuman & Kreuger (2003), only by utilizing hard data, one can examine the proposed framework. Hence the data collected is then tested by utilizing different statistical tools. Deductive is also suited for the current study as it is associated with quantitative studies, whereas the inductive approach is more suitable for qualitative research (Bryman & Bell, 2015). The steps involved in the deduction approach are enlisted in the figure below.

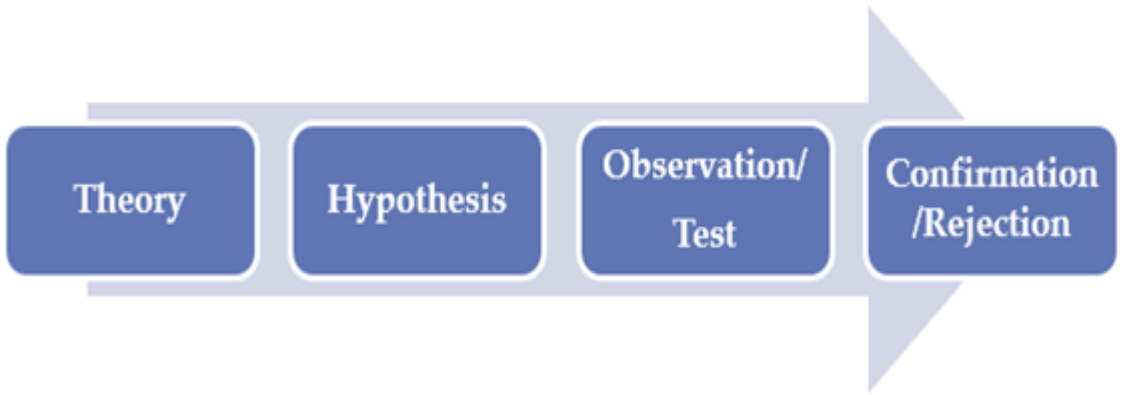

Figure 3-2-Deductive Approach

3.3. Research Design

Research design is the basis that provides a framework for data collection and analysis (Ghauri & Grønhaug, 2005). In studies as the study in focus, where we are trying to analyze the impact of behavioral factors on a stock market index, for which the longitudinal design of the research is most appropriate and to understand the behaviors of individual

investors in real-world hence a cross-sectional design of the research is best suited for analyzing the behavior of investors instead of case study, experimental (Collis & Hussey, 2013; Saunders et al., 2009).

In this research, we need to examine a relatively large sample group and a single index through a specific period. When we use cross-sectional design in research, data is collected from more than one sample unit at one single time is analyzed. In a longitudinal design, a single variable is analyzed at different points in time.

As proposed through literature, the association is then examined using the collected quantitative or quantifiable data (Saunders et al., 2009). The cross-sectional design involves using different research strategies, and hence is beneficial for this study because it allows collecting both quantitative and qualitative data. The typical methods to collect quantitative data in this approach are social surveys and structured observations from a sample at a single time. The typical forms used to collect qualitative data are qualitative interviews or focus groups at a single point in time (Bryman & Bell, 2015). For the first part of our research, longitudinal, quantified data from a secondary source will be analyzed through statistical tests, presenting a multimethod or mixed design of research with triangulation of methodology.

3.4. Sample

The first part of this research focuses on the stock market index for which data is collected from the Pakistan stock market website for ten years from 2009 till 2019, which incorporates sufficient observations to run statistical tests. The data include daily observations of KSE-100 index's closing value and the respective trading volume of KSE-100 index. Another reason for selecting this time period is that prior to that the world faced a global financial crisis, which adversely impacted the stock markets. As it is already

established in the existing literature that during the times of crisis, investors behave abnormally/irrationally and tend to herd. Therefor inclusion of that period can inflate the results of biased behavior and the aim of the study is to establish the existence of behavioral factors in normal functioning of the stock market.

In the second part research, the main focus is on the decision making of investors operating in the Pakistan stock market (PSX); hence a relatively large sample is recommended to achieve a representative sample, as it is well known that the larger the size is, the more representative is the sample and the more reliable and generalizable are the results (Saunders et al., 2009) but still it depends upon the researcher to select the appropriate sample size after analyzing the available time, finances and various other constraints.

There are different standards set by different texts and researchers for an exact sample size. One of which suggests that in dealing with quantitative research, one should have data from at least 100 respondents to fulfill the analysis standard required as per statistical methods (J. F. Hair, Andreson, Tahtam, & Black, 1998). Another rule of thumb for multivariate research is to have preferably ten times more respondents than the number of variables in the research (Sekaran, 2006) there is a formula also for sample size calculation which is;

$$S.S = \frac{Z^2 * (p) * (1-p)}{c^2}$$

Equation 3-1: Sample Size

With adjustment for a known population;

$$New\ S.S = \frac{S.S}{1 + \frac{S.S - 1}{POP}}$$

Equation 3-2: Adjusted Sample Size

Where,

S.S= Sample Size

New S.S= Population adjusted sample size

POP= Total Population

Z= Z value (e.g. 1.96 for 95% confidence level)

p = percentage picking a choice expressed as a decimal (0.5 for Sample size needed)

c = confidence interval, expressed as decimal (5 for 95 % confidence interval)

According to this formula by putting values for the known population of approximately 225354 individual investors registered at National clearing company of Pakistan as of June 2018 ("The Clear Call," 2018), the minimum respondents estimated is 384 respondents at 95 percent confidence level and with a confidence interval of 5 percent, as it is widely used and accepted levels in social sciences. Hence by keeping in view the required standards, Questionnaires are distributed among the investors in the hope of receiving back more than 384 questionnaires valid for analysis. This sample size is also affirmed by studying studies conducted on similar topics in different environments like Waweru et al. (2008), Kudryavtsev et al. (2013), and several others, where a sample size ranging from 170 to 230 is used.

Based on the assumption that the entire population of investors operating in Pakistan is evenly distributed among individual brokers as the brokers are mainly operating in the cities of Karachi, Islamabad, and Lahore and these cities are the financial hub of the country and investors from across the country covering every demographic aspect are present in those cities. A two-staged sampling technique will be applied. First, we utilized cluster sampling to

randomly select the brokers from the list available on the NCCPL website. One hundred thirty-nine brokers are selected randomly using SPSS based on the sample size formula discussed earlier out of a total population size of 217 brokers. The second stage convenience sampling technique is used to select the respondents to, as it gives you the highest response rate. It also saves time and resources (Bryman & Bell, 2015). It is also the best way of getting some basic information from respondents quickly and efficiently (Sekaran, 2006).

A detailed questionnaire consists of adopted measures from different sources about the relevant variables used to collect primary data from a sample of 550 investors from Pakistan's stock market. The sample is selected by randomly selecting the brokers at the stock market using SPSS, and after taking their consent, we approached their clients at random to fill up the questionnaires. At least three questionnaires are collected from the brokers in the sample list. The list of brokers randomly picked through SPSS for data collection are given in appendix 9.1.

3.5. Variable Measurements

This section will focus on the measures used to collect data for variables used in the current study as the study focuses on both primary and secondary aspects of data. The proposed variable measurement is also elaborated by keeping in view both aspects of the variables under consideration. After establishing the variable measurement, the summary of the model variables and their measurement is provided in table 3-2 at the end of this section. To clarify the variables, the current study's definition is also reported before the variable measurement method.

3.5.1. Stock Market Return

A stock market index is the measurement of a section of the market and describes the overall market. Our focus is on KSE 100 index but given the prime motive of investors

instead of focusing on predictability of KSE 100 index the predictability of daily rate of return of KSE-100 index is considered, which is going to be incorporated as the dependent variable to analyze the predictability in Pakistan Stock Exchange while we are going to take the first lagged returns as an independent variable and based on Akaike information criterion (AIC) the remaining subsequent lagged returns are taken as control variables.

$$R_t = \log \frac{P_t}{P_{t-1}}$$

3.5.2. Investors Sentiment

Market or Investor sentiments, also known as crowd psychology, can be defined as investors' collective behavior towards a stock market. As discussed earlier, we are using investor's sentiments as a proxy for behavioral factors affecting stock market indices. Different proxies and measures are implied to measure investor sentiment, including direct measures like surveys and indirect measures like trading activity and derivative variables. Previous research has utilized trading volume as a proxy of investor sentiment by creating a high low volume variable (Mazviona, 2015) that enabled them to distinguish between bullish and bearish sentiments. If the trading volume is higher than the previous five-day average, it will indicate a bullish trend and be represented by one; and otherwise, it will be 0. It will represent a bearish trend in the market.

Still, the problem with that approach is that higher volume is not only associated with bullish sentiments but also with panic trading in which investors will trade excessively and by adopting volume as a proxy will result falsely as a bullish trend in the market hence is not a reliable proxy to use. Panic trading exists globally from the Wall Street crash of 1929 to the financial crisis of 2008. In Pakistan, traces of panic trading can be found on the trading day of 15 August 2016 when the Chinese Yuan depreciated during the protests and sit in's in

Islamabad during August 2014. On July 3rd, 2017, in the wake of the JIT report on Panama leaks (Hussain, 2017) As a result in the current study as a contribution to the existing literature, it is proposed to use stock market return as a proxy for investor's sentiments as it will capture investor's behavior in a more accurate manner. A greater than the previous five days' average return will indicate the bullish trend in the market. Otherwise, there will be a bearish trend, while this new approach will also not be effected by the panic trading.

$$S = \begin{matrix} r_t > SMA_5 = 1 \\ r_t \leq SMA_5 = 0 \end{matrix}$$

3.5.3. Personality traits

Personality traits refer to peoples/investors unique patterns of thoughts, feeling and behavior that distinguishes one's behavior from another and the measure for measuring dimensions of personality traits in the current study is a shorter version adopted from the study of Mayfield et al. (2008) who operationalized the items from Costa and McCrae's (1992) big five inventory and used them in the context of investment.

3.5.4. Overconfidence Bias

According to Shefrin (2007), overconfidence is a bias that leads people to believe to be better than their actual abilities. Such investors believe to know more than they know.

Primary Measurement: This current study adopted eight items for measuring the degree of overconfidence from Gul and Akhtar (2016) derived from the studies of Allen and Evans, (2005), Chen et al. (2007), García et al. (2007), Glaser and Weber (2007) and Rekik and Boujelbene (2013).

Secondary Measurement: In the previous studies of Gervais and Odean (2001) and Odean (1998), it is established that the study of change in trading volume can provide a valid

basis for testing the existence of overconfidence in the stock market. According to De Long, Shleifer, Summers, and Waldmann (1990), overconfident investors are prone to a very strong illusion of their control over the outcome, and overconfident investors have an innate tendency to be overconfident and hence is not limited to individual security thus it's logical to study the overall market behavior.

Overconfident investors trade excessively when they realize high returns even if the rest of the market is enjoying the same (Gervais & Odean, 2001) hence based on this. A dummy variable is proposed to indicate the existence of overconfidence in the stock market by calculating the change in return of the stock market index so that if the lagged change in return is positive and is resulting in increased trading volume, it will exhibit overconfidence on the part of investors and will be denoted by 1 and otherwise 0.

$$O.C = r_{t-1} > r_{t-2} \rightarrow V_t > V_{t-1}$$

3.5.5. Availability Heuristics

Availability bias refers to a heuristic in which investors make decisions using readily available information instead of complete analysis.

Primary Measurement: This measure consists of five items adopted from the measure of Kudryavtsev et al. (2013), Phuoc Luong and Thi Thu Ha (2011) and Waweru et al. (2008), which were later used by Rasheed, Rafique, Zahid, and Waqar (2018).

Secondary Measurement: Availability bias which refers to the situation when investors make decisions according to readily available information and relevant instances that came to mind while decision making (Tversky & Kahneman, 1973), which result in cases of financial market crisis or declining market for investors to suffer more than of market due to their overreaction based on availability bias (Marcus & Goodman, 1991) and sometimes

decisions of investors change by keenly observing just the actions and news at the stock exchange (Stearns & Mizruchi,1993). Hence, depending on just a chunk of information, investors change their investment decisions. Information about stock exchange gain/losses and macroeconomic factors influence investors' decisions (Bulmash, 2001).

Therefore based on the preceding discussion, to quantify availability bias, we are going to utilize stock market gain/loss as a proxy for most readily available information to the investors and base on stock market gain/loss if the trading volume is increasing that will indicate the presence of availability bias and is indicated as one and otherwise 0.

$$A.H = r_{t-1} > r_{t-2} \rightarrow V_t > V_{t-1} \;\&\; r_{t-1} < r_{t-2} \rightarrow V_t > V_{t-1}$$

3.5.6. Representativeness Heuristics

According to DeBondt and Thaler (1995), Representativeness can be explained as the degree of similarity that an event has with its parent population.

Primary Measurement: This measure consists of five items that are adopted from the studies of Kudryavtsev et al. (2013), Phuoc Luong and Thi Thu Ha (2011) and Waweru et al. (2008), and further established by Rasheed, Rafique, Zahid, and Waqar (2018).

Secondary Measurement: Representativeness can be explained as the degree of similarity that an event has with its parent population (Tversky & Kahneman, 1973). Investors prone to representativeness will attribute the overall decision to a single benchmark in their mind instead of analyzing complete information. They will weigh on recent experience and ignore the average long-term rate (Ritter, 2003). Representativeness can cause investors to infer the company's long-term growth rate from some recent increases (Waweru et al., 2008). Representativeness can also lead investors towards irrational decisions by

making them overreact, and it's when investors try to buy "hot" stock instead of poorly performed ones.

Therefore based on the preceding discussion, to quantify availability bias, we are going to utilize stock market gain/loss as a proxy for the most recent and influential information and base on stock market gain/loss if the trading volume is increasing the same measure will also indicate the presence of representative bias along with availability bias and is indicated as one and otherwise 0.

$$R.H = r_{t-1} > r_{t-2} \rightarrow V_t > V_{t-1} \;\&\; r_{t-1} < r_{t-2} \rightarrow V_t > V_{t-1}$$

3.5.7. Disposition effect

Disposition impact is a phenomenon in which investors' display an inclination to understand the gains while hesitant to acknowledge losses

Primary Measurement: In the current study, the tool used for measuring disposition effect is adopted from the instrument used in the study of Gul (2014) derived from the studies of Chen et al. (2007) and Kudryavtsev et al. (2013).

Secondary Measurement: To measure disposition effect, Odean (1998) analyzed the trading pattern and observed that investors tend to hold the losers and tend to sell the winner stocks and as 100 companies of KSE 100 index represent almost 86% of the Pakistan Stock Exchange (PSX) (Zafar & Hassan, 2016) that's why it is appropriate to consider KSE 100 index return's trend as a proxy of individual security's trend hence a positive stock market return under disposition effect will result in overall higher trading volume as more investors will sell their winning stock and a negative stock market return will result in holding on to the losing stocks resulting in decreased trading volume.

Therefore by deriving on to this discussion a dummy variable is proposed to identify the existence of disposition effect in the stock market. This will consider the increase in trading volume and a positive stock market return and decrease in trading volume with negative stock market return as 1, indicating disposition effect and otherwise 0.

$$D.E = r_{t-1} > r_{t-2} \rightarrow V_t > V_{t-1} \,\&\, r_{t-1} < r_{t-2} \rightarrow V_t < V_{t-1}$$

3.5.8. Decision Making

Our focus in current research is on the intuitive decision-making style, which can be defined as to act based on your feelings that can be influenced by emotions and cognition instead of facts. Complex decision-making in high uncertainty, often based on intuition and intuition, is crucial in most financial decisions (Kahneman & Riepe, 1998). The measure we used for measuring this decision-making style is known as "The General Decision Making Style Inventory developed by Scott and Bruce (1995) which measures five dimensions of decision making including rational, intuitive, dependent, avoidant and spontaneous, as our concern in current research is the use of intuition in investment decisions we adopted five items from the instrument that deals with intuitive decision style.

In a survey questionnaire for primary data collection, all the items are measured at a five-point Likert scale, which is the most commonly used scale in the social sciences, as it provides a central point to the respondent and also provides the most concise and comprehensive set of alternatives making it convenient for the respondent. The survey instrument is divided into four parts; in the first part, nominal and ordinal measures are used to gather personal information regarding investors in Pakistan, which help classify and rank the data in different categories (Ghauri & Grønhaug, 2005). The second, third, and fourth parts of the instrument deal with personality traits, behavioral biases, and individual investors' decision-making style. In these parts, a five-point Likert scale is used. Which ranged from 1 strongly disagree to strongly agree.

The measurement type and their corresponding questions are listed in table 3-1 below, and the completed instrument is reported in Appendix 9.2 of the study.

Table 3-1- Survey Questionnaire

Group	Variables	Question No.	Measurement
Personal Information	Marital Status	1	Nominal Scale
	Gender	2	
	Specialization	6	
	Location	7	
	Age	3	Ordinal Scale
	Investment Experience	4	
	Qualification	5	
Personality Traits	Extraversion	08-11	5 Points Likert Scale
	Agreeableness	12-15	
	Openness to Experience	16-20	
Behavioral Factors	Overconfidence Bias	21-28	5 Points Likert Scale
	Availability Heuristic	29-33	
	Representativeness	34-39	
	Heuristic	40-45	
	Disposition Effect		
Decision Making	Intuition	46-50	5 Points Likert Scale

The instrument and the measures used for primary and secondary data analysis are listed in table 3-2, with sources from which they are inferred or adopted for further use.

Table 3-2: Proposed measurement of variables

Variables	Measurement	Tool/Method	Reference
Stock Market Index	Primary	N/A	N/A
	Secondary	Logged Index	(Nofsinger, 2005; Xue & Zhang, 2017)
Personality Traits	Primary	Questionnaire	(Costa & McCrae, 1992; Nandan & Saurabh, 2016; Rasheed, 2018)
	Secondary	N/A	N/A
Investors Sentiments	Primary	N/A	N/A
	Secondary	Dummy Variable $R_{t\ (index)}$ > Average of last five days return= 1 $R_{t\ (index)} \leq$ Average of last five days return= 0	(Xue & Zhang, 2017)
Overconfidence	Primary	Questionnaire	(Allen & Evans, 2005; G. Chen et al., 2007; García et al., 2007; Glaser & Weber, 2007; Gul, 2014; Gul & Akhtar, 2016; Rekik & Boujelbene, 2013)
	Secondary	Dummy Variable $R_{t-1} > R_{t-2}$ & $V_t > V_{t-1}$=1 otherwise =0	(Gervais & Odean, 2001; Odean, 1998)
Availability and Representativeness Heuristics	Primary	Questionnaire	(Kudryavtsev et al., 2013; Phuoc Luong & Thi Thu Ha, 2011; Rasheed, Rafique, Zahid, & Akhtar, 2018; Waweru et al., 2008)
	Secondary	Dummy Variable 1- $R_{t-1} > R_{t-2}$ & $V_t > V_{t-1}$=1 2- $R_{t-1} < R_{t-2}$ & $V_t > V_{t-1}$=1 otherwise =0	(Marcus & Goodman, 1991; Stearns & Mizruchi, 1993; Tversky & Kahneman, 1974)
Disposition Effect	Primary	Questionnaire	(G. Chen et al., 2007; Gul, 2014; Kudryavtsev et al., 2013)
	Secondary	Dummy Variable 3- $R_{t-1} > R_{t-2}$ & $V_t > V_{t-1}$=1 4- $R_{t-1} < R_{t-2}$ & $V_t < V_{t-1}$=1 otherwise =0	(Odean, 1998; Zafar & Hassan, 2016)
Intuitive Decision-Making	Primary	Questionnaire	(Rasheed, Rafique, Zahid, & Akhtar, 2018; Scott & Bruce, 1995)
	Secondary	N/A	N/A

R= Log Return V=Trading Volume

All the proposed measurements are scrutinized by the supervisor, co-supervisor, internal reviewer, and external reviewer of the synopsis, alongside other subject specialists. Their suggestions and valuable feedback is incorporated in the final draft and after final approval from the supervisor. Apart from that regarding the survey instrument, it was further recommended by the worthy subject specialists, including reviewers, to go for a pilot study before proceeding with final data collection and analysis. Hence, a pilot study has been conducted before the final data selection to look for any issue in Pakistan's instrument.

3.6. Statistical Techniques

This section will focus on the techniques that are going to be used for data analysis in the upcoming section. There are different statistical techniques available for data analysis, and the appropriate technique should be selected in accordance with the characteristics of data and the nature of variables. Some preliminary techniques are also utilized to explore the nature of data and its suitability for further analysis.

3.6.1. Descriptive Statistics

This section includes the information regarding data gathered for analysis and to be used for further analysis. Descriptive statistics are utilized to elaborate on the basic features and nature of the data and provide us with insight regarding the suitability of data before any further. It covers the sample and variables under study. It includes Mean, minimum, maximum, range, standard deviation, and variance, etc. Descriptive statistics also help classify samples into some subsamples with similar characteristics (Trochim & Donnelly, 2001). This test is done regardless of whether data is primary or secondary and is considered a basis for every quantitative study. Descriptive statistics are differentiated from inferential statistics.

Contrary to inferential statistics, it focuses on presenting data collected for the study in a manageable and simplified form instead of inferring some relation or conclusion. Although the measures used in descriptive statistics don’t represent the data accurately and there is a risk of distortion or omission of vital details but combined with graphical tools, it aids in sensibly present data and provides a summary for comparison variables under study (Trochim & Donnelly, 2001). Descriptive statistics comprise univariate analysis meaning that it

examines variables one at a time and explores three aspects of each variable under consideration: the distribution, central tendency, and dispersion. Each aspect is measured by utilizing different statistical techniques. The distribution of a variable consists of the frequency of values associated with a variable and the range it covers. It also includes frequency distribution. Frequency distribution presents all data values in a variable in different groups and categories using percentages, e.g., education, income, gender, etc. It can also be presented in the form of a graph or a chart. The second aspect in focus is central tendency measures, which focus on identifying the central value for the variable's given data under consideration. The statistical methods which are mostly used for this purpose include Mean, median, and mode. Among these methods, the mean or average is the most commonly used method for describing and establishing the central tendency of a variable in the studies (Trochim & Donnelly, 2001). If the variable comprises a normal distribution, the results of the mean median and mode will be identical and vice versa. The third and last dimension, which is included in descriptive statistics, is the measures of dispersions. Dispersion in a variable indicates the variation existing in data around its central value. It can be measured through the range that provides the maximum and minimum value in a variable's data. Still, a much better picture regarding data can be obtained by utilizing standard deviation. Standard deviation is a more accurate and detailed estimate of the variation in data because a single outlier can impact the results of range and be misleading (Guilford, 1965; Trochim & Donnelly, 2001). Hence descriptive statistics play a vital role in understanding the nature of data and selecting the appropriate inferential statistical tools for testing proposed relationships.

3.6.2. Techniques for Secondary Data

As the current study is divided into two parts. The first part of the study relies on secondary data. The latter is tested using primary data, and the nature of data also differs across these two approaches; hence for the first part of the research, which is based on time-series data of the stock market, such data is longitudinal where a single variable is observed repeatedly at different intervals, E-Views is used as it is the most commonly used software for such analysis. The current study focused on the existing relevant and most recent literature on time series data to explore the techniques that are most appropriate by keeping in

view the scope and aim of the current study and after considering different views provided by researchers in the literature the current study is convinced to select threshold autoregressive model for further analysis of the data and for any time series data analysis like the one in the current study it is of vital importance to check for unit root and to make data stationery, which is done using unit root test before final analysis. After stationarity of the data is established, other statistical techniques are applied, which include vector autoregression for appropriate lag selection using Akaike information criteria and Wald test for verification of significance among different threshold variables coefficients.

3.6.2.1. Threshold Autoregressive Model

Time series data can be defined as values of a single variable collected after some specific interval (Saunders et al., 2009). Time series data fails to fulfill ordinary least squared (OLS) regression assumptions regarding the independence of variance term, and there is a covariance among the disturbance terms. This covariance among these terms is known as autocorrelation, or serial correlation, which makes ordinary least square regression estimates biased instead of best linear unbiased estimators (BLUE) as other estimators with smaller variance can be found; hence the simple ordinary least square regression is not the best available technique for such data (Dougherty, 2011). Different linear techniques that are used to overcome the issue of autocorrelation includes autoregressive model (AR), moving average model (MA), autoregressive moving average model (ARMA), autoregressive integrated moving average model (ARIMA), vector autoregression (VAR), autoregressive conditional heteroscedasticity (ARCH), generalized autoregressive conditional heteroscedasticity (GARCH) and their other extensions are utilized. Still, the linear time series models have proven of limited or inadequate value when analyzing the macroeconomic and financial time series data (Galvao, Montes & Olmo, 2011) because the said data is effected with nonlinear characteristics including positive and negative shocks, different tail behavior of the distribution and heteroscedasticity of data and also linear model will fail to provide us with the deeper understanding of the observed data and its mechanism (Tong & Lim, 1980). Like the unemployment rates that decrease and remain less persistent in economic expansion but become more persistent during contraction and increase at a higher level, it isn't reasonable to rely on a single linear model to capture these distinctive behaviors.

Traditionally in stock markets also the linear methods were employed to test time-series data. Still, due to skewness and asymmetry in the stock market return series, it is not appropriate to test such data using linear autoregressive models (Tong & Lim, 1980; Xue & Zhang, 2017). This was also affirmed by Kahneman & Tversky (1979), who attributed this asymmetry of stock market behavior to the difference of investors' behavior to gains and losses. Hence the current study will employ a nonlinear autoregression model, namely the threshold autoregressive (TAR) model, for a better and realistic understanding of stock market behavior. The said model is also aligned with the study's aim, which focuses on the difference in the stock market's behavior in the presence/absence of different behavioral aspects instead of a uniform and rational one.

Economic time series data are conventionally assumed to be non-stationary (Hansen, 2011). Many models have been introduced to overcome the nonlinearity problems in such data, including the threshold autoregressive model (TAR) (Galvao Jr et al., 2011; Koenker & Bassett Jr, 1978). The threshold autoregressive model was initially introduced by Tong (2011). Since its inception, the model has influenced the field of finance significantly (Hansen, 2011). Relevance and significance of the nonlinear models can be observed in the recent literature of finance, including Fong et al. (2017), Hansen (2011), Tong (2011), Tong & Lim, (1980) and Xue and Zhang (2017), all of which and many others who applied advocated and relied on nonlinear models. The recent books on applied econometrics are also now focusing on nonlinear models, and a major portion of these texts now covers these models like threshold autoregressive models (Hansen, 2011). The said model is a part of state-dependent or regime-switching models and bilinear and exponential autoregressive (EAR) models (Gibson & Nur, 2011). A regime-switching model allows a dependent variable to depend upon the system's state (Enders, 2008).

Similarly, a threshold regression is a simple nonlinear model that allows for a piecewise linear analysis. It allows the regime-switching when a variable crosses a certain threshold. Thresholds can be defined as the value which delineates one state from another. There exists one effect up to the specific threshold and another effect beyond that threshold. Such models are usually applied to time series data. These models are applied to obtain a coefficient on both sides of the threshold value. In other words, the threshold autoregressive model is a

statistical technique that provides insight into the relationship of when the variable under consideration exceeds a certain threshold as expressed in the following equation.

$$y_t = \begin{cases} \mu_1 + \theta_1(y_{t-1}) + \cdots + \mu_{1t}\,, & if \;\; S\ or\ S_{t-k} < \gamma \\ \mu_1 + \theta_2(y_{t-1}) + \cdots + \mu_{2t}\,, & if \;\; S\ or\ S_{t-k} \geq \gamma \end{cases}$$

Equation 3-3: Threshold Autoregressive Model

Threshold autoregression is also popular because of its relative ease of estimation, interpretation, and ability to provide comprehensive and interesting nonlinear dynamics. These models, as discussed earlier, are a special variant of regime-switching models and use a threshold variable to determine two separate autoregressive models depending upon the value of thresholds (γ), where $S\ or\ S_{t-k}$ is the state of the determining variable or threshold variable and where (k) represents the lags impacting the regime at the time (t) for self-existing threshold autoregression (SETAR). Still, in the current study, our focus is on exogenous threshold variables (S) and depending upon the threshold value (γ) of the exogenous threshold variable (S), we will estimate the desired piecewise autoregression of higher and lower regimes, which is best suited with the aim of the current study as discussed earlier that the focus is one analyzing the changes in the predictability of stock index during bearish and bullish regimes and during the presence/absence of different behavioral biases establishing the fact that behavioral factors do influence the stock market behavior.

3.6.2.2. Akaike Information Criterion

As an autoregressive model where the value of a time series variable is regressed on its previous values like if the variable under study is y_t.It will be regressed ony_{t-1}. These previous values of the variables are known as lags. The next question is to select the number of lags to be regressed as an independent variable in an autoregressive model. The lag length selected for the model will be the lags or the past values that impact the current value. To determine the appropriate lags, different methods and criteria are available. They can be employed according to the study's nature, but the two most commonly used methods are Akaike Information Criteria (AIC) and Schwartz Bayesian Information Criterion (SIC). Even though both of these criteria have similar outcomes and objectives. Although both systems follow the same likelihood function system, the Schwartz Bayesian Information Criterion

(SIC) is applicable for finite models. Hence, Akaike Information Criteria (AIC) is recommended for the lag selection as it minimizes the probability of model underestimation and increases the chances of true lag determination (Liew, 2004). Akaike Information Criteria (AIC) is a criterion that estimates the out of sample errors of prediction and hence is applied as a test for the quality of the model. Akaike first introduced the Akaike Information Criteria (AIC). It utilized two measures maximum likelihood, which is used for estimation, and Kullback-Leibler Information, which is used to minimize the loss of information (Burnham & Anderson, 2001) and defined Akaike Information Criteria (AIC) as,

$$AIC = 2K - 2Log(L)$$

Equation 3-4: Akaike Information Criteria

The equation refers to the number of predictors in the model, and L is the maximum likelihood function. Still, it should keep in mind that only a single value of Akaike Information Criteria (AIC) doesn't mean anything. Instead, it is desired to achieve the minimum value of Akaike Information Criteria (AIC) in a model; hence the number of lags for a study is selected from different models considering different lag lengths, and the number of lags is determined through the model where minimum Akaike Information Criteria (AIC) is achieved.

3.6.2.3. Wald Test

A third statistical technique for the secondary data analysis of the study is the Wald test. After selecting autoregression techniques and establishing the number of lags to be considered in the threshold autoregressive model, the next step involves testing the existence and significance of the threshold effect in the model. Wald test is named after Abraham Wald. This test is also known as the Wald Chi-Square test and is used to find the explanatory variables' significance in a study. The test's null hypothesis is that the variable under study's coefficient equals some particular value, and that value could be zero. In general, it is used to test that if the value of a coefficient of an explanatory variable is zero or not. A significantly different value from zero indicates that the variable is significantly impacting the relation under study. The Wald test can be estimated as

$$W_T = I_n(\hat{\theta})[\hat{\theta} - \theta_0]^2$$

Equation 3-5: Wald Test

Where $\widehat{\boldsymbol{\theta}}$ represents the maximum likelihood estimators and $\boldsymbol{I_n(\widehat{\theta})}$ represents the expected fisher information and $\boldsymbol{\theta_0}$ represents the value of the null hypothesis, and as we can observe, the test focuses on the difference between two values of a coefficient ($\boldsymbol{\widehat{\theta} - \theta_0}$). Wald test can also be used for testing in nonlinear relationships hence as recommended in the studies of Andrews and Ploberger (1994), Galvao Jr et al. (2011) and Hansen (2011) and utilized to study stock market in china by Xue and Zhang (2017) the study relied on the spectrum wald test to detect the threshold effect and the composite hypothesis for testing linearity of the model through Wald test can be written as.

$$H_0: R\theta_\gamma(\tau) = 0 \text{ for all } \gamma(\tau) \epsilon\, T \text{ against } H_1: R\theta_\gamma(\tau) \neq 0 \text{ some } \gamma(\tau) \epsilon\, T$$

The null hypothesis indicates that there is no threshold effect. The coefficient among upper and lower threshold is equal to zero for the given threshold γ, and the alternative hypothesis is that there is one threshold effect from the given threshold γ and the coefficients are significantly different.

3.6.3. Techniques for Primary Data

For the second part of our research, we rely on primary data. The data is cross-sectional, meaning that observations have been collected from different subjects simultaneously regarding a variable. The said data will be statistically analyzed using IBM Statistical Package for Social Sciences (SPSS) and Smart Partial Least Square (Smart PLS), which are most commonly used for such data. Data will be analyzed using statistical tests like Descriptive analysis, Reliability analysis, Correlation analysis, Regression analysis, Structural equation modeling (SEM), and mediation analysis through bootstrapping and Analysis of variance (ANOVA).

3.6.3.1. Structural Equation Modeling (SEM)

The structural equation modeling technique is a multivariate statistical technique for testing structural theory (Tan, 2001). This technique belongs to second-generation multivariate techniques and simultaneously incorporates both observed and latent variables (J. F. Hair et al.,

2017). Where latent and observed variables are terminologies associated with variables included in the study. Latent variables are variables that can't be measured directly; instead, these variables are translated into the behavior caused by their impact, and data is collected using statements (also known as observed variables) believed to represent the behavior representing a latent variable; hence a single latent variable includes two or more observed variables in structural equation modeling. The study's latent variables are further divided into exogenous and endogenous latent variables where exogenous or independent latent variables cause fluctuation in the endogenous or dependent latent variable's value. This impact can be direct or indirect. Structural equation modeling factor analysis, path analysis, and regression (Ong, 2017). This research is used for testing the relationship between investment decision-making style, personality traits, and behavioral factors. Four separate models are going to be tested using Smart PLS. Structural equation modeling or SEM is also used to ensure the instrument's validity through factor analysis. Structural equation modeling enables researchers to test interrelated relationships using path analysis based on theory.

The term structural equation modeling represents a causal relationship through several structural regressions or equations. It provides a way to test the suitability of the collected data with the proposed structural equations. Two schools of thought on structural equation modeling are covariance-based, and the other is partial least square SEM. In the current study, we focus on the latter approach using smart PLS, which is better suited for theory development and prediction (Chin, 1998). Also, it is preferred because, in reality, it is difficult to find data sets that fulfill the requirements of covariance-based structural equation modeling, and that's why PLS-SEM is preferred (K. K. Wong, 2013). PLS-SEM has been applied in many filed including behavioral sciences like by Bass et al. (2003). This approach is especially useful when the data distribution is skewed, e.g., conducting a female-only survey (K. K. Wong, 2011) and is also appropriate in the context of current study where data of investors is skewed towards male participants only. Structural equation modeling consists of two aspects namely measurement model for psychometrics check and structural model for hypothesis testing. For further understanding of the structural equation modeling, basic assumptions and requirements are enlisted below.

1. No missing values in the data.

2. The study's latent variables' measurement level can be nominal, ordinal, interval, and ratio scale.
3. All measured variances, including errors, are useful for predicting and explaining the model (Chin, 1998).
4. The number of latent variables should be below the number of observed variables.
5. The study's data is preferred to be normal, and it is needed to access the skewness and kurtosis of each variable in the study (West et al., 1995).
6. Structural equation modeling (SEM) assumes the proposed relationships to be linear. In the non-linear relationship among latent variables, the model proposed by Kenny and Judd (1984) can be used.
7. Regarding sample size for structural equation modeling (SEM), there is a difference in opinion among researchers. Generally, the large sample size is considered in studies, and different authors suggested different sample sizes. Still, a consensus is that a sample size of below 150 observations leads toward unreliable results, and most researchers utilized a sample size between 200 to 400 (Kudryavtsev et al., 2013). Apart from that, as a rule of thumb, it is required to take 10 to 20 times more observations as sample cases as the variables under consideration in the study (Sekaran, 2006).
8. The relationship between exogenous and endogenous latent variables in structural equation modeling is stochastic, indicating that not all the variance in endogenous latent variables is explained through exogenous latent variables (Kunnan, 1998).

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \varepsilon$$

$$X_1 = \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \varepsilon$$

$$X_2 = \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \varepsilon$$

$$X_3 = \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \varepsilon$$

$$X_4 = \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \varepsilon$$

Equation 3-6 PLS-SEM

Where,

Y= Intuitive decision making, X_1= Overconfidence Bias, X_2= Availability Heuristics,

X_3= Representativeness Heuristics, X_4= Disposition Effect, X_5= Agreeableness,

X_4= Extroversion, X_5= Openness to Experience β= Coefficient & Ɛ= Error Term

3.6.3.2. Mediation Analysis

Mediation analysis tests are used to test causal relationships where the independent variable (X) affects a mediator variable (M). The mediator (M) in results impact the dependent variable (Y) as the mediating variables are used to describe the how and why of the relationship between two variables. Therefore they are sometimes referred to as an intermediary variable. Two approaches are commonly used for mediation analysis. The first one is based on the rules set by Baron and Kenny (1986) that utilizes simple ordinary least squared regression estimates. The second approach is the mediation through bootstrapping, as proposed by Preacher and Hayes (2004) that relies on maximum likelihood-based structural equation modeling testing (SEM). It provides better sense (Hayes, 2017). The latter approach also allows an in-depth analysis of the mediation effect by testing partial and full mediation effects. Apart from that, this method uses a large number of random samples through bootstrapping for estimation, so contrary to the traditional Baron and Kenny (1986) approach of ordinary least squared regression, it doesn't assume the data to be normal, and hence it is appropriate even for smaller sample size. According to Iacobucci et al. (2007), the use of structural equation modeling (SEM) based model is also more appropriate in comparison with traditional ordinary least squared regression-based models as it allows you with much more options, details, and control over the process and also structural equation modeling (SEM) based models provides with different measures to check the overall fit of the model and hence provide with the option of comparability with other models and the biggest advantage associated with such model is the incorporation of both latent and observed variables. Hence, it reduces the chances of random measurement error resulting in biased and lower results in other models (Hayes, 2017). Therefore the latter will be used in the current study for testing mediation. In mediation analysis, we test for the existence of the indirect effect. The steps involved and possible outcomes in testing mediation through the method proposed by Preacher and Hayes (2004) are enlisted below.

1. There exists a direct and significant effect between the independent variable (X) and the dependent variable (Y) without mediation.
2. There exists a direct and significant effect between the independent variable (X) and the mediating variable (M) without mediation.

3. There exists a direct and significant effect between the mediating variable (M) and the dependent variable (Y) mediation.
4. Only after establishing the direct effects without mediation can the mediation test proceed further, and the proposed mediation model is estimated. The results of the mediated model can be interpreted as follows,
    i- There will be no mediation if indirect effects are not significant.
    ii- The relationship will be partially mediated if direct and indirect effects exist significantly in the mediation model.
    iii- There exists full mediation if direct effect without mediation is significant, and in the mediation, model results indicate nonsignificant direct effect and significant indirect effect.

$$Total\ effect = E\langle Y|X+1\rangle - E\langle Y|X\rangle = \beta_{XY} + \beta_{MY} * \beta_{XM}$$

$$Direct\ effect = E\langle Y|X+1, M(X)\rangle - E\langle Y|X, M(X)\rangle = \beta_{XY}$$

$$Indirect\ effect = E\langle Y|X+1, M(X+1)\rangle - E\langle Y|X+1, M(X)\rangle = \beta_{MY} * \beta_{XM}$$

Equation 3-7 Mediation Analysis

Where

Y=Dependent variable, X= Independent variable, M= Mediating Variable,

β_{XY}= Coefficient of X when regressed against Y,

β_{XM}= Coefficient of X when regressed against M,

β_{MY}= Coefficient of M when regressed against Y

3.6.3.3. Analysis of Variance

Analysis of variance (ANOVA) is a statistical test used to test the relationship between categorical independent variables and continuous dependent variables, and this test is used in this study to test whether there are differences between respondent's demographic profile (i.e., gender, income group, and age) and decision-making style of investors. The analysis of variance test (ANOVA) utilizes the same grounds as multiple regression models for estimation. It is conducted using a statistical package for social sciences (SPSS) and resultantly it enables us to test nonmetric independent and metric dependent variables. Whereas in the comparative analysis of a moment structures (AMOS) and smart PLS utilizes maximum likelihood method which only allows for pairwise comparison of categorical

variables, hence the analysis of variance (ANOVA) has opted for this study as this study different non-metric variables having two and more than two categories. Analysis of variance is a model that allows us to compare means among different groups and reports with the significance of the differences. It can be expressed as,

$$\frac{Y}{Metric} = \frac{X_1 + X_2 + X_3 + \cdots + X_n}{Nonmetric}$$

Equation 3-8: ANOVA

ANOVA, in which we compare only two mean groups, is also known as F-test, i.e., to analyze the impact of gender. The test focuses on the variance concept and calculates different variances from data based on the demographic variable. It then estimates a statistic from the ratio of these estimated variances among and within groups of demographic variables. The resulting ratio is F-Test. A significant value of the test indicates that the population means are significantly different. The test is based on a couple of assumptions that need to be fulfilled before the test, which is enlisted below,

1. The measurement assumption level states that the test's exogenous variable should be categorical or nominal scale, and the endogenous variable should be measured on an interval or ratio scale.
2. The test or endogenous variable is normally distributed, tested by Q-Q plots and other graphical methods, and estimates skewness and kurtosis of the dependent variable.
3. The variance of the test or dependent variable population is homogenous, tested using Levene's Test. If the Levene test's value is significant, then equal variances are not assumed, resulting in heterogeneity and vice versa for homogeneity.
4. If homogeneity of variance can't be established, an alternative measure of the Welch test can be used. The significant value of the Welch test is considered valid for ANOVA analysis.

4. Pre Testing of the Instrument

A research study isn't considered established unless the study's quality meets the standards, especially in management sciences studies where abstracts terms are used for quantitative measurement of latent variables. The research instruments used to collect

primary data need to establish its reliability and validity. The first step in testing an instrument is the pilot study, where we test the instrument at a much smaller sample to find out insight on instruments working. Validity includes measurement validity, internal validity, external validity, and ecological validity, tested through content validity, convergent validity, discriminant validity, criterion-related validity, nomological validity, and unidimensionality. In comparison, an instrument's reliability is measured through stability measurement, internal reliability, and inter-observer consistency.

4.1.1. Pilot Testing

Pilot testing can be defined as a small-scale version of a study that can be conducted for various purposes that includes a trail of the complete study to have an idea about the feasibility, or it can be done to test the instrument used in the research. 10 to 20 percent of the total sample is believed to be a reasonable number to be included in the pilot study (Baker & Risley, 1994). The pilot study's main benefit is that it will warn about any items' complexities and remove them. To avoid any at later stages. A pilot study is not exploratory. Rather than it’s more of a feasibility study, it addresses methodological issues and helps assess the sample's suitability, costs analysis, and other issues. Pilot testing can also help in assessing and evaluating the outcomes of the study. A pilot study can be an external pilot and an internal pilot. If the pilot study is conducted in the final analysis, it will be an internal pilot. In contrast, if the pilot study data is set aside and not considered in the final analysis, it is an external pilot.

In this study, we are conducting an external pilot to ensure our questionnaire's general validity and reliability from a sample of 32 investors at Pakistan Stock Exchange (PSX). The questionnaire was shared using google forms electronically on an online group of creative business and social research (CBSR), which consisted of 239 researchers from different social sciences fields. CBSR is a research platform that conducts training, market research, seminars, and provides research consultancy. CSBR can be accessed at

http://cbsr.com.pk/

As stated earlier, data is gathered using a questionnaire created using google forms and the link is provided in the appendix alongside results of data analysis. Out of the total group

members, 32 having relevant experience of investing and knowledge filled the questionnaire. The data gathered is then analyzed through SPSS. While conducting pilot testing, it is suggested that respondents look for the questions for which respondents provided different answers for the same questions or comments on the questionnaire. If that so, that means that instrument is unreliable and needs revision. Along with that, we will test the instrument's reliability through Cronbach's alpha and correlation coefficient to affirm the linkage between variables as predicted by the literature.

They are two types of correlation coefficients that are typically used in social sciences research. First is the Pearson correlation coefficient is the most commonly used measure. Still, it applies to data that is normally distributed. Still, as in every other study in our pilot study, a limited number of observations are considered. In such cases where data is not normally distributed, the Spearman correlation coefficient is recommended. Hence, using the later approach correlation coefficient is obtained. It can be observed in the results shown in appendix that all the study variables are positively and significantly correlated as proposed in the study. Although some correlation values are pretty high, which can lead to problems for causal relationship testing but as the pilot study is conducted only with the purpose to catch a glimpse of the study's outcomes and to decide that if it is worthwhile to pursue further and complete the study and also to access that resources applied will not be wasted, hence the casual estimation is not an issue to be considered at this stage. We can also observe that all the coefficients are associated with each other as predicted by the literature.

The Cronbach's alpha values in the table indicate the reliability of measurement from the survey for all the variables above 0.60, which is the minimum level of acceptance for the instrument's reliability in this research. This table shows that the items included in the instrument for extraversion, openness to experience, agreeableness, overconfidence bias, availability bias, representative bias, and investment decision making are reliable enough to follow further analysis and check the relations. A detailed description of Cronbach's alpha criteria and other established standards will be discussed in the later part, explaining the sample data's reliability and validity tests.

During pilot testing, respondents suggested providing the target audience with a translated version of the instrument to better understand and apply it in the local context.

Hence the research instrument was translated with experts from English, Urdu, and management sciences. Translation of the statements in Urdu is also provided alongside the English statements of the questionnaire. As the study's focus isn't on creating an instrument, a standalone version is not tested; instead, the translation helps the audience better understand the questions being asked in the local context.

4.1.2. Instrument's Translation

There are various translation techniques present in the field of management sciences introduced by Usunier (1998). Saunders et al. (2009) characterized these approaches as direct translation, back translation, parallel translation, and mixed techniques translation. Every method has its pros and cons, but the most commonly used method is the back-translation method. According to the framework provided by Tsang et al. (2017), the questionnaire's back-translation is a four stepped process. First of which is forward translation. In forward translation, the instrument is translated from its original translation to the targeted language. The forward translation is done by a person whose native language is the target language. In the current scenario, Urdu and the person are also familiar with the instrument's original language, i.e., English in this case. The translator should preferably be a person from the relevant field, knowing the instrument's area. Hence experts from the field of management sciences are requested to translate the questionnaire. According to Usunier (1998) and World Health Organization (WHO), during the translation of an instrument, it should be kept in mind that translation should be made on a conceptual basis and not on word to word (literal) basis. The translation should be simple and clear, targeting a common audience instead of a professional audience and hence use jargons and complex terminology should be avoided; besides that translator should also avoid the use of any words which are offensive to the target population (*WHO | Process of Translation and Adaptation of Instruments*, 2020). The translated version will then be reviewed by the language experts of both the original and target language, i.e., English and Urdu. They can suggest any replacement/amendment related to grammar and word choice.

The second step involves back-translation from the expert in the original language; hence the instrument will be translated back to English. This step will ensure that there were no misunderstood words during forward translation, and if such words exist, they can be

rectified. According to Tsang et al. (2017), the back translator's mother language should be the original language, and to avoid bias, the back translator should not be familiar with the intended concepts. Hence, an English language expert with no knowledge of management terminologies is requested to translate back the instrument.

The third step involves reviewing the back translation, forward translation, and the original instrument by the experts in the relevant field. The experts should be familiar with the instrument's constructs. The experts will determine that all versions of the questionnaire are equivalent. Any discrepancy will be resolved, and the experts will reach a consensus on all items.

The original items with forward and backward final translation are reported in table provided in the appendix 9.6, and the list of validators are provided in appendix 9.4. Apart from the validation process discussed above, the translated instrument was further validated by considering a couple of individual investors and institutional investment officials.

The fourth and final step involved in this process is pilot testing of the instrument. The same procedure was repeated and an online survey form in Urdu is created using google forms, the link for which is provided in the appendix alongside results,

The above-mentioned form is circulated among investors groups online, and twenty-nine respondents participated and provided feedback. The results of pilot testing are given in the appendix. As can be observed from the results, all the results are consistent with the prior pilot study and according to the existing literature. We can conclude that the instrument's reliability is slightly increased from its English version if we analyze and compare.

With the pilot, all the research instrument’s translation requirements and fulfilled as recommended by the relevant literature. The instrument can still further validate by re-establishing the instrument's reliability and validity after a complete study. The focus of the current study is not creating a standalone instrument in Urdu on the topic. Hence this step is skipped, and the Urdu translation is provided with the original items to understand better the questions asked.

5. Empirical Analysis and Findings

This section of the study will focus on the data gathered and its analysis through various software, including Microsoft Excel, SPSS, Smart PLS, and E-Views. As the current study comprises two distinct models based on the types of data utilized, this section will first explain and report the secondary data analysis. Then later, the subsequent section will focus on primary data and its analysis. The analysis's focus in both sections will remain on behavioral aspects in the individual investors' stock market behavior and attitude.

5.1. Stock Market Model

This secondary data used in this study is of the historical values return based on the daily closing values of KSE-100 index from 2008 till 2019. The reason for selecting the said period is that before 2008 stocks markets worldwide were facing the impacts of the financial crisis. It is a fact in the existing literature that investors do behave irrationally during times of financial crisis. Their overreaction causes such crises. The current study believes that the impact of these behavioral factors exists even during normal times, and hence the said period with normal market conditions is selected. The KSE-100 index is selected to study the market's overall behavior because the 100 companies in the index represent 86% of the overall Pakistan stock market. According to Sheikh and Riaz (2012), the Pakistan stock exchange is an active market compared with other markets of the same capitalization and size. Hence the return associated with the Pakistan stock market is also higher, and so is its volatility representing its influence from the behavioral factors. The study's focus is to establish predictability/autocorrelation in the stock market, which will negate the traditional view of the random walk as proposed in the efficient market hypothesis (EMH) and will affirm the theoretical grounds provided by the theory of social mood. Although the random walk is associated with the stock market prices, the focus of an investor in a market is on the predictability of return rather than stock prices. The use of stock market return as a proxy for market movement is also of significance. It allows us to overcome the problem of abnormality in stock market prices data by calculating log return. Hence stock market return is considered for final analysis. The stock index return data and trading volume are utilized to calculate dummy variables for behavioral factors based on investors' behavior as predicted by

the existing literature. Before proceeding with the final analysis, a descriptive analysis of the study's variables is done. In this section of the study, two data types are utilized variables like return, and trading volume is data based on a ratio scale. In contrast, the dummy variables, i.e., investors' sentiment, biases, heuristics, and framing effects, are dichotomous variables; hence they are separately reported according to their nature.

Table 5-1-Descriptive Statistics (Market Variables)

	RETURN	VOLUME
Mean	0.001	114000699.310
Median	0.001	103098360.000
Maximum	0.053	384499936.000
Minimum	-0.051	008046634.000
Std. Dev.	0.011	058724056.909
Skewness	-0.198	000000000.960
Kurtosis	5.832	000000004.071
Jarque-Bera	873.390	516.448
Probability	0.0000	0.0000
Observations	2562	2562

Table 5-1 shows the results of the descriptive analysis of the variables of return and volume. The descriptive analysis includes the mean, median, and range describing minimum and maximum values of the variables. On average, we can observe that the Pakistan stock market provided a 0.072% daily return with an average daily trading volume of almost 114000700 shares on average daily. The range of the variables provides the minimum and maximum values associated with variables which indicate the volatility associated with trading at Pakistan stock market, and it can be observed from the given statistics that from the prospect of trading volume that the Pakistan stock market is highly volatile and is ranging from 8046634 shares per day to 384499936 per day. The stock market return volatility can't be captured using daily return data because of the stock market "circuit breaker" that avoids any sudden decline in the stock market behavior by halting trading. The value standard deviation in the table can also describe the volatility in the variables' mean values. The higher the standard deviation values compared with the mean return, the higher the volatility will be. It can be observed the average daily return of 0.072% is associated with a fluctuation of ±1.05% of standard, and the average value of trading volume 114000700 shares is associate with a standard deviation of ±58724057 shares. The reported values of skewness and kurtosis are associated with the normal distribution of the variables. The ideal values of skewness and kurtosis for a normal distribution are 0. Still, skewness values up to ±1 and value of kurtosis up to 3 are considered valid and normal, but as can be observed from both the variables that

they are not normally distributed, which is further affirmed using the Jarque-Bera test. The Jarque-Bera test operates under the null hypothesis that data is normally distributed. Based on the p-values associated with both variables, the alternative hypothesis that the data is not normally distributed is accepted hence further affirming the use of non-linear models like the threshold autoregressive model. After explaining all the relevant properties of the study variables in the study, the no. of observations (2562) included in the study are reported, which are sufficient for further statistical analysis.

Table 5-2-Descriptive Statistics (Dummy Variables)

	SENTIMENT	BIASES	HEURISTIC	FRAMING_EFFECT
Mean	0.477	0.254	0.501	0.528
Maximum	1.000	1.000	1.000	1.000
Minimum	0.000	0.000	0.000	0.000
Observation(0)	1338	1909	1280	1207
Observations(1)	1224	653	1282	1355
Total	2562	2562	2562	2562

As explained previously, dummy variables were created using return and volume of the KSE 100 index to be considered threshold variables to gauge investor sentiment and behavioral factors' impact on the stock market's predictability. 0 indicates the absence of these factors, and 1 indicates behavioral factors, whereas for investor’s sentiments, 0 represents the bearish trend, and 1 represents the bullish trend. Dummy variables have two values, only 0 being the lowest and one the highest, which can be observed in the values of the range provided in table 5-2. The total number of observations is 2562 same as the observations of market variables. These values are divided into 0 and 1 among the variables listed in table 5-2. Out of total observation of 2562, 1224 observations indicate a bullish trend in the stock market, and 1338 observations indicated a bearish trend in the Pakistan stock market.

Regarding behavioral factors, 653, 1282, and 1355 observations indicated biases, heuristic, and framing effects in the Pakistan stock market, respectively. The value of mean is of no significant use for describing data. In the case of dummy variables, it can describe Pakistan stock market investors' inclination towards these behavioral factors. Based on the mean values, it can be inferred that the investors in Pakistan were more affected by the framing effect during the sample period of 2009 to 2019. The impact of the biases was minimal, and the market's overall trend remained more inclined toward bearish behavior.

5.1.1. Lag Selection

After a thorough explanation of the data characteristics, the next step before final analysis involves selecting appropriate lags for autoregression. Before analyzing time series data, it is of vital significance to check the data for stationarity. If the data is non-stationary, then it must transform in such a way to make it stationary. The term stationary indicates that the statistical properties of the data don't change with time. Nonstationary data have mean and variance value which changes with time and doesn't remain the same across data and indicates an unpredictable systematic pattern or trend. It is vital to remove any trend from the data to avoid biased or misleading results. Different techniques can be applied to remove trends from the time series, including taking logs, ratios, first or higher-order differences, error correction, cointegration, etc. The time series under consideration for further analysis is the return of the stock market index. The trend in the data can simply be observed by simply plotting the data.

As can be observed from figure that it seems that the time series of stock index return is stationary. This can be attributed to how the stock market return is calculated by taking the log of the change in the index value.

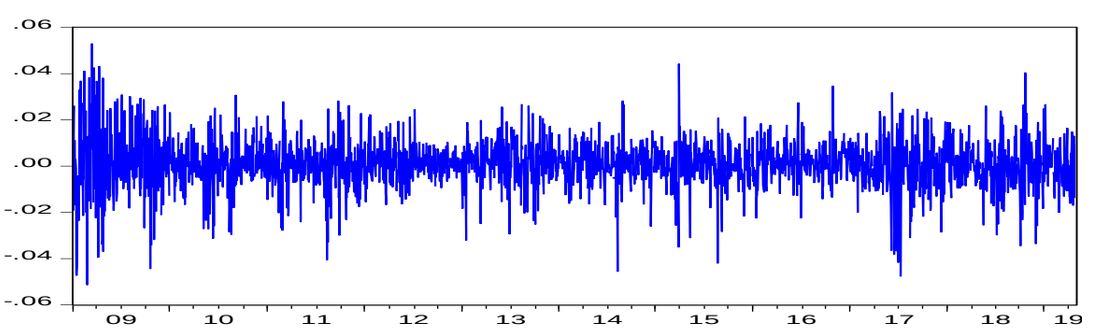

Figure 5-1-KSE-100 Index Return

To statistically check for stationarity of data unit root test in e-views is used. The unit root test can be done using various approaches, and the current study utilizes the augmented dickey fuller test (ADF) to test for unit root. The value of the augmented dickey fuller test (ADF) is negative, and the more negative it is, the more it indicates the rejection of the hypothesis that there is a unit root. The test has a simple basic autoregressive model AR (-1), which can be expressed as,

$$Y_t = \beta Y_{t-1} + \varepsilon_t \; or \; \Delta Y = (\beta - 1) Y_{t-1} + \varepsilon_t \; or \; \Delta Y = \delta Y_{t-1} + \varepsilon_t$$

Equation 5-1-Unit Root Test

Where

Y_t = Variable understudy

β = (β-1) = σ = Coefficient of lag of variable understudy

Ɛ= Error term

The augmented dickey fuller test (ADF) relies on assuming a statistically independent error term having a constant variance, usually not fulfilled in time series data. To overcome this shortcoming, unit root can also be tested using the Phillip Perron test, which allows for varying error terms. Hence, the return variable's unit root test will be analyzed using both the Augmented dickey fuller test (ADF) and Phillip Perron test (PP).

Table 5-3- Unit Root Analysis

	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic	-44.668	0.000
Phillips-Perron test statistic	-44.721	0.000

As discussed earlier that due to the transformation caused during stock index return calculation, there is no unit root in the time series. Results of both augmented dickey fuller test (ADF) and Phillip Perron test (PP) in table 5-3 revealed that the time series under study is stationary and the null hypothesis of both tests is rejected that the data has a unit root and the alternative hypothesis is accepted at 1% level of significance. After establishing the stationarity in the data vector autoregression model (VAR) can be applied to estimate the optimal number of lags based on Akaike information criteria (AIC), which will then be used in the threshold autoregressive model.

The Vector autoregressive model is mostly used and easy to use to describe different time series. Each variable in this model has its equation as its lag, and the lags of other variables in the study impact the variable's current value. According to Ozcicek and McMillin (1999), a critical aspect vector autoregressive model is appropriate lag selection, so the current study is interested in utilizing the vector autoregressive model because, in e-views, it provides an option to select the appropriate number of lags through the option of lag length

criteria. We included a maximum of 26 lags for lags length criteria, which were automatically determined during the unit root test depending on the nature of data. As discussed earlier, the selection of lags can be made using different model fit criteria. Still, the most common criteria for model selection is the Akaike information criteria (AIC). The lower the value of Akaike information criteria (AIC), the better the model is; hence the value of lag is selected where minimum Akaike information criteria (AIC) value is achieved. In e-views, the value is selected automatically. As shown in table 5-4, by observing the results, we can conclude that based on the minimum value of Akaike information criteria (AIC), ten lags of the stock market are appropriate for final analysis. Hence, in the final analysis through a threshold autoregressive model, 10 lags of return will be regressed against the current day return at Pakistan's stock market.

Table 5-4- Lag Length Criteria

Lag	LogL	AIC	Lag	LogL	AIC
0	8025.571	-6.328	14	8049.186	-6.336
1	8038.886	-6.338	15	8049.219	-6.335
2	8038.888	-6.337	16	8051.389	-6.336
3	8039.006	-6.336	17	8053.788	-6.337
4	8040.003	-6.336	18	8054.544	-6.337
5	8040.024	-6.335	19	8054.564	-6.336
6	8043.407	-6.337	20	8054.756	-6.335
7	8043.841	-6.337	21	8054.757	-6.334
8	8044.458	-6.337	22	8054.916	-6.334
9	8044.781	-6.336	23	8056.462	-6.334
10	8048.855	-6.339*	24	8056.774	-6.334
11	8048.867	-6.338	25	8056.807	-6.333
12	8048.877	-6.337	26	8056.855	-6.332
13	8049.114	-6.336	* Minimum AIC		

5.1.2. Results of Threshold Autoregressive Model

A threshold regression is a simple nonlinear model that allows for a piecewise linear analysis. It allows the regime-switching when a variable crosses a certain threshold. Thresholds can be defined as the value which delineates one state from another. There exists one effect up to the specific threshold and another effect beyond that threshold. Such models are usually applied to time series data. These models are applied to obtain coefficients on both sides of the threshold values selected for analysis. The current study applied this model to test the threshold effect of investors' sentiments and behavioral factors, including biases, heuristics, and framing effect. The threshold model is calculated using investors' sentiments, biases, heuristic, and disposition effect, respectively. The models regressed results are

reported below in the tables. The results reported are calculated using the option of threshold regression in e-views 9. The model is applied to test the hypothesis H_1 and its sub hypothesis $H_{1a,}$ $H_{1b,}$ and $H_{1c.}$ The analysis was conducted by utilizing the custom user-specified threshold value. These tests were conducted by focusing on first lagged return as a determinant of current day return by keeping in view that it will have a greater direct impact (Xue & Zhang, 2017). The second lag up to the tenth lag is also included in the model as a control variable. The results of which are reported in appendix 8.6.

5.1.2.1. Results for Investors' Sentiments

The results of threshold autoregression for investors' sentiments are reported in table 5-5. The result indicated significant autoregression in both regime's higher and lower regimes. The higher regime indicated bullish behavior on investors, and the lower regime is associated with investor's bearish behavior. The model's overall result indicated that the model is statistically significant as indicated by the F. statistics (3.825903) of the model, which is significant at the level of P<0.001, indicating the overall fitness of the model. According to Ahsan et al. (2009), Alam and Yasin (2010), and Garson (2012), the value of Durbin Watson is acceptable between the range of 1.5 and 2.5, which will indicate the independence of observations of the model. The value of Durbin Watson is also well within the acceptable range, indicating the model's robustness.

Table 5-5- Threshold Results for Sentiments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SENTIMENT < 1 – 1333 observations				
RETURN(-1)	0.136	0.030	4.475	0.000
1 <= SENTIMENT – 1219 observations				
RETURN(-1)	0.102	0.026	3.913	0.000
S.E. of regression	0.010	Akaike info criterion		-6.315
F-statistic	3.826	Durbin-Watson stat		1.994
Prob(F-statistic)	0.000			

The results of the threshold regression for hypothesis testing indicates that there exists a significant positive relationship between stock market return. It's first and second lagged return having t-statistics of 4.474861 and 2.760356 respectively, where the first lag is highly influencing the current stock market return at a P<0.001 whereas the second lag is significant at a P<0.005 but still the first two lags in case of bearish market trend influence the current market return at 99% level of significance.

Whereas in part two of the results where the threshold value is one, or there is a bullish trend in the stock market, the results indicate that the first lagged stock market return highly influences the current day market return at 99% confidence interval. These results are in line with Olson's (2006) and Prechter's (2016) theory of social mood, which posits that there exists a social mood among investors that influence the overall stock market. By considering the overall investor's sentiments, we can understand the stock market behavior and predict the future.

5.1.2.2. Results for Overconfidence Bias

The results of threshold autoregression for investors' overconfidence behavior are reported in table 5-6. The result indicated significant autoregression in the higher regime. A higher regime indicates overconfidence behavior on the part of investors, and a lower regime is associated with the absence of overconfidence. The overall result of the model indicated that the model is statistically significant as indicated by the F. statistics (6.782794) of the model, which is significant at the level of P<0.001 indicating the overall fitness of the model and as discussed earlier, the value of Durbin Watson is acceptable between the range of 1.5 and 2.5 which indicates the independence of observations for the model.

Table 5-6- Threshold Results for Biases

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BIASES < 1 -- 1902 observations				
RETURN(-1)	0.016	0.024	0.681	0.496
1 <= BIASES -- 650 observation				
RETURN(-1)	0.331	0.038	8.704	0.000
S.E. of regression	0.010	Akaike info criterion		-6.338
F-statistic	6.783	Durbin-Watson stat		2.016
Prob(F-statistic)	0.000			

The threshold effect of overconfidence bias indicated that in the absence of overconfidence behavior, the impact of lagged return on current market return is not consistent and mostly insignificant only the second lag. These results are under the existing literature, positing that the market follows a random walk in the absence of behavioral factors. The lagged value doesn't predict the current value of the stock market. As far as the higher regime or market behavior results in overconfidence, the results are consistent with the proposed sub hypothesis. There is a significant impact of lagged return on current market return. The first lagged return is significantly impacting the current-day stock market return,

where the first and second lagged returns are significant at a 99% level of significance, having t-statistics of 8.703758 3.657636. The overall evidence from the data indicates the existence of strong autocorrelation in the presence of overconfidence behavior. The coefficient values in the presence of overconfidence are also fairly high in comparison value of autoregression coefficients in its absence.

5.1.2.3. Results for Heuristics Biases

The results of threshold autoregression for investors' heuristic behavior based on their mental shortcuts are reported in table 5-7. The result indicated significant autoregression in the higher regime. A higher regime indicates behavior based on heuristic biases on the part of investors, and a lower regime is associated with the absence of heuristic behavior. The model's overall result indicated that the model is statistically significant as indicated by the F. statistics (5.479663) of the model, which is significant at the 99% level of significance, indicating the model's overall fitness. As discussed earlier in the chapter, Durbin Watson's value is also acceptable at 2.005034, which is between the acceptable range of 1.5 and 2.5, which indicates the independence of observations for this model.

Table 5-7-Threshold Results for Heuristics

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HEURISTIC < 1 -- 1274 observations				
RETURN(-1)	-0.002	0.029	-0.066	0.947
1 <= HEURISTIC -- 1278 observations				
RETURN(-1)	0.196	0.027	7.245	0.000
S.E. of regression	0.010	Akaike info criterion		-6.329
Sum squared resid	0.262	Schwarz criterion		-6.280
F-statistic	5.479	Durbin-Watson stat		2.005
Prob(F-statistic)	0.000			

The hypothesis testing results regarding the threshold impact of heuristics biases are also consistent with the proposed market behavior. As suggested, the presence of predictability of stock market return based on its own lagged values is highly insignificant and inconsistent with various coefficients having negative values indicating price correction behavior in the absence of heuristic biases (Mumtaz et al., 2016; Xue & Zhang, 2017) and also indicating a decrease in autocorrelation. Whereas in the higher regime of the threshold variable or existence of the heuristic behavior among investors at Pakistan stock market, the results indicate the presence of highly significant existence of stock market autocorrelation, affirming the proposed behavior that the existence of heuristic biases lead to market predictability and deviation from the rational behavior. Investors' utilization of mental

shortcuts makes them prone to follow the same pattern repeatedly based on their prior knowledge and experience of stock market return, causing stock market predictability.

The results as shown in the table indicates that in the presence of heuristic behavior of investors, the first, second, third, sixth, and tenth lagged return is found to be significantly impacting and predicting the current day return, where the first lagged return is highly influencing the current day value having t-statistics of 7.244675, which is significant at 99% level of confidence, indicating the increase in predictability in the presence of heuristics behavior affirming the hypothesis of the study.

5.1.2.4. Results for Framing Effect

The results for hypothesis testing regarding the threshold effect of framing effects at the stock market in Pakistan are also according to the proposed model, which posits that there is significant autocorrelation or predictability in the presence of the behavior influenced by framing effects. That predictability decreases or diminished in the absence of these framing effects.

Table 5-8-Threshold Results for Framing Effect

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FRAMING_EFFECT < 1 -- 1203 observations				
RETURN(-1)	-0.031	0.028	-1.0795	0.280
1 <= FRAMING_EFFECT -- 1349 observations				
RETURN(-1)	0.225	0.027	8.423	0.000
S.E. of regression	0.0100	Akaike info criterion		-6.3478
Sum squared resid.	0.2572	Schwarz criterion		-6.2997
F-statistic	8.0605	Durbin-Watson stat		2.0064
Prob(F-statistic)	0.0000			

The results indicate that in the absence of framing effects, the predictability of current-day market return through its lagged return values is inconsistent and insignificant in most cases, especially for the prior day return. The values of autoregressive coefficients are also less compared to the coefficients in the presence of these framing effects. These results of the threshold autoregressive model are consistent and are in line with proposed theoretical outcomes. The first two lagged variables are significantly impacting the current day return of KSE-100 index return with t-statistics values of 8.422986 and 4.884628, both of which are highly significant at a 99% confidence interval. As discussed earlier, these autoregressive coefficients' values are also high compared to the coefficients in the absence of framing

effects, which affirms that behavioral factors like framing effects positively influence the stock market autocorrelation.

5.1.3. Results of the Wald Test

As discussed earlier in the methodology section, after applying the threshold autoregressive model autoregression on established the number of lags, the next step involves testing the existence and significance of the model's threshold effect, which is to be done by utilizing the Wald test. Wald test will establish that the behavior (coefficient) of the stock market in the higher regime is significantly different from, the lower regime's behavior, which will further add significance to the variables under study's explanatory power. So Wald test is conducted using E-Views, and the results are reported in Table 5-9 below.

Table 5-9-Results of Wald Test

Threshold Regression			**Wald Test**	
Variable	**Coefficient (Low)**	**Coefficient (High)**	**T-Stat**	**P-Value**
Sentiments				
Return(-1)	0.136	0.102	-1.5935	0.111
Biases				
Return(-1)	0.016	0.331	-6.9206	0.000
Heuristics				
Return(-1)	-0.002	0.195	-4.9746	0.000
Framing Effect				
Return(-1)	-0.031	0.225	-6.5723	0.000

Results for investors' sentiments indicate no significant difference in investors' behavior in the lower regime and higher regime, i.e., during bullish and bearish trends. The p-value of the Wald test is insignificant at 0.1112, which is slightly greater than the ten percent level of significance. This insignificance can be associated with the fact that both of these market trends are the outcome of the overall social mood in the market, which manifests behavioral factors at an aggregate level. Hence as the results indicated that the prior day return is significantly associated with the current day return in both bullish and bearish regimes, are according to the theory of social mood, and that is the reason why the behavior of stock market autocorrelation in both regimes is not significantly different from each other.

Whereas the Wald test results for biases, heuristics, and framing effects indicate a significant difference between lower and higher regime coefficients, i.e., in the absence and presence of these behavioral factors. According to the theory of behavioral finance, these results are also indicate that the presence of behavioral factors cause the stock markets to

deviate from stock market efficiency and leads to stock market predictability. As reported earlier in the results of threshold autoregression, there is a significant autoregression in the presence of biases, heuristics, and framing effects. The results of autoregression coefficients are insignificant in the absence of these behavioral factors. The Wald test results are also pointing towards the same conclusion that this behavior is also significantly different.

5.2. Investors' Models

This part of the study is based on a survey questionnaire adopted from various methodology sections. For the data collection purposes, the scholar relied on the professional data collection services provided by the Creative Business and Social Research (CBSR), Rawalpindi, Pakistan. The Creative Business and Social Research (CBSR) Institute is a registered training and research consultancy institute with experience in conducting training, seminars, and consultancy and services to the researchers. The head office of Creative Business and Social Research (CBSR) is located at Office # F-18, First Floor, Malikabad Shopping Complex, Main Murree Road, 6th Road Rawalpindi, Islamic Republic of Pakistan. The institute is established under the patronage of Dr. Ayaz-ul-Huq, Assistant Professor, Islamabad Business School, Quaid-e-Azam University, Islamabad Pakistan. The data was collected by adhering to the study's requirements through the adopted survey questionnaire. This collection of primary data from independent third parties will further enhance the study's reliability and validity, which is already established in chapter 4. According to Kimberlin and Winterstein (2008), reliability and validity are the key indicators of the research instrument's quality or questionnaire. The data collection certificate is attached in appendix 8.5. The Creative Business and Social Research (CBSR) team has collected data on behalf of the scholar from the stock market investors in Karachi, Lahore, and Islamabad. The upcoming section will explain the data and will proceed with hypothesis testing.

5.2.1. Data Background

From the total 550 questionnaires distributed among Pakistan stock market investors from Islamabad, Lahore, and Karachi. A total of 493 questionnaires were received, indicating a return percentage of 89%. This is significantly high as compared to the previous studies of Gul and Akhtar (2016), Kudryavtsev et al. (2013), Rasheed, Rafique, Zahid, and Akhtar

(2018), and Waweru et al. (2008). This fact can be attributed to the professional services of CBSR used for data collection. The data is further refined for outliers and missing values, and a total of 426 responses were utilized for final analysis. Making the final valid percentage of almost 77%.

The data background can be further divided into two sections. As the first part of the questionnaire deals with the respondents' demographic characteristics, including Gender, Marital status, Age, Experience, Qualification, Specialization, and location. The second part of the instrument consists of responses on a five-point Likert scale regarding personality, behavior, and decision style. Hence, depending on the difference between these two sections, data is further explained by providing frequency distribution of the demographic variables and then detailed descriptive statistics of the second part of the instrument.

5.2.1.1. Demographic Distribution

The overall demographic distribution of the sample is provided in table 5-10 below. Out of the total respondents, 230 were married, 152 were single, and the remaining 44 selected another status. The table shows that a very high majority of the respondents were male totaling almost 90% of the overall sample size, and only 43 respondents were female. They were showing a very low representation of females in our sample.

The majority of the respondents in the sample have investment experience ranging from 00 to 05 years, which accounts for almost 62% of the population after which came the investors with having experience of 06 to 20 years, which accounts for 24% of the population and only 14% of the investors in the sample were having experience of 21 years and above.

The respondents' age group shows that most of the respondents range from 31 to 50 years, accounting for almost 45.5% of the sample, and only 15.5% aged 51 and above. The remaining 39% belonged between the ages of 18 to 30 years.

The investors' educational qualification was also considered, as you can observe in the table that most sample investors are having a bachelor or higher qualification. Almost 57% of the sample is having an education in the field of business education. Lastly, the respondents'

location is also recorded, and it can be observed that most of the respondents are from Karachi, followed by respondents from Lahore and Islamabad, respectively.

These variables will be further analyzed in the upcoming analysis section for their role in an investor's decision-making style.

Table 5-10 - Demographic Distribution

Characteristics	Frequency	Percent
Marital Status		
Married	230	54.0
Single	152	35.7
Other	44	10.3
Gender		
Male	383	89.9
Female	43	10.1
Other	0	0.0
Age		
18 to30	166	39.0
31 to 50	194	45.5
51 & Above	66	15.5
Investment Experience		
00-05 Years	264	62.0
06-20 Years	102	23.9
21 Years & Above	60	14.1
Qualification		
Matriculation	20	4.7
Intermediate	24	5.6
Bachelors	143	33.6
Masters	167	39.2
M.Phil.	41	9.6
Ph.D.	9	2.1
Others	22	5.2
Specialization		
Business Related	243	57.0
Other	183	43.0
Location		
Islamabad	103	24.2
Lahore	125	29.3
Karachi	198	46.5

5.2.1.2. Descriptive Statistics

In this part of the study, the results of the descriptive statistics of the data collected against reflective measures of personality, behavioral factors, and decision-making style are reported and discussed. The detailed results are reported in Table 5-11 below. It includes the number of observations (N), the minimum and the maximum values or the range associated with the items, the mean of the collected data and its standard deviation, skewness, and kurtosis for assessing the normality of the collected data. As discussed earlier, the total number of observations included in the analysis after screening for outliers and missing

values is 426. Hence each item consists of the same 426 observations. The data is collected using a 5 points Likert scale; hence the minimum and maximum value associated with the items is 1 and 5. The mean values of the responses ranged from 2.10 to 4.10, which indicates that most of the respondents were inclined to agree with the provided statements. The standard deviation of the responses is reported next, which ranged from 0.919 to 1.411. Given the range of 5, these values indicate that final analysis responses comprise almost every type of investor regarding personality traits, behavioral factors, and decision-making style. Lastly, it is of vital significance to assess data for normality. The normality of sample distribution is key in determining the appropriate statistical technique for final analysis. One way of assessing data normality is through skewness and kurtosis. Hence the values of skewness and kurtosis are reported in table 5-11, where skewness is the degree of asymmetry in a bell-shaped curve. A distribution can be normally distributed or skewed towards left or right. The ideal value of skewness in a normal distribution is 0. A value higher or lower than 0 indicates skewness.

Similarly, kurtosis refers to the tails of distribution that differs from the normal distribution. A value of 3 is associated with a perfectly normally distributed bell curve. Still, in software like SPSS, excess kurtosis is reported to make a reported value of 0 for the ideal normal distribution. As a general rule of thumb, a reported value of skewness and kurtosis between -1 to +1 is significantly close to a normal distribution. The test assuming a normal distribution of underlying data can be applied (Wong, 2013). Although most items fulfill this criterion for normality, some of the items are not normally distributed, and the value of skewness and kurtosis exceeds the said threshold. These results made the inferential techniques of simple linear regression and covariance-based structural equation modeling invalid for analysis. As both of these techniques require normally distributed data for analysis instead of structural equation modeling, using the partial least square method can provide valid results for non-normal data and, hence, be applied for further analysis.

Table 5-11 - Descriptive Statistics (Questionnaire)

Items	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
E_1	426	1	5	3.60	1.243	-.823	-.261
E_2	426	1	5	3.71	1.062	-.937	.236
E_3	426	1	5	3.58	1.164	-.629	-.344
E_4	426	1	5	3.68	1.061	-.866	.257

A_1	426	1	5	2.14	1.102	1.011	.472
A_2	426	1	5	2.69	0.919	.945	.021
A_3	426	1	5	2.42	1.375	.800	-.671
A_4	426	1	5	3.72	1.108	-1.009	.447
O_1	426	1	5	3.72	1.341	-.952	-.289
O_2	426	1	5	3.67	1.093	-.835	-.061
O_3	426	1	5	2.18	1.016	.807	.358
O_4	426	1	5	3.83	1.117	-1.048	.531
O_5	426	1	5	3.67	1.168	-.749	-.251
O.C_1	426	1	5	3.62	1.109	-.882	.138
O.C_2	426	1	5	3.19	1.220	-.281	-.999
O.C_3	426	1	5	3.63	1.294	-.798	-.474
O.C_4	426	1	5	3.66	1.120	-.906	.069
O.C_5	426	1	5	3.64	1.128	-.693	-.219
O.C_6	426	1	5	3.96	1.226	-.888	-.322
O.C_7	426	1	5	3.67	1.095	-.751	-.008
O.C_8	426	1	5	3.82	1.138	-1.012	.371
A.B_1	426	1	5	3.55	1.301	-.677	-.662
A.B_2	426	1	5	3.64	1.270	-.801	-.394
A.B_3	426	1	5	3.97	1.336	-1.201	.165
A.B_4	426	1	5	3.42	0.930	-.847	.213
A.B_5	426	1	5	3.06	1.082	-.419	-.678
R.B_1	426	1	5	3.67	1.358	-.866	-.506
R.B_2	426	1	5	3.72	1.072	-1.049	.529
R.B_3	426	1	5	3.65	1.181	-.692	-.275
R.B_4	426	1	5	3.67	1.110	-.847	-.006
R.B_5	426	1	5	3.79	1.108	-.867	.065
R.B_6	426	1	5	4.00	1.209	-1.057	.028
D.E_1	426	1	5	2.97	1.095	-.108	-.599
D.E_2	426	1	5	3.62	1.411	-.702	-.888
D.E_3	426	1	5	3.77	1.133	-.869	.000
D.E_4	426	1	5	3.67	1.142	-.795	-.026
D.E_5	426	1	5	2.18	1.139	.883	-.028
D.E_6	426	1	5	3.90	1.089	-.990	.363
D.M_1	426	1	5	3.54	1.051	-.668	-.196
D.M_2	426	1	5	3.90	1.182	-1.199	.695
D.M_3	426	1	5	4.10	1.128	-1.267	.806
D.M_4	426	1	5	3.56	1.037	-.781	.013
D.M_5	426	1	5	3.59	1.014	-.686	.052

E=Extraversion, A=Agreeableness, O= Openness to Experience, OC=Overconfidence Bias, AB, Availability Heuristics, RB= Representativeness Heuristics, DE= Disposition Effect, D.M=Intuitive Decision Making

5.2.2. Correlation Analysis

Before proceeding towards causal analysis, it is mandatory to first test for the dataset's correlation. If there is a significant correlation among variables under study, we can only test it further for its direction and causal impact using regression analysis.

The software we used for this analysis is SPSS. In the first stage, the reserve questions were recorded. By taking an average of the items, an overall variable is created, and then the correlation among those variables is calculated. They are two types of correlation coefficients that are typically used in social sciences research; first is the Pearson correlation coefficient, which is the most commonly used measure, but it is applicable on data that is normally distributed, but where data is not normally distributed, Spearman correlation coefficient is recommended. Hence, our study's data is not ideally distributed, so using the later approach correlation coefficient is obtained. The results of which are reported in Table 5-12 below.

Table 5-12 - Correlation Analysis

	E	**A**	**O**	**OC**	**AB**	**RB**	**DE**	**DM**
E	1.000							
A	0.575**	1.000						
O	0.552**	0.511**	1.000					
OC	0.549**	0.589**	0.600**	1.000				
AB	0.555**	0.578**	0.481**	0.434**	1.000			
RB	0.520**	0.520**	0.545**	0.652**	0.491**	1.000		
DE	0.448**	0.453**	0.529**	0.477**	0.468**	0.561**	1.000	
DM	0.577**	0.610**	0.601**	0.583**	0.582**	0.624**	0.606**	1.000

***=p<0.001, **=p<0.05, *=p<0.1

E=Extraversion, A=Agreeableness, O= Openness to Experience, OC=Overconfidence Bias, AB, Availability Heuristics, RB= Representativeness Heuristics, DE= Disposition Effect, D.M=Intuitive Decision Making

The results indicate that there exists a significant positive correlation among all the variables of the study. The degree of correlation varies from 0.434 to 0.624, and also it can be observed that all these correlations are highly significant. The direction and strength of the relationships are per the proposed theory. All the personality traits are correlated, indicating that one trait is linked with the other two traits. All three traits under study operate in the same direction, hence backing the proposed theory that the impact of these three personality traits is similar.

All the behavioral factors are also correlated with each other, indicating that reliance on one type of behavioral bias can make an individual rely on other behavioral factors. These results are also in line with the study's proposed theoretical model and line with the previous studies of Kudryavtsev et al. (2013) and Waweru et al. (2008). Kudryavtsev et al. (2013) that all these biases are moderately correlated and reliance of investors on one bias increase the

chances of reliance on other behavioral biases. This effect is likely to increase in a collectivist society like Pakistan.

It can also be observed that the correlation among selected personality traits and behavioral biases is also significantly positive, indicating that the proposed theoretical relationship exists and one factor does lead or impacts the another, which can be further verified through the causal model.

Lastly, the intuitive decision-making style is also significantly associated with the selected personality traits and behavioral factors, which is also under the study's proposed hypothesis. Inferring that there is some positive impact of these factors on each other. The direction and strength of which can now be further affirmed using causal models.

After establishing the linkage between variables under study, the next step is to test for a causal model. The model selected for testing the hypothesis is structural equation modeling using the partial least square method. As discussed earlier, structural equation modeling consists of two models: the measurement and structural models. The outer model or the measurement model defines the relationship between observed variables and unobserved variables. It links and validates the underlying constructs with their respective items through the confirmatory factor analysis (CFA). The confirmatory factor analysis focuses on validating the proposed model and not explains the relationship between constructs. Hence the said tool is used for accessing the validity and reliability of the model. It can confirm two aspects of the study; it confirms the hypothesized factor structure and its validity. In Smart-PLS, the validity of the underlying data of the model is assessed via the PLS algorithm.

The second part structural model defines the relationship between unobserved variables. Such a causal model defines and specifies the relationships between two latent variables and elaborates on how to change one variable effect or change another variable. Therefore, the structural model is associated with hypothesis testing and is tested after establishing the model's validity and reliability and its constructs. Hence, the section explains the validity and reliability of the proposed model under study. This two-step approach, where the measurement model precedes the structural model, as suggested by Anderson and Gerbing (1988). This study used Smart-PLS 2 and 3 for causal analysis. Although in Smart-

PLS 3, there are two types of configurations for the structural equation: traditional and consistent configurations. THE consistent PLS approach is a refined approach for models with only reflective measures and variables, but for mixed models with different types of variables, traditional PLS is appropriate (Dijkstra & Henseler, 2015). This study utilized a mixed model. It incorporated formative variables in the shape of demographic variables alongside reflective measures; hence, the traditional PLS approach is used, which can be conducted conveniently through Smart-PLS 2. Apart from that, traditional PLS remains the algorithm of choice for formative and mixed models. In some cases, this approach is preferred even for pure reflective models, where the research goal aligns with this methodology (Garson, 2012).

5.2.3. Univariate and Multivariate Normality

According to Geary (1947), "Normality is a myth; there never was, and never will be a normal distribution." Although the statement exaggerates the facts, it does represent the difficulties of achieving a normal distribution in a dataset. It is of vital significance to utilize tools to access normality of data, when we drift away from this desired normality (K. V. Mardia, 1980), normality is also important because many famous statistical techniques like ordinary least square regression and covariance-based structural equation modeling rely on it as one of their core assumptions. One way of assessing data normality is through skewness and kurtosis. Hence the values of skewness and kurtosis are reported in table 5-11, where skewness is the degree of asymmetry in a bell-shaped curve. A distribution can be normally distributed or skewed towards left or right. The ideal value of skewness in a normal distribution is 0. A value higher or lower than 0 indicates skewness. Similarly, kurtosis refers to the tails of distribution that differ from the normal distribution. A value of 3 is associated with a perfectly normally distributed bell curve. Still, in software like SPSS and SMART-PLS, the value of excess kurtosis is reported making a reported value of 0 for ideal normal distribution. As a general rule of thumb, a reported value of skewness and kurtosis between -1 to +1 is significantly close to a normal distribution. The test assuming a normal distribution of underlying data can be applied (Wong, 2013). This section will discuss both the univariate and multivariate normality of the data. In statistics, univariate normality deals with the probability distribution of a single variable, and multivariate normality refers to probability

distribution of multiple variables is assed at multidimensional levels. The test utilized in the current study to access multivariate normality is Mardia's multivariate skewness and kurtosis. The test was developed by Mardia (1970). Multivariate normality is an important issue because normality is assumed in some of the most common statistical techniques used in social sciences. A skewness value between -1 to +1 and a kurtosis value between -20 to +20 is considered normal enough for further statistical analysis based on the normality of data. If the values exceed beyond these thresholds, then techniques like simple SMART-PLS algorithm and bootstrapping are recommended. Apart from that, Mardia's test is conducted under the null hypothesis that there exists multivariate normality; hence a p-value of above 0.05 indicates normality of data. To test for it, the standardized values of data associated with each variable as provided in the SMART-PLS Algorithm results are utilized for accessing normality at both levels. Test for univariate and multivariate normality is conducted via an online tool provided at;

https://webpower.psychstat.org/models/kurtosis/

The said online tool is based on the book of Zhang and Yuan (2018). The results of the test are reported in table 5-13.

Table 5-13 - Univariate and Multivariate Normality

	Skewness	**Kurtosis**
Agreeableness	-1.009	0.340
Extraversion	-0.888	0.062
Openness to experience	-1.010	0.456
Overconfidence	-0.859	-0.074
Availability	-0.761	-0.035
Representativeness	-0.961	0.351
Disposition	-0.689	-0.438
Decision Making	-1.148	0.948
Mardia's multivariate skewness and kurtosis		
	β	**z**	**p-value**
Skewness	011.674	828.903	0.000
Kurtosis	108.713	23.426	0.000

The univariate results indicate that agreeableness, openness to experience, and decision-making are negatively skewed and beyond the allowed limit of -1. Hence univariate normality of the variables is not established, and the values of Mardia's multivariate skewness and kurtosis also 11.67 and 107.71, respectively. These values are far above the allowed range for normal distribution based statistical analysis. This can be further affirmed

through the test's p-value, which is highly significant even at a 1% ($p<0.001$) confidence interval. The null hypothesis of multivariate normality can't be established, indicating that data doesn't follow a normal distribution in higher dimensions. Hence the simple PLS-algorithm and bootstrapping are suitable for further analysis as it incorporates for abnormality of data. These results further add legitimacy and validity to the technique selected for the current study.

5.2.4. Validation of the Model

A confirmatory factor analysis (CFA) is conducted using Smart-PLS 2 and 3 to assess the model's validity and reliability. Smart-PLS provides the results of the reliability and validity of the measurement model using the PLS algorithm. According to Mark Saunders et al. (2003), validity is the extent to which data measures what it intends to measure, whereas reliability indicates the degree of consistency and bias-free measures. To ensure the reliability and validity of the measurement model, following checks using various indicators were carried out.

Reliability:

1. Stability of measure
2. Indicator Reliability
3. Internal Consistency Reliability

Validity:

1. Content Validity
2. Criterion-related Validity
3. Discriminant Validity
4. Convergent Validity

The measurement model run to establish reliability and validity using PLS-Algorithm is reported in figure 5-2 below, and detail of reliability and validity results is provided and explained in the forthcoming heads. After establishing the reliability and validity of the measurement model, some additional factors must be considered.

1. Unidimensionality
2. Common method variance
3. Model fit
4. Multicollinearity
5. Explained Variance (R^2)

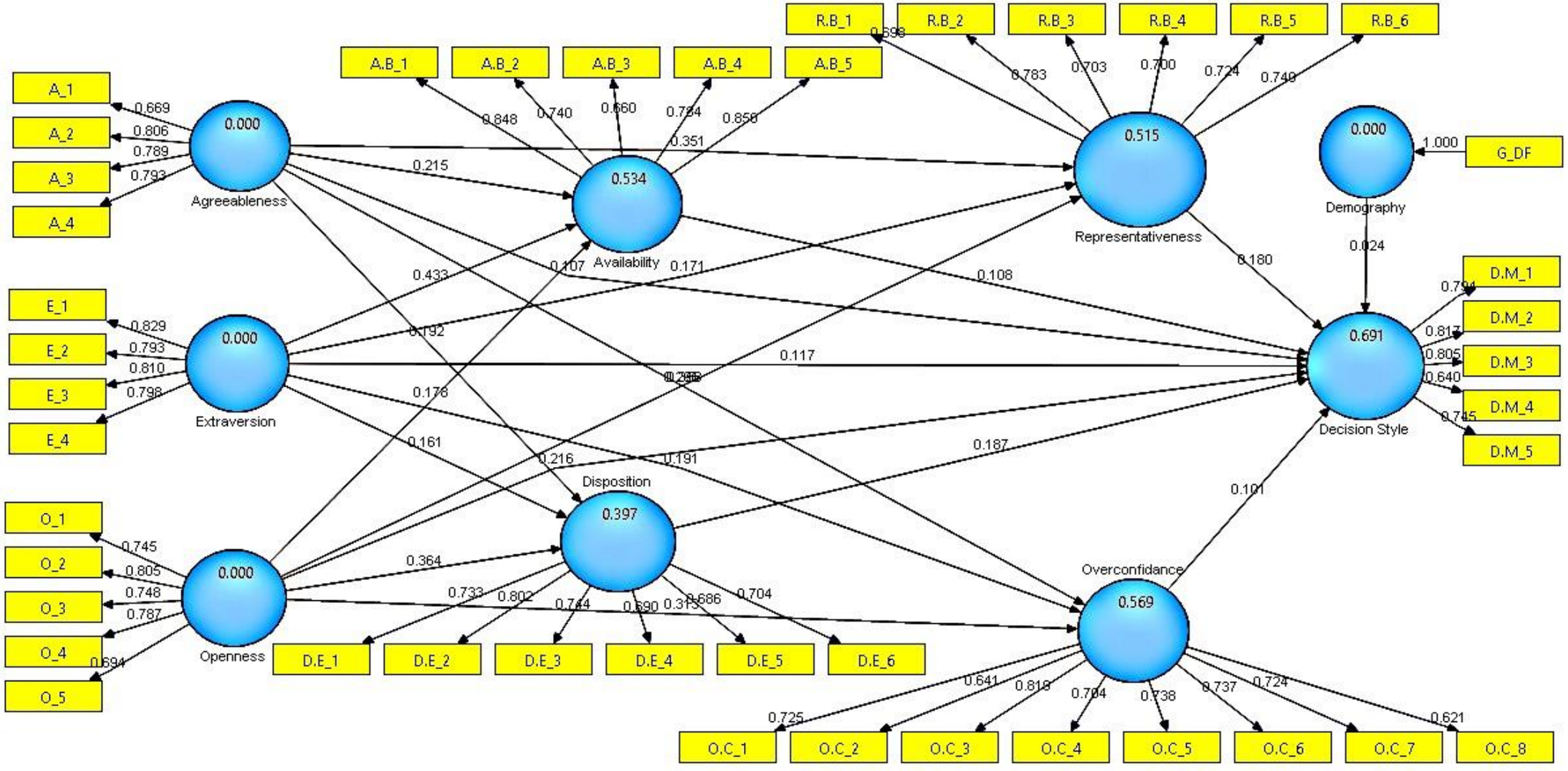

Figure 5-2 - Measurement Model

Reliability is known as the consistency or the reproducibility of the instrument utilized in the study. According to Carmines and Zeller (1979), the instrument can produce the same results in repeated trials. The scope of reliability also extends to the consistency of a variable's multiple measures (Hair et al., 1998). Concerning a single variable, it assesses the degree to which the items used to measure a latent variable are homogenous. Different reliability measures are used to assess the overall reliability of the variables used in a study, which includes Factor loadings, t-tests, Cronbach's alpha (α), Composite reliability (C.R), Average Variance Extracted (AVE), and rho_A. These measures are associated with measuring reliability, which are discussed and established in the upcoming sections.

5.2.4.1. Stability of measurement

Test-retest and parallel form reliability is associated with the stability of the measures used in a study. Test-retest reliability indicates how the measures remain unchanged regardless of respondents and conditions the instrument was administered. According to Sekaran (2006), reliability is achieved when an instrument is applied with the same measures on the same population set a second time. Then the correlation scores between the two sets of responses represent the test-retest reliability. The higher the correlation is, the higher will be the test-retest reliability. The instrument we are using for data collection is adopted from previous studies. Those are tested repeatedly in similar or the same population with different combinations of variables. The studies of Gul and Akhtar (2016), Rasheed et al. (2020), Rasheed, Rafique, Zahid and Waqar (2018), Sadi et al. (2011), and Sheikh & Riaz (2012) used these variables in their studies on stock market investors in Pakistan. They produced similar correlation results with the variables indicating the test-retest reliability of the measures. Another form associated with the stability of the measures is Parallel form reliability. According to Sekaran (2006), it is established when the same measures with the item having some amendments or change in order or language are administered. The results obtained after that are highly correlated among both responses. This validity can also be established through a review of the existing literature. Numerous studies applied measures for the variables in different languages, context, and population, and each is producing similar correlation among the variables and their proposed relationships (Gul & Akhtar, 2016; Kudryavtsev et al., 2013; Rasheed, Rafique, Zahid, & Akhtar, 2018; Waweru et al., 2008).

The stability of measures is established when an instrument is initially constructed and tested. Already established or prior instruments don't require to reestablish this. The current study utilized already well-established and grounded measures for each variable and tested them in various contexts and settings. The current study only focused on establishing the reliability of the current data set.

Table 5-14 – Reliability and Validity of Data

Variable	Items	Loadings	AVE	CR	Rho_A	α
Extraversion	E_1	0.829	0.653	0.882	0.825	0.823
	E_2	0.793				
	E_3	0.810				
	E_4	0.789				
Agreeableness	A_1	0.668	0.587	0.850	0.791	0.768
	A_2	0.806				
	A_3	0.789				
	A_4	0.793				
Openness to experience	O_1	0.745	0.573	0.870	0.822	0.814
	O_2	0.805				
	O_3	0.748				
	O_4	0.787				
	O_5	0.694				
Overconfidence	O.C_1	0.724	0.512	0.893	0.865	0.862
	O.C_2	0.640				
	O.C_3	0.818				
	O.C_4	0.704				
	O.C_5	0.738				
	O.C_6	0.737				
	O.C_7	0.724				
	O.C_8	0.624				
Availability	A.B_1	0.847	0.608	0.885	0.847	0.836
	A.B_2	0.739				
	A.B_3	0.658				
	A.B_4	0.787				
	A.B_5	0.852				
Representativeness	R.B_1	0.697	0.526	0.869	0.824	0.820
	R.B_2	0.779				
	R.B_3	0.701				
	R.B_4	0.699				
	R.B_5	0.725				
	R.B_6	0.746				
Disposition Effect	D.E_1	0.734	0.529	0.871	0.828	0.822
	D.E_2	0.800				
	D.E_3	0.740				
	D.E_4	0.689				
	D.E_5	0.686				
	D.E_6	0.710				
Intuitive Decision Making	D.M_1	0.798	0.582	0.873	0.819	0.818
	D.M_2	0.820				
	D.M_3	0.806				
	D.M_4	0.635				
	D.M_5	0.742				

5.2.4.2. Indicator Reliability

Indicator reliability refers to the degree of indicator variable variance explained through the latent variable (Hamid et al., 2017). The value of indicator reliability through reflective loadings ranges from 0 to 1. According to Hair et al. (2017), the desired value of outer loading is 0.70 or higher. Still, if the value lies between 0.40 and 0.70, then the item should only be deleted if it increases composite reliability and average variance extracted. Still, if the value of loadings is below 0.40, it must be dropped, but according to Hulland (1999), a factor loading value of 0.50 or higher indicates good indicator reliability. Hence the current study tested for factor loadings using SMART-PLS Algorithm to establish indicator reliability. The results are shown in Table 5-14, and it can be observed that the values of factor loadings of each item are above the minimum acceptable value of 0.50. The minimum value of factor loading is 0.624, associated with the second item associated with measuring overconfidence among investors. Hence overall, the data set represents significant indicator reliability to test causal relationships using structural equation modeling.

5.2.4.3. Internal Consistency Reliability

According to Sekaran (2006), internal consistency reliability refers to the homogeneity of the items associated with a latent variable. In simple words, it indicates that the set of questions used to measure a concept is highly interdependent and interrelated, which can affirm that the items used are measuring the very same concept. The two most common measures used to establish internal consistency of the scale are Cronbach's alpha and composite reliability (Hamid et al., 2017). The values of both of these indicators range from 0 to 1 and are desired to have a minimum value of 0.70 or higher (Nunnally, 1994).

Composite reliability measures the overall reliability of the items associated with a concept. As stated earlier that the value of composite reliability ranges from 0 to 1, and a value of 0.70 or higher indicates good reliability, but if the construct validity of the instrument is well established, then the value between 0.60 and 0.70 is also acceptable (Fornell & Larcker, 1981; Hair et al., 2017) hence the internal reliability is tested using Composite reliability (C.R). The formula for calculating said reliability is given below.

$$C.R = \frac{(\Sigma \lambda_i)^2}{(\Sigma \lambda_i)^2 + (\Sigma \delta_i)^2}$$

Where ƛ represents the standardized factor loadings and σ is the measurement error associated with each item. The results of composite reliability are given in table 5-13. The values of composite reliability for each variable of the study above the desired threshold of 0.70 as the minimum value of composite reliability is 0.850, significantly higher than the threshold.

As discussed earlier, the inter-item reliability of the item can also be established using Cronbach's alpha. Nowadays, rho_A is a much more recommended measure similar to Cronbach's alpha. The value of which also ranges from 0 to 1 and is also preferred to be higher than 0.70 (Nunnally, 1994), but a value of 0.60 or higher is also acceptable (Shelby, 2011). Still, on the other hand, a value of above 0.90 is not desired, and a value of above 0.95 is undesirable (Nunnally, 1994). It analyzes all the items associated with a variable and the correlation between them. According to Sekaran (2006), this measure represents the inter-item reliability of the measure. Cronbach's alpha is the most commonly used measure in social sciences to represent the data's reliability. Hence the current study tested for both of these measures to establish inter-item reliability. The results are shown in Table 5-14, and it can be observed that values of factor loadings of each item and Cronbach's alpha for each latent variable within the acceptable range. The minimum value associated with Cronbach's alpha is 0.768 which is also significantly above the minimum acceptable value of 0.60. Hence overall the data set represents significant indicator reliability to test causal relationships using structural equation modeling.

The next section focuses on discussing the measures used to access the validity of the data set. According to Sekaran (2006), by establishing the data's validity, we ensure the instrument's ability to measure the intended variables. Validity ensures that the question we ask for a concept is measuring what we intend it to measure. Like reliability, validity also has various dimensions needed to be established to achieve a valid analysis instrument. Validity can be accessed through different statistical techniques and tests. According to Sekaran (2006), validity tests can be divided into content validity, criterion-related validity, and construct validity, where construct validity is further divided into convergent and

discriminant validity. For testing validity in structural equation modeling, factor analysis is used, further categorized into exploratory, confirmatory factor analysis (EFA), and confirmatory factor analysis (CFA). The factor analysis primarily focuses on the goodness of the link between latent and observed variables. This is measured through the factor loadings, and hence loadings are mainly focused on establishing validity. Exploratory factor analysis is used where the link between observed and latent variables is unclear and uncertain (Cudeck, 2000). Therefore it is utilized to design a new instrument to analyze the relationship between latent and observed variables. Hence, in the current study where we adopted the measures for already established instruments that are also retested in various studies, only confirmatory factor analysis is used. The confirmatory factor analysis is utilized based on already established instruments where you propose a new relationship between latent variables, which is conducting by analyzing the measurement model through SMART-PLS Algorithm and reported in the forthcoming heads.

5.2.4.4. Content Validity

The concept of face validity is associated with the content validity of an instrument. It is the first step involved in establishing validity. According to Sekaran (2006), face validity ensures that items seem to measure the concepts they are intended to measure. Establishing face validity doesn't require any quantitative data or test. Instead, it relies on the opinion of experts to be established. Although the current study utilized an adopted instrument still during the pilot study, experts of the field were reviewed, including a review from supervisor, co-supervisor, internal and external examiner alongside a couple of investors operating in the Pakistani stock market. After getting validation from them, it is safe to assume that the instrument possesses reasonable content validity.

5.2.4.5. Criterion Related Validity

Criterion-related validity refers to an instrument's ability to categorize individuals based on latent variables they are measuring (Saunders et al., 2003; Sekaran, 2006). It is further categorized into two categories, namely concurrent validity, and predictive validity. Concurrent validity of an instrument is associated with its ability to distinguish individuals who are known to be different in the prospect of that particular variable, and their scores are

different from each other. In contrast, predictive validity is associated with the instrument's ability to predict future behavior related to that particular latent variable. Criterion-related validity, just like content validity, is also established when the instrument is initially developed. Like the ones utilized in the current study, an already established instrument is utilized on a priori basis. Still, to ensure and establish criteria, relevant literature is explored. It is observed in the studies of Davis et al. (2007), Durand et al. (2013), Gul and Akhtar (2016), Hair and Graziano (2003), Kudryavtsev et al. (2013), Lauriola and Levin (2001), Rasheed et al. (2020), Rasheed, Rafique, Zahid, and Akhtar (2018), Sultana and Pardhasaradhi (2012) and Waweru et al. (2008) that when similar correlation exited among these latent and observed variables repeatedly in different contexts and environments. The measures used in the current study repeatedly produced similar results as proposed and established in the initial studies, establishing predictive validity of the instrument. As far as the concurrent validity is concerned existing studies of Gul (2014), Rasheed et al. (2020), Rasheed, Rafique, Zahid, and Akhtar (2018) and Sultana and Pardhasaradhi (2012) also indicated that the instrument was able to distinguish and identify the difference existing in the sample. In current study concurrent validity can also be analyzed by exploring the descriptive statistics provided in table 5-11. Where it can be observed that the responses for each item range from 1 to 5, indicating the instrument's ability to distinguish respondents based on their personality, behavioral factors successfully, and decision-making style. Hence it can be stated that reasonable criterion-related validity exists in the measurement model for further causal analysis.

5.2.4.6. Discriminant Validity

Discriminant validity is related to the extent to which each construct is significantly different from the other statistically (Hamid et al., 2017). In simple words, to establish discriminant validity, the loadings of items on its latent variable should be higher than loadings on other latent concepts. The discriminant validity is assessed using the various statistical measure. The SMART-PLS established it using cross-loadings analysis, the Fornell and Larcker criterion, and the Heterotrait-Monotrait (HTMT) ratio of correlation.

According to Fornell and Larcker, criterion discriminant validity is established by comparing squared values of average variance extracted (AVE). The latent variable's average

variance should be higher than the squared correlation existing between those variables (Chin, 1998; Fornell & Larcker, 1981). In SMART-PLS, the square root of the average variance extracted is reported alongside correlations among the variables. The test establishes that the average variance extracted for a single variable is more than their inter-variable relationship. As a rule of thumb, any value greater than the inter-variable correlation is considered adequate for discriminant validity (Chin, 1998). The results of which are reported in table 5-15. From the results, the lowest square root value of the average variance extracted given diagonally in the table is 0.716, which is higher than the maximum value of correlation existing among variables, which is 0.710.

Table 5-15 - Fornell-Larcker Criterion

	A	**AB**	**IDM**	**DE**	**E**	**O**	**OC**	**RB**
A	**0.766**							
AB	0.626	**0.780**						
IDM	0.678	0.646	**0.763**					
DE	0.533	0.588	0.659	**0.727**				
E	0.691	0.688	0.659	0.513	**0.808**			
O	0.630	0.573	0.702	0.582	0.601	**0.757**		
OC	0.686	0.530	0.672	0.531	0.626	0.653	**0.716**	
RB	0.656	0.568	0.703	0.607	0.592	0.620	0.710	**0.725**

E=Extraversion, A=Agreeableness, O= Openness to Experience, OC=Overconfidence Bias, AB, Availability Heuristics, RB= Representativeness Heuristics, DE= Disposition Effect, D.M=Intuitive Decision Making

To verify the discriminant validity through Heterotrait-Monotrait ration (HTMT) through SMART-PLS. PLS-Algorithm is used, and the results are reported in table 5-16. According to Henseler et al. (2016), a statistical test is applied to establish discriminant validity with the null hypothesis that the value of HTMT ratio of correlation is below one, which will conclude that significant discriminant validity exists vs. the alternative hypothesis that the value of HTMT ratio of correlations is equal or above 1. That will be concluded as no discriminant validity exists in the dataset. It can be observed from the data provided in the following table that all the values of the HTMT ratio are below one, and the highest value is 0.842. Hence the overall discriminant validity of the latent concepts is established under Heterotrait-Monotrait ratio criteria. In simple words that it can be stated that by fulfilling Heterotrait-Monotrait criteria, it is ensured that each latent variable is unique and can be distinguished among others, and resultantly each variable is discriminant.

Table 5-16 - Heterotrait-Monotrait Ratio

	A	AB	IDM	DE	E	O	OC	RB
A								
AB	0.739							
IDM	0.819	0.767						
DE	0.637	0.700	0.786					
E	0.837	0.821	0.792	0.615				
O	0.764	0.673	0.842	0.692	0.675			
OC	0.825	0.616	0.786	0.624	0.742	0.774		
RB	0.801	0.674	0.839	0.720	0.666	0.744	0.825	

E=Extraversion, A=Agreeableness, O= Openness to Experience, OC=Overconfidence Bias, AB, Availability Heuristics, RB= Representativeness Heuristics, DE= Disposition Effect, D.M=Intuitive Decision Making

Lastly, to further establish the discriminant validity, another measure used is by comparing the items' cross-loadings. The results of which are reported in Table 5-17 below. According to Chin (1998), cross-loadings are analyzed. The loadings should be higher for the construct it measures than loadings on the other latent variables, and loadings are higher on their respective construct, establishing the discriminant validity.

Table 5-17 - Cross Loadings

	AB	A	DE	DM	E	OC	O	RB
A.B_1	**0.847**	0.512	0.341	0.464	0.600	0.383	0.373	0.372
A.B_2	**0.739**	0.471	0.337	0.384	0.506	0.311	0.310	0.325
A.B_3	**0.658**	0.376	0.463	0.485	0.409	0.420	0.571	0.472
A.B_4	**0.787**	0.497	0.619	0.587	0.501	0.449	0.501	0.450
A.B_5	**0.852**	0.566	0.502	0.569	0.645	0.480	0.468	0.568
A_1	0.270	**0.668**	0.233	0.328	0.372	0.388	0.329	0.355
A_2	0.691	**0.806**	0.473	0.602	0.754	0.572	0.583	0.575
A_3	0.466	**0.789**	0.478	0.552	0.448	0.559	0.500	0.541
A_4	0.396	**0.793**	0.388	0.535	0.474	0.548	0.466	0.494
D.E_1	0.468	0.422	**0.734**	0.572	0.444	0.490	0.457	0.656
D.E_2	0.481	0.479	**0.800**	0.513	0.382	0.411	0.491	0.449
D.E_3	0.404	0.414	**0.740**	0.431	0.385	0.389	0.437	0.377
D.E_4	0.345	0.337	**0.689**	0.421	0.364	0.376	0.394	0.373
D.E_5	0.455	0.315	**0.686**	0.395	0.324	0.317	0.369	0.355
D.E_6	0.404	0.333	**0.710**	0.518	0.326	0.306	0.374	0.391
D.M_1	0.571	0.526	0.692	**0.798**	0.451	0.478	0.576	0.497
D.M_2	0.439	0.438	0.437	**0.820**	0.461	0.399	0.555	0.438
D.M_3	0.426	0.432	0.454	**0.806**	0.440	0.434	0.442	0.558
D.M_4	0.488	0.554	0.411	**0.635**	0.550	0.515	0.481	0.528
D.M_5	0.507	0.598	0.482	**0.742**	0.585	0.687	0.589	0.629
E_1	0.659	0.550	0.455	0.573	**0.829**	0.486	0.477	0.475
E_2	0.520	0.556	0.351	0.490	**0.793**	0.502	0.494	0.470
E_3	0.501	0.521	0.366	0.457	**0.810**	0.503	0.438	0.461
E_4	0.532	0.602	0.473	0.596	**0.798**	0.533	0.530	0.505
O.C_1	0.379	0.630	0.372	0.474	0.462	**0.724**	0.447	0.535
O.C_2	0.423	0.556	0.337	0.440	0.398	**0.640**	0.398	0.460
O.C_3	0.493	0.548	0.409	0.566	0.522	**0.818**	0.507	0.568
O.C_4	0.379	0.487	0.379	0.463	0.423	**0.704**	0.489	0.530
O.C_5	0.342	0.434	0.403	0.454	0.456	**0.738**	0.457	0.480
O.C_6	0.330	0.414	0.336	0.432	0.445	**0.737**	0.464	0.485

O.C_7	0.352	0.490	0.380	0.481	0.457	**0.724**	0.482	0.518
O.C_8	0.314	0.342	0.416	0.523	0.408	**0.624**	0.491	0.472
O_1	0.573	0.521	0.521	0.563	0.463	0.534	**0.745**	0.550
O_2	0.495	0.529	0.509	0.613	0.482	0.530	**0.805**	0.504
O_3	0.373	0.423	0.414	0.495	0.436	0.484	**0.748**	0.447
O_4	0.356	0.490	0.391	0.508	0.470	0.477	**0.787**	0.448
O_5	0.314	0.396	0.322	0.448	0.419	0.428	**0.694**	0.361
R.B_1	0.468	0.493	0.418	0.479	0.372	0.538	0.456	**0.697**
R.B_2	0.447	0.542	0.434	0.493	0.495	0.617	0.481	**0.779**
R.B_3	0.328	0.405	0.422	0.444	0.411	0.475	0.447	**0.701**
R.B_4	0.338	0.445	0.356	0.455	0.381	0.469	0.399	**0.699**
R.B_5	0.415	0.419	0.456	0.476	0.410	0.476	0.420	**0.725**
R.B_6	0.457	0.528	0.533	0.669	0.487	0.507	0.483	**0.746**

E=Extraversion, A=Agreeableness, O= Openness to Experience, OC=Overconfidence Bias, AB, Availability Heuristics, RB= Representativeness Heuristics, DE= Disposition Effect, D.M=Intuitive Decision Making

5.2.4.7. Convergent Validity

Convergent validity is the analysis of the correlation level between multiple indicators of a single latent variable. Convergent validity is established when items of a latent variable are highly correlated with each other. To establish convergent validity factor loadings, average variance extracted (AVE) and composite reliability measure is considered (Hamid et al., 2017). The values of which are already reported in table 5-13. According to Fornell and Larcker (1981), the threshold associated with these measures for establishing convergent validity is provided below. The values of these measures range from 0 to 01.

1. The value of factor loadings should be significant and preferably above 0.70.
2. The value of Composite reliability (C.R) should be more than 0.80.
3. The value of the average variance extracted (AVE) should be greater than 0.50.

After analyzing the results through SMART-PLS provided in table 5-14, it can be observed that the majority of the factor loadings values are greater than 0.70, and the minimum value associated with items is 0.640. Still, according to Hair et al. (2017), a factor loading value between 0.60 and 0.70 is acceptable for already established constructs. Hence the overall results of factor loadings indicate reasonable convergent validity. Further, after analyzing values of composite reliability associated with the latent variable, it is established that all the latent concepts used in the study displayed satisfactory convergent validity as the minimum value of composite reliability is 0.850, which is significantly higher than the minimum threshold of 0.80 which further added to the convergent validity of the dataset. Lastly, the average variance extracted (AVE) values are analyzed, which indicate the overall

variance explored by utilizing those items. After going through all the results of average variance extracted reported in table 5-14. It can be said that significant convergent validity exists, as all the values of the average variance extracted are higher than the minimum threshold of 0.50. The minimum value associated is 0.526 fulfilling the condition as explained earlier. Resultantly it can be safely stated that by incorporating and testing all these three measures. The overall model represents significant convergent validity to test for causal relationship/model.

Conclusively, it is safe to state that the measurement model bears reasonable statistical validity and reliability properties, and reliable results of the casual model can be calculated.

5.2.4.8. Unidimensionality

According to Jackson et al. (2005), a construct's unidimensionality is established when the questions are linked to the measuring construct. It is the instrument's quality to measure only the single respective construct, and its item doesn't overlap with other constructs. By its definition, we can sense that an instrument's unidimensionality plays a vital role in establishing an instrument's overall reliability and validity. According to Nunnally (1994), Cronbach's alpha reports a measure's reliability in terms of its unidimensionality. It represents how well items of the same scale are correlated as a single group. Nowadays, a modern measure of rho_A is used for the very same purpose. Both are reported in table 5-14, and all the values are statistically up to the standards established in social sciences. Apart from that, the unidimensionality of items can be observed from table 5-18, which represented the items' cross-loadings in the scale. It can be observed that all the items are loaded significantly higher on their respective construct, indicating unidimensionality of the item. According to Ketikidis et al. (2006), unidimensionality can further be established by checking the factor loadings' significance in confirmatory factor analysis (CFA). The results of which are obtained through SMART-PLS bootstrapping and are reported in table 5-18. It can be observed that all the values of factor loadings are statistically significant with their respective latent variables. Hence the unidimensionality of the instrument is reasonably established for further analysis.

5.2.4.9. Common Method Variance

Common method variance is also referred to as common method bias. This bias is caused when the results are believed to be inflated/deflated than their actual values, which is attributed to respondents self-reporting of both dependent and independent variables and variables relating to their qualities (Conway & Lance, 2010) and according to Chang et al. (2010) recently editorial community in social sciences is asserting on the significance of establishing non-existence common method bias, especially in the field of business education. This can be occurred due to the respondents' desire to provide or portray a positive picture instead. The issue of common method bias can be addressed through procedural remedies and can be ensured by various statistical techniques. The procedures to avoid common method bias include separate data collection for dependent and independent variables and even for simultaneous data collection separation of dependent and independent by engaging participants in between them and by avoiding standardized scale but the method this study relied on is by grouping items under their relevant heads and by providing a header of the latent variable the items are measuring, which can enhance the chances of that the respondent will respond consistently.

Table 5-18 – Unidimensionality, Multicollinearity, Common Method Bias and Model Fit

	Items	Loadings	VIF	% of Variance	
Extraversion	E_1	0.829*	1.795	37.579*	
	E_2	0.792*	1.717		
	E_3	0.809*	1.810		
	E_4	0.789*	1.629	*Harman one-factor test<50%	
Agreeableness	A_1	0.667*	1.429	**SRMR**	
	A_2	0.805*	1.569	Saturated	Estimated
	A_3	0.790*	1.624	0.084*	0.089*
	A_4	0.793*	1.684		
Openness to experience	O_1	0.745*	1.531	*SRMR<0.10	
	O_2	0.805*	1.791	**RMS Theta**	
	O_3	0.747*	1.730	0.133*	
	O_4	0.786*	2.313		
	O_5	0.692*	1.816	*RMS Theta ≈ 0.000 or RMS Theta ≤ 0.120	
Overconfidence	O.C_1	0.724*	1.932		
	O.C_2	0.640*	2.384	**Global Fit Measure (GoF)**	
	O.C_3	0.819*	2.957	Overconfidence	0.582*
	O.C_4	0.703*	1.801	Availability	0.631*
	O.C_5	0.737*	2.028	Representativeness	0.456*
	O.C_6	0.736*	2.427	Disposition Effect	0.544*
	O.C_7	0.723*	1.909	Decision Making	0.518*
	O.C_8	0.623*	1.616	Overall Model	0.548*

Availability	A.B_1	0.847*	2.641
	A.B_2	0.738*	1.853
	A.B_3	0.657*	1.385
	A.B_4	0.786*	1.856
	A.B_5	0.851*	2.421
Representativeness	R.B_1	0.696*	1.566
	R.B_2	0.778*	1.941
	R.B_3	0.701*	1.511
	R.B_4	0.698*	1.545
	R.B_5	0.724*	1.657
	R.B_6	0.746*	1.583
Disposition Effect	D.E_1	0.734*	1.593
	D.E_2	0.800*	1.951
	D.E_3	0.739*	1.740
	D.E_4	0.688*	1.538
	D.E_5	0.686*	1.539
	D.E_6	0.709*	1.543
Intuitive Decision Making	D.M_1	0.799*	2.199
	D.M_2	0.820*	2.544
	D.M_3	0.804*	2.024
	D.M_4	0.634*	1.420
	D.M_5	0.741*	1.519
*=p<0.001			

*GoF≥0.36		
Chi Square		
Saturated		Estimated
5227.519*		5314.432*
Chi Square (p-value) ≤ 0.05		
Squared Euclidean distance		
Saturated Model		
d_ULS*	95%	99%
1.786	2.086	2.231
Estimated Model		
2.000	2.355	2.553
Geodesic distance		
Saturated Model		
d_G*	95%	99%
0.658	0.754	0.807
Estimated Model		
0.664	0.762	0.813
d_ULS & d_G ≤ 99%		

Lastly, to check the effectiveness of the strategy adopted to avoid common method variance, a statistical technique is required to establish its and to check for common method variance Harman one-factor test statistically is applied using SPSS, which identify the degree of inherent biases in items variance proportion distribution (Yeap et al., 2016). The test takes all the items of the instrument and produces a single unrotated factor. According to Guide and Ketokivi (2015), the resultant factor indicates an absence of common method bias if it explains less than 40% of the total variance. Still, Podsakoff and Organ (1986) took a lenient approach and recommended that the resultant factor is acceptable. It explains up to 50% of the total variance. Hence the test was conducted, and the results are reported in table 5-18. The results were calculated by limiting the unrotated factor to 1 in SPSS. The results indicated that single unrotated factor produced by including all the items through factor analysis explained almost 37% of the total cumulative variance and as the value of the unrotated variance is well below the maximum threshold of 50% (Podsakoff & Organ, 1986). Common method bias is not an issue in the current study.

5.2.4.10. Model Fit

Lastly, in the validation of the study's proposed model, the overall model fit is also considered. According to Hair et al. (2017), the overall model fit in SMART-PLS are in their early stages and need further exploration for understanding and appropriate implementation. Therefore researchers should take extra caution in reporting and relying solely based on model fit. Initially, Lohmöller (1989), in their research, proposed measures of overall model fit. The criteria used to establish overall model fit in the current study includes global fit index (GoF), Standardized Root Mean Square Residual (SRMR), Normed Fit Index (NFI), Squared Euclidean distance (d_ULS), Geodesic distance (d_G), Chi-square ($\varkappa^2$) and RMS Theta. All these measures in SMART-PLS are calculated in two phases. Firstly the initial estimates are calculated through a simple PLS algorithm, and then confidence intervals of the measures are established through PLS bootstrapping. All the values of measuring fitness for a model are reported in table 5-18 and discussed in the following passages.

Global fit measure (GoF) for a model is initially suggested by Tenenhaus et al. (2004) to measure the overall fitness of the model, and it can be calculated following the steps provided in the study of Tenenhaus et al. (2005). The measure is calculated as the geometric mean of the average variance extracted (AVE) and the average R^2 of all the dependent variables in the study. Which can be expressed as;

$$GoF = \sqrt{\overline{AVE} \times \overline{R^2}}$$

The value of the global fit index (GoF) ranges from 0 to 1, and a value of 0.1 up to 0.25 indicates small fitness, a value between 0.25 and 0.36 indicates medium fitness. In contrast, a value of 0.36 or higher indicates a large fitness value (Akter et al., 2011). The study calculated the global fit index (GoF) following the steps explained by Wetzels et al. (2009). According to Akter et al. (2011), the global fit index's minimum acceptable value for a well-fitted model is 0.36. The current study's resultant value is 0.548, which is significantly higher than the minimum acceptable value of 0.36 for the current study and indicates a statistically significant model fit.

The next and the most commonly used measure nowadays in SMART-PLS-based research is the standardized root mean square residual (SRMR). The traditional root means

square residual (RMSR) is based on the variance absolute mean of the covariance residuals (Hair et al., 2017). Simultaneously, this measure transforms the sample and predicted covariance matrix into a correlation matrix and derives its value from that by comparing both matrices and acting as an absolute measure of model fit (Hair et al., 1998). The value of standardized root mean square residual (SRMR) ranges from 0 to 1, and a value of less than 0.08 is preferred for overall model fit. Still, a value of less than 0.10 is also acceptable and indicates a good model fit (Hu & Bentler, 1998). The values of standardized root mean square residual (SRMR) for the current study are reported in table 5-18. The values are 0.084 and 0.089 for saturated and estimated models, which are well within the maximum allowed limit of 0.100. Hence indicates the overall model fit for the study.

The value of RMS-Theta is also considered for establishing the overall model fit. The measure based on the outside model's covariance matrix and drives its value from the root mean squared residual covariance matrix by accessing the correlation between their residuals. This fit index is recommended only for reflective models because, in formative models, outer model covariance is not meaningful. This index's value also ranges from 0 to 1, and the RMS-Theta value should be close to zero. The closer the value is from 0, the better fit the model is, and the higher the value is, the higher less will be the model fit. According to Hair et al. (2014), a value of 0.120 indicates a very good model fit. RMS-Theta results for the current study are slightly higher at 0.133 than this benchmark value of 0.120 but still very close to 0, indicating reasonable model fit and considering other fitness measures that are reported earlier, it is safe to conclude the same.

The chi-square value is the basic index for overall model fit and its comparison with the study's degree of freedom. The significance level for the chi-square value can be calculated. The degree of freedom can be calculated through;

$$df = \frac{(K^2 + K)}{2} - t$$

K represents the number of observed variables, and t represents the number of independent variables used to calculate the covariance matrix. A significant value of chi-square t statistics indicates that the model is fit, and an insignificant value indicates that the model doesn't have sufficient model fit (Hair et al., 1998). The chi-square values for the

study are also reported in table 5-18, which statistically significant, indicating the overall model fit.

Lastly, the values for d_ULS (Squared Euclidean distance) and d_G (Geodesic distance) is reported. These values measure for discrepancies among models through bootstrapping (Dijkstra & Henseler, 2015). The bootstrapping results for both methods are also reported in table 5-18. For assessing model fit, both values are compared against a lower and a higher confidence interval, i.e., 95% and 99%. These indices' value should be lower than the higher band's confidence interval value, i.e., 99%. The values of both of these statistics are below the higher confidence interval as reported in table 5-18, indicating the overall model fit for the current study.

5.2.4.11. Multicollinearity

Multicollinearity refers to the condition wherein a causal model, two or more variables are highly correlated. The existence of multicollinearity in the dataset can lead to unreliable results in the causal model. The structural path models cannot be used (Garson, 2012), and if there is multicollinearity in a model, then it is recommended to merge the correlated constructs or to drop the redundant one(D. Garson, 2012; J. F. Hair et al., 1998; Saunders et al., 2003). The SMART-PLS results of multicollinearity for both the inner and outer models are calculated and reported through the PLS algorithm. The measure used to access multicollinearity is the variance inflation factor (VIF). The value of which is recommended to be below three and is acceptable till 5. Any value beyond five will indicate multicollinearity in the model making the model unfit for causal analysis, as the estimates will be inflated. Hence the variance inflation factor (VIF) is evaluated and reported for both internal and external models. The value of variance inflation factor (VIF) for external model are reported in table 5-18 and the values for internal model are reported in the table 5-17. Generally the main focus is on the inner model and the collinearity between latent variables, but as can be observed from the reported values of the inner and outer model that the results are below the maximum acceptable value of 3. Indicating that multicollinearity is not an issue in the current study and the variables are well fitted in the proposed model.

5.2.4.12. Explained Variance (R^2)

R squared is the statistical measure used to represent the dependent variable's overall variance explained by the independent variables. In research, it is also referred to as the coefficient of determination (Saunders et al., 2003). R square value in simple words indicates how much the independent variable explains the change in the dependent variable. According to Chin (1998) and Höck and Ringle (2006), an R squared value of 0.67, 0.33, and 0.19 represents the "substantial," "moderate," and "weak" value of R square. R square value must be range between moderate and strong for a study, but depending on the previous literature and results, R square's reported value is low. It's up to the researcher's discretion to determine the R square's appropriate level based on the significance of the factors under study (Garson, 2012). The value of the adjusted R square for the current study is reported in table 5-19. It can be observed that all of the values of R square are above the minimum criteria of 0.33 with the lowest value of 0.392 associated with disposition effect (DE) and the value of R- square decision making style (DM), which is our prime variable of interest is 0.684. Indicating that substantial variance of dependent variable of the study is being explained by the proposed model, hence further adding to the overall validation of the model.

Table 5-19 - Multicollinearity and R-Square

	OC	AB	RB	DE	IDM
R-Square	0.566	0.530	0.512	0.392	0.684
E	2.099	2.099	2.099	2.099	2.604
A	2.222	2.222	2.222	2.222	2.701
O	1.760	1.760	1.760	1.760	2.269
OC					2.700
AB					2.344
RB					2.635
DE					1.945

E=Extraversion, A=Agreeableness, O= Openness to Experience, OC=Overconfidence Bias, AB, Availability Heuristics, RB= Representativeness Heuristics, DE= Disposition Effect, D.M=Intuitive Decision Making

After concluding the overall structural model validation with the model deemed overall fit alongside establishing validity, reliability, and all other necessary psychometric checks are made and satisfactorily fulfilled. The process of model validation is now completed. We can proceed further for hypothesis testing through the causal/path model. This will be done using Excel, SPSS, and SMART-PLS. Starting from the upcoming sections, results for hypothesis testing are going to be reported and discussed sequentially. Statistically,

the hypothesis is tested using SMART-PLS utilizing the bootstrapping option. Hypothesis two, three, four, and five are going to be tested using SMART-PLS bootstrapping option. Bootstrapping is a process in which subsamples are created randomly from the sample, and regression results are calculated from that subsamples. For final results calculations, the number of subsamples in bootstrapping should be around five thousand. Bootstrapping will be conducted using the complete bootstrapping option provided in the software for the path model. The default option of Bias-Corrected and Accelerated (BCa) bootstrap will be utilized to estimate the confidence interval. For the subsequent hypothesis regarding demographic impact, SPSS will be utilized for conducting the ANOVA test.

5.2.5. Impact of Behavioural Biases on Decision Making

This section will test the impact of selected behavioral biases: overconfidence, availability, representativeness, and disposition effect upon the intuitive/irrational decision-making style of an individual investor in Pakistan. Hence, hypothesis two was further divided into four sub hypotheses. The main hypothesis is the relationship between behavioral biases and intuitive decision-making. Each sub hypothesis's linkage is tested to establish the overall relationship between biased behavior and an investor's decision-making style. The results are calculated using bootstrapping and are reported in Table 5-20 below. The results indicate that the overconfidence bias on investors' irrational or intuitive decision-making style is significant. A single unit increase in the availability bias level will increase in irrationality by ($\beta=0.096$, $p<0.05$). This means that the more an investor is prone to use availability bias, the more intuitive decisions are expected, hence affirming our Hypothesis 2a.

Similarly, the results indicate that the effect of availability bias on investors' irrational or intuitive decision-making style is also significant. One unit increase in the availability bias level will increase irrationality by ($\beta=0.110$, $p<0.05$). This means that the more an investor is prone to use availability bias, the more intuitive decisions are expected, proving our Hypothesis 2b. The relationship between representativeness bias and intuitive decision-making style is also in line with the expectations. A unit increase in representativeness bias is associated significantly with an increase in the degree of intuitiveness by ($\beta=0.183$, $p<0.05$) hence statistically establishing our Hypothesis 2c. Lastly, the impact of disposition effect on intuitive decision making is also found to be statistically significant. In line with the proposed

relationship and resultantly, a unit increase in disposition effect is associated with an increase in the degree of intuitive decision making by (β=0.193, p<0.01), hence supporting our hypothesis 2d. Resultantly establishing all the sub hypothesis for our hypothesis two as statistically significant and in line with the proposed theory indicating a completely supported and accepted hypothesis.

Table 5-20 - Behavioural Biases and Decision Making

Relationship	β	std. β	Std. Error	t-stat.	p-value
Overconfidence -> Decision Making	0.099	0.096	0.048	2.035	0.042
Availability -> Decision Making	0.109	0.110	0.053	2.069	0.039
Representativeness -> Decision Making	0.182	0.183	0.058	3.120	0.002
Disposition -> Decision Making	0.191	0.193	0.045	4.260	0.000

5.2.6. Impact of Personality Traits on Decision Making

This section proposes the proposed relationship between personality traits and the intuitive decision-making style of individual investors investing in the Pakistan stock exchange. The relationship was proposed under hypothesis three of the study and is further divided into three sub hypotheses. These hypotheses establish links between selected personality traits for the study, namely agreeableness, extraversion, and openness to experience with the intuitive decision-making style. These results are also obtained through bootstrapping in SMART-PLS and are reported in table 5-21 below. The results indicate that the effect of an individual with the trait of agreeableness can cause investors to be irrational or intuitive, which is significant, and a single unit increase in the level of agreeableness will result in an increase in irrationality by (β=0.105, p<0.05), hence affirming our Hypothesis 3a.

Similarly, the results indicate that the effect of the trait of extraversion on investors' irrational or intuitive decision-making style is also significant, and one unit increase in the level of extraversion will result in an increase in irrationality by (β=0.115, p<0.1). The more an investor is extroverted, the more intuitive decisions are expected, proving our Hypothesis 3b. Lastly, the impact of the trait of openness to experience to experience of an investor on its intuitive decision making is also found to be statistically significant and in line with the proposed relationship and resultantly, a unit increase in the degree of openness to experience is found to be associated with an increase in the degree of intuitive decision making by (β=0.216, p<0.01), hence supporting our hypothesis 3c and with that it can be conclusively

established that all the sub hypothesis for our hypothesis three are statistically significant and in line with the proposed theory indicating a completely supported hypothesis.

Table 5-21 - Personality Traits and Decision-Making

Relationship	β	std. β	Std. Error	t-stat.	p-value
Agreeableness -> Decision Making	0.105	0.104	0.050	2.106	0.035
Extraversion -> Decision Making	0.115	0.114	0.056	2.041	0.051
Openness to experience -> Decision Making	0.216	0.214	0.055	3.947	0.000

5.2.7. Impact of Personality Traits on Biased Behavior

This section will focus on the proposed relationship between personality traits and individuals' biased behavior in the Pakistan Stock Exchange. The main hypothesis proposed a relationship between selected personality traits and biases for the study, and the proposed relationship was further divided into sub twelve sub hypothesis, which considered each relationship between selected personality traits, namely agreeableness, extraversion, and openness to experience with the selected biases, namely overconfidence, availability, representativeness, and the disposition effect. The results are reported in Table 5-22 below. Firstly the relationship between agreeableness and behavioral biases is tested. The results indicated that the effect of agreeableness on overconfidence is significant. A single unit increase in the level of agreeableness will result in an increase in overconfidence behavior by (β=0.358, $p<0.01$). The more an investor is agreeable, the more overconfidence behavior is expected, hence affirming our Hypothesis 4a.

Similarly, the results indicate that the effect of agreeableness on availability bias is also significant. One unit increase in agreeableness will increase availability derived biased behavior by (β=0.216, $p<0.01$). The more an investor is prone to use agreeable behavior, the more availability derived biased behavior is expected, proving our Hypothesis 4b. The results for the relationship between agreeableness and representativeness bias are also in line with the expectations. A unit increase in the agreeableness trait is associated significantly with an increase in the degree of availability bias by (β=0.353, $p<0.01$), hence establishing our Hypothesis 4c. Lastly, the impact of agreeableness on disposition effect is also found to be statistically significant and in line with the proposed relationship and resultantly, a unit increase in agreeableness is found to be associated with an increase in the degree of disposition effect by (β=0.194, $p<0.01$), hence supporting our hypothesis 4d.

After establishing the relationship between agreeableness and behavioral biases, the next step relationship between extraversion and behavioral biases is tested. The results indicated that the effect of extroversion on investors' overconfidence behavior is significant, and a single unit increase in the level of extroversion will increase overconfidence behavior by (β=0.189, $p<0.01$). The more an investor is extroverted, the more overconfidence behavior is expected, hence affirming our Hypothesis 4e. Similarly, the results indicate that the effect of extroversion on availability bias is also significant. One unit increase in extroversion level will increase availability derived biased behavior by (β=0.433, $p<0.01$). This means that the more an investor is prone to extrovert behavior, the more availability derived biased behavior is expected, proving our Hypothesis 4f. The results for the relationship between agreeableness and representativeness bias are also in line with the expectations. A unit increase in the extroversion trait level is associated significantly with an increase in the degree of availability bias by (β=0.170, $p<0.01$), hence establishing our Hypothesis 4g. Lastly, the impact of extroversion on disposition effect is also found to be statistically significant and in line with the proposed relationship and resultantly, a unit increase in extroversion is found to be associated with an increase in the degree of disposition effect by (β=0.159, $p<0.05$), hence supporting our hypothesis 4h.

Lastly, the relationship between openness to experience and the select behavioral biases is tested and reported. The results indicated that openness to experience on investors' overconfidence behavior is significant, and a single unit increase in the level of openness to experience will increase overconfidence behavior by (β=0.315, $p<0.01$). The more an investor is extroverted, the more overconfidence behavior is expected, hence affirming our Hypothesis 4i. Similarly, the results indicate that openness to experience on availability bias is also significant, and one unit increase in openness to experience will result in an increase in availability derived biased behavior by (β=0.178, $p<0.01$). The more an investor is prone to openness to experience behavior, the more availability derived biased behavior is expected, proving our Hypothesis 4j. The relationship between openness to experience and representativeness bias is also in line with the expectations. A unit increase in openness to experience trait level is associated significantly with an increase in the degree of availability bias by (β=0.296, $p<0.01$) hence statistically establishing our Hypothesis 4k. Lastly, the impact of openness to experience on disposition effect is also found to be statistically

significant and in line with the proposed relationship and resultantly, a unit increase in openness to experience is found to be associated with an increase in the degree of disposition effect by (β=0.367, $p<0.05$), hence supporting our hypothesis 4h. This conclusively established all the sub hypotheses for our hypothesis four as statistically significant and in line with the proposed theory indicating a completely supported and accepted hypothesis for the study.

Table 5-22 - Personality Traits and Biased Behavior

Relationship	β	std. β	Std. Error	t-stat.	p-value
Agreeableness -> Overconfidence	0.356	0.358	0.052	6.891	0.000
Agreeableness -> Availability	0.215	0.216	0.059	3.624	0.000
Agreeableness -> Representativeness	0.352	0.353	0.060	5.880	0.000
Agreeableness -> Disposition	0.192	0.194	0.073	2.617	0.009
Extraversion -> Overconfidence	0.191	0.189	0.055	3.480	0.001
Extraversion -> Availability	0.433	0.433	0.051	8.550	0.000
Extraversion -> Representativeness	0.171	0.170	0.058	2.965	0.003
Extraversion -> Disposition	0.162	0.159	0.065	2.481	0.013
Openness -> Overconfidence	0.314	0.315	0.048	6.537	0.000
Openness -> Availability	0.177	0.178	0.054	3.261	0.001
Openness -> Representativeness	0.295	0.296	0.058	5.132	0.000
Openness -> Disposition	0.364	0.367	0.063	5.776	0.000

5.2.8. Effect Size and Predictive Relevance

After establishing all the direct relationships between the study variables, we will focus on the relationship's effect size alongside their predictive relevance. These two stats are unique to the SMART-PLS, where predictive relevance (f^2) refers to the strength of each exogenous variable's explanatory power regarding the endogenous variable. It derives its value from the value of R-square. The change in R-square with and without any particular exogenous variable is calculated. Based on the difference in the R-square value, predictive relevance (f^2) is calculated. According to Lachenbruch (1989), a value of up to 0.15 indicates a weak value of up to 0.35, indicating moderate, and a value of above 0.35 indicates strong predictive relevance (f^2). The results reported in table 5-23 indicated that all of the values of predictive relevance (f^2) are in the weak and moderate range, but considering that all the values are statistically significant and can significantly shape real-life behavior are still valid for current research. The overall predictive relevance (f^2) of the model's variables indicates satisfactorily strong predictive relevance (f^2) except for overconfidence bias. The second reported index in table 5-23 is Effect size (Q^2). Effect size (Q^2) enables researchers to access the study's exogenous variables' collective contribution in explaining the endogenous

variable. This indicator is calculated using the blindfolding approach in SMART-PLS. Based on an omission interval between 5 and 10, the SMART-PLS estimate model for each block omits each data group. According to Henseler et al. (2016), a value of up to 0.15 indicates a weak value of up to 0.35, indicating moderate, and a value of above 0.35 indicates strong effect size (Q^2). As each dependent variable reported, the value of effect size (Q^2) ranges from moderate to high effect size. All the behavioral biases reported moderate effect size (Q^2) from personality tarts of agreeableness, extraversion, and openness to experience that ranges from 0.204 to 0.316 for availability, and the overall decision-making style of the individual investors indicate an effect size (Q^2) of 0.379. This is above the minimum value of 0.35 for the existence of high effect size (Q^2), and being the main variable of interest, this also affirms the proposed model of the study. The proposed model of an individual investor's linked personality traits through behavioral biases towards their decision-making style has a significant effect size (Q^2).

Table 5-23 - Effect Size (Q^2) and Predictive Relevance (f^2)

		f^2					
`	**Q^2**	**DM**	**OC**	**AB**	**RB**	**DE**	**Total**
Agreeableness		0.014	0.134	0.044	0.114	0.028	0.334
Extraversion		0.017	0.040	0.191	0.029	0.021	0.298
Openness to experience		0.067	0.125	0.037	0.099	0.121	0.449
Overconfidence	0.286	0.012					0.012
Availability	0.316	0.016					0.016
Representativeness	0.264	0.040					0.040
Disposition	0.204	0.059					0.059
Decision Making	0.379						

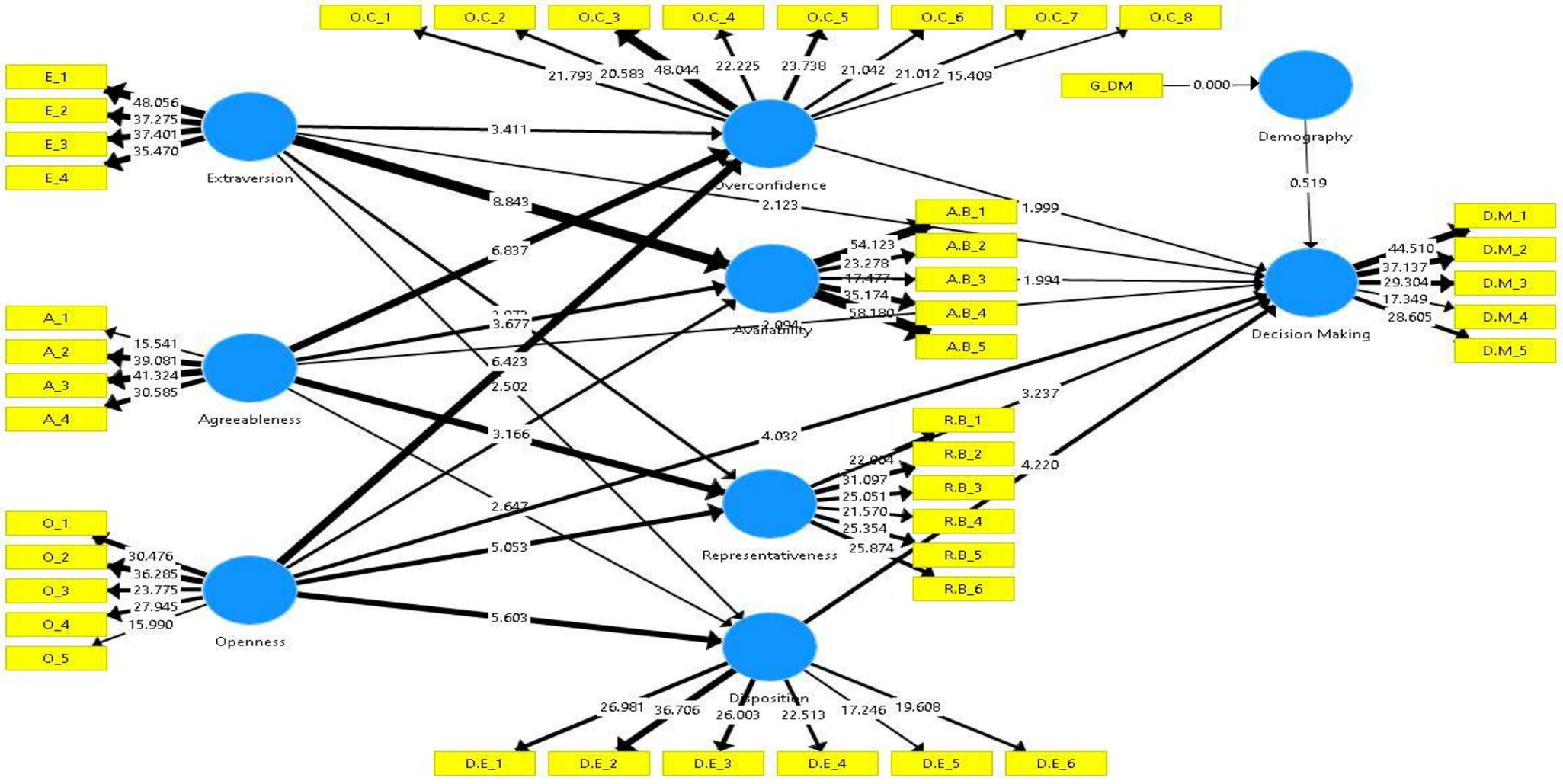

Figure 5-3 - Path Model

5.2.9. Mediating Role of Behavioral Biases

This section will focus on behavioral biases as a mediator between personality traits and the decision-making style of the stock market investor in Pakistan. As discussed earlier, to establish the mediating relationship, the current study will use Preacher and Hayes (2004) methodology, which allows for the analysis of partial and complete mediation effect. In SMART-PLS, the PLS algorithm results and bootstrapping produce direct, indirect, and total effects allowing for a mediator analysis. The results for the relationships provided in SMART-PLS are represented in figure 5-4 below.

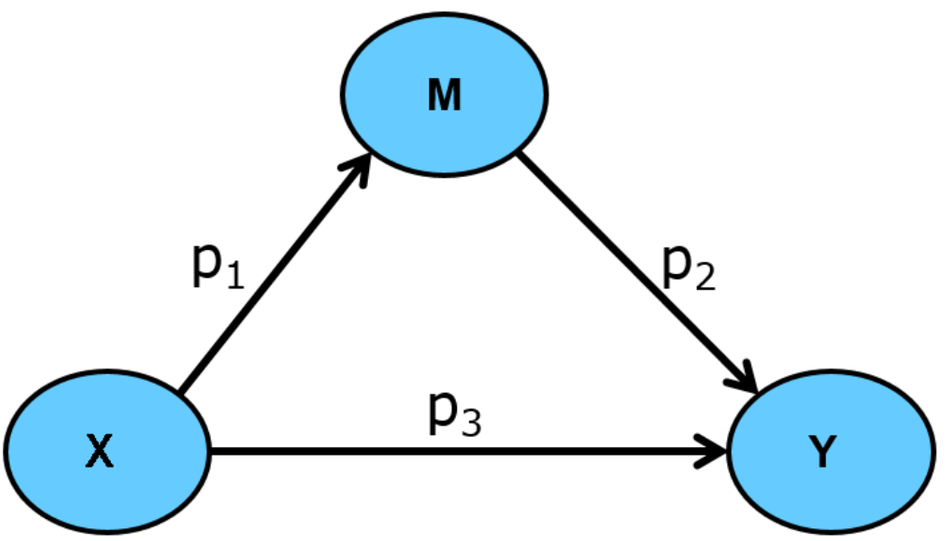

Figure 5-4 - Mediation Relationship

Where X represents an independent variable, M represents a mediator variable, and Y is the dependent variable. The P_1, P_2, and P_3 are paths or relationships. In SMART-PLS, the P_1 and P_2 represent indirect effects, and P_3 is the direct effect. The total effect reported in SMART-PLS is the sum of P_1 and P_2. This is a simple model explaining the mediator relationship and the outcomes associated with mediation analysis in SMART-PLS, but the SMART-PLS can also incorporate multiple mediators and complex relationships through its path model (Hair et al., 2017; Hayes, 2017) where the total effect can be used to analyze the overall mediating relationship between two variables through multiple mediators (Zhao et al., 2010).

The studies of Carrión et al. (2017), Hair et al. (2017), and Nitzl et al. (2016) explained the process to be followed in SMART-PLS for mediation analysis and its interpretation, which is explained in figure 5-5 below.

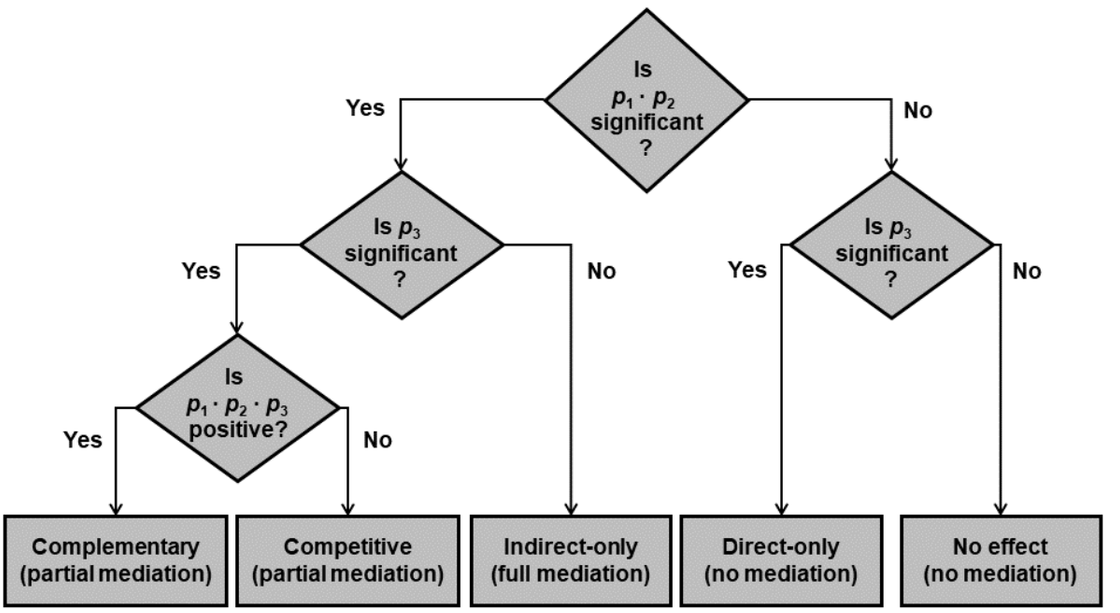

Figure 5-5 - Mediation Interpretation

Hence following the given mechanism for mediation analysis, a separate model was created to analyze the impact of path one or independent mediator relationship and path two mediator dependent relationship. The results of which are reported in Table 5-24 below. In the first step, the relationship of independent variables with mediator variables without the mediating relationship is reported. In the second step, the relationship between the dependent and mediating variables, namely behavioral biases, is tested and reported.

Table 5-24 - Direct Effects

Relationship	β	std. β	Std. Error	t-stat.	p-value
Direct Relationships without Mediation (P_1)					
A -----> OC	0.355	0.355	0.052	6.827	0.000
E -----> OC	0.191	0.192	0.056	3.403	0.001
O -----> OC	0.315	0.315	0.049	6.453	0.000
A -----> AB	0.215	0.219	0.060	3.607	0.000
E -----> AB	0.430	0.427	0.051	8.359	0.000
O -----> AB	0.180	0.181	0.055	3.304	0.001
A -----> RB	0.351	0.350	0.058	6.014	0.000
E -----> RB	0.170	0.172	0.057	3.007	0.003
O -----> RB	0.297	0.298	0.058	5.136	0.000
A------> DE	0.191	0.191	0.073	2.611	0.009
E------> DE	0.160	0.161	0.066	2.437	0.015
O -----> DE	0.366	0.367	0.063	5.797	0.000
Direct Relationships without Mediation (P_2)					
OC ---> IDM	0.243	0.242	0.050	4.867	0.000
AB ----> IDM	0.232	0.233	0.044	5.304	0.000
RB ----> IDM	0.253	0.252	0.056	4.495	0.000
DE ---> IDM	0.243	0.245	0.045	5.423	0.000

E=Extraversion, A=Agreeableness, O= Openness to Experience, OC=Overconfidence Bias, AB, Availability Heuristics, RB= Representativeness Heuristics, DE= Disposition Effect, D.M=Intuitive Decision Making

The results indicate that all the relationship between personality traits and behavioral biases of investors is significant at ($p<0.05$) and is positive as predicted by the theory, hence establishing the first step of the mediation analysis. The second path among mediator and dependent variables is also highly significant ($p<0.001$). Figure 5-6 represents the model conducted to establish direct relationships.

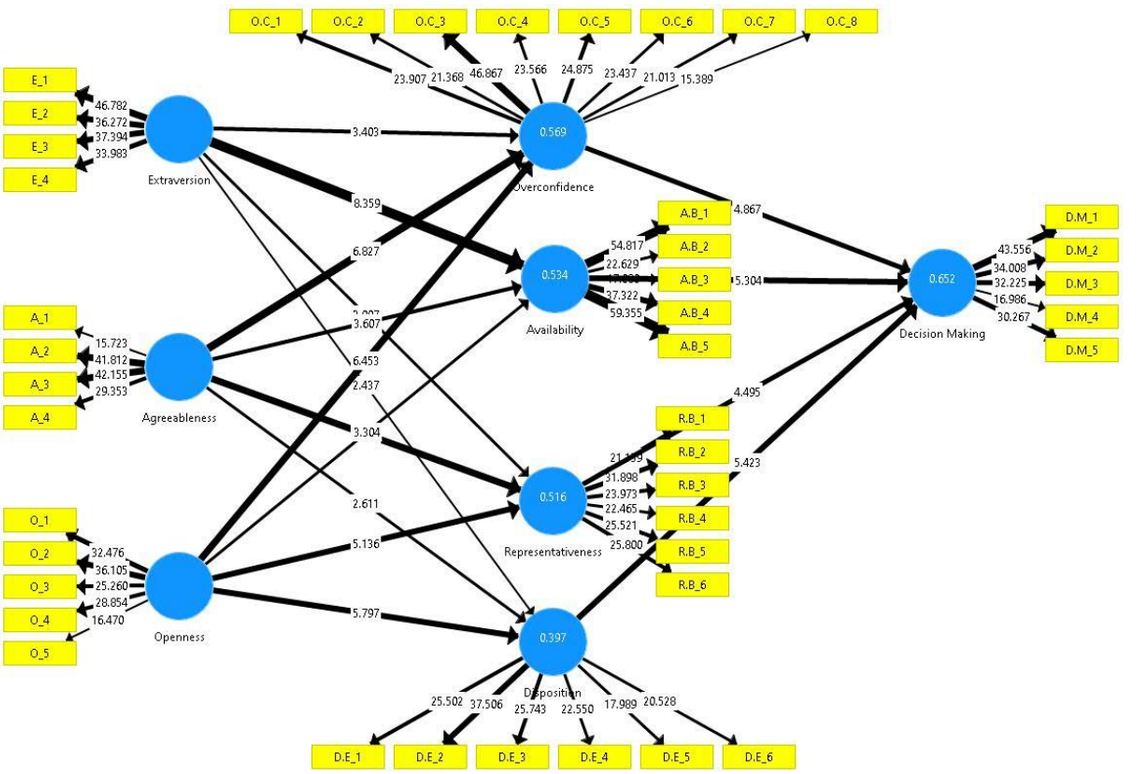

Figure 5-6 - Direct Effects (Without Mediation)

After establishing the complete causal model results presented in figure 5-6, it is analyzed for mediation analysis. The results for direct effects and indirect effects in the presence of mediating relationships are reported in table 5-24 below. In step 3 of the process, when controlling for personality traits through mediators in the relationships, the results indicate that the relationship between personality traits and decision-making style is still significant in case of mediation of overconfidence bias with the agreeableness impacting at ($\beta=0.034$, $p<0.05$), extraversion impacting at ($\beta=0.018$, $p<0.1$) and openness to experience impacting at ($\beta=0.031$, $p<0.1$) respectively. For mediation of availability bias, the relationship between personality traits and decision-making style is also significant for agreeableness impacting at ($\beta=0.024$, $p<0.1$), extraversion impacting at ($\beta=0.048$, $p<0.05$), and openness to experience impacting at ($\beta=0.019$, $p<0.1$) respectively. For mediation of representativeness bias, the relationship between personality traits and decision-making style is also significant for agreeableness impacting at ($\beta=0.064$, $p<0.05$), extraversion impacting

at (β=0.031, p<0.05), and openness to experience impacting at (β=0.054, p<0.05) respectively. Lastly, For mediation of disposition effect, the relationship between personality traits and decision-making style is also significant for agreeableness impacting at (β=0.037, p<0.05), extraversion impacting at (β=0.031, p<0.05), and openness to experience impacting at (β=0.71, p<0.05) respectively and hence indicating that all the specific indirect relationships through mediators are significant and in line with the proposed model. But before continuing towards step 4, the SMART-PLS also provides us with the overall impact of all the mediating variables or the total effect, which indicates the overall impact of the single independent variable through all the mediators of the model. The results of which are also reported in table 5-25 below. Which indicate that the mediation of all the biases in the model causes the relationship between personality traits and decision-making style to be significant for agreeableness impacting at (β=0.160, p<0.001), extraversion impacting at (β=0.128, p<0.001), and openness to experience impacting at (β=0.173, p<0.001) respectively. These results are highly significant, indicating the overall validness of the proposed mediating relationships.

Table 5-25 - Mediation Analysis

Relationship	B	std. β	Std. Error	t-stat.	p-value
Indirect Relationships (Specific)					
A ---> OC ---> IDM	0.035	0.034	0.018	2.005	0.045
E ---> OC ---> IDM	0.019	0.018	0.011	1.720	0.085
O ---> OC ---> IDM	0.031	0.031	0.017	1.842	0.066
A ---> AB ---> IDM	0.023	0.024	0.014	1.693	0.090
E ---> AB ---> IDM	0.047	0.048	0.024	1.969	0.049
O ---> AB ---> IDM	0.019	0.019	0.011	1.713	0.087
A ---> RB ---> IDM	0.064	0.065	0.024	2.661	0.008
E ---> RB ---> IDM	0.031	0.031	0.015	2.105	0.035
O ---> RB ---> IDM	0.054	0.054	0.020	2.693	0.007
A---> DE ---> IDM	0.037	0.037	0.017	2.195	0.028
E---> DE ---> IDM	0.031	0.031	0.014	2.160	0.031
O ---> DE ---> IDM	0.069	0.071	0.022	3.166	0.002
Indirect Relationships (Total)					
A ---> BB ---> IDM	0.159	0.160	0.031	5.196	0.000
E ---> BB ---> IDM	0.128	0.128	0.034	3.816	0.000
E ---> BB ---> IDM	0.173	0.175	0.033	5.229	0.000
Direct Relationships with Mediation (P_3)					
A ----> IDM	0.106	0.104	0.050	2.106	0.035
E ----> IDM	0.115	0.114	0.056	2.001	0.051
O ----> IDM	0.216	0.214	0.055	3.947	0.000

E=Extraversion, A=Agreeableness, O= Openness to Experience, OC=Overconfidence Bias, AB, Availability Heuristics, RB= Representativeness Heuristics, DE= Disposition Effect, D.M=Intuitive Decision Making

In Step 4, the direct relationship between independent and dependent variables is analyzed in mediating variables, and the results are reported in table 5-26. While controlling for mediating variables, the relationship between personality traits of agreeableness and investors' decision-making style is still significant at ($p<0.05$), indicating partial mediation. In contrast, the relationship between extraversion and investors' decision-making style is not significant at ($p<0.05$), indicating complete mediation of behavioral biases. Lastly, the relationship between openness to experience and decision-making style is highly significant ($p<0.01$), indicating partial mediation. The coefficients for partial mediation of agreeableness and openness to experience are both positive, indicating complementary partial mediation as proposed in the study earlier.

5.2.10. Impact of Demography on Decision Making

This study's last hypothesis pertains to the impact of demographical variables, including marital status, gender, age, investment experience, qualification, educational specialization, and location on investors' decision-making style in Pakistan. As discussed in the methodological session, given the nature of these demographical variables, the appropriate technique for such analysis is ANOVA analysis. The current study utilizes SPSS to conduct the tests, and the results are reported and discussed in the forthcoming sub-sections individually. For every relationship, it is needed to establish homogeneity of variance through Levene's test that uses post hoc tests assuming equal variances; the failure to establish homogeneity will lead to the use of Welch test and consecutively post hoc tests for assumption equal variance not assumed will be considered for results interpretation (Moder, 2007, 2010). The Tukey post hoc test is reported in case of equal variances are assumed, and the results of the Games-Howell test are reported in case equal variances are not assumed. Welch test results justify the use of ANOVA analysis.

5.2.10.1. Impact of marital status on decision-making style

To conduct a one-way ANOVA test for marital status, firstly, Levene's and Welch's test results are reported in Table 5-26 below. The results of Levene's test of homogeneity of variance are significant, indicating that equality of variance can't be assumed or the variance

is heterogeneous, and post hoc analysis techniques like Tukey's with the assumption of the equality of variance can't be considered.

Table 5-26 - Homogeneity Test (Marital Status)

	Statistic	df1	df2	Sig.
Levene	038.280	2.000	423.000	0.000
Welch	157.078	2.000	264.047	0.000

In such a condition, the Welch test is considered and which is also reported in table 5-26. The Welch test results are significant, indicating that ANOVA analysis with post hoc tests without assuming the equality of variance like Games-Howell can be considered. Therefore a one-way ANOVA analysis among investors is conducted to compare the effect of marital status on investors' intuitive decision-making style given their relationship status as married, single, and any other status. The results of the ANOVA test are reported in table 5-27. The results indicate that there exists a highly significant impact of marital status on investor's intuitive decision-making style at a ($p<0.01$) for the three categories of Married, Single, and other [$F(2,423) = 125.535$, $p=0.000$].

Table 5-27 - ANOVA (Marital Status)

	Sum of Squares	Df	Mean^2	F	Sig.
Between Groups	108.158	002.000	54.079	125.535	0.000
Within Groups	182.223	423.000	00.431		
Total	290.382	425.000			

Now coming towards the analysis of the difference between these three marital conditions, the results of descriptive and post hoc analysis using the Games-Howell test are reported in table 5-28. The results indicated that the mean score of a married investor ($M=3.277$, $S.D=0.759$) is significantly different from the mean score of a single investor ($M=4.318$, $S.D=0.575$) at ($p<0.01$) and is different from the mean score of investors having any other marital status ($M=4.164$, $S.D=0.078$) at ($p<0.01$). The results indicated that the mean score of single investors ($M=4.318$, $S.D=0.575$) and investors having any other marital status ($M=4.164$, $S.D=0.078$) is not significantly different; hence partial support for our hypothesis H6a is established.

Table 5-28 - Mean Comparison (Marital Status)

	N	Mean	Std. Dev	Std. Error	Groups	Sig.
Married	230	3.277	0.759	0.050	Single	0.000
Single	152	4.318	0.575	0.047	Other	0.354
Other	044	4.164	0.078	0.012	Married	0.000

5.2.10.2. Impact of gender on decision-making style

To conduct a one-way ANOVA test for marital status, firstly, Levene's and Welch's test results are reported in Table 5-29 below. The results of Levene's test of homogeneity of variance are non-significant, indicating that equality of variance can be assumed or the variance is heterogeneous, and post hoc analysis techniques like Tukey's with the assumption of the equality of variance can be considered. The results of the Welch test are also reported in table 5-29. The Welch test results are insignificant, indicating that ANOVA analysis with post hoc tests without assuming the equality of variance like Games-Howell can't be considered. Our data include only two outcomes/groups, i.e., male and female. Therefore, post hoc comparison between groups can't be calculated as in such conditions, and the overall results ANOVA model represents the same group's significance.

Table 5-29 - Homogeneity Tests (Gender)

	Statistic	df1	df2	Sig.
Levene	1.426	1.000	424.000	0.233
Welch	1.388	1.000	49.246	0.244

Although an independent sample t-test is usually conducted for such variables, having only two values and ANOVA is recommended for variables having three or more categories. However, ANOVA can still be used for such analysis (Moder, 2010). Resultantly ANOVA analysis among investors is conducted to compare the effect of investor's gender on their intuitive decision-making style given their gender as male and female. The results of the ANOVA test are reported in table 5-30. The results indicate an insignificant impact of gender on investors' intuitive decision-making style for the two categories of male and female [F (1,424) =1.762, p=0.185].

Table 5-30 - ANOVA (Gender)

	Sum of Squares	Df	Mean^2	F	Sig.
Between Groups	001.202	001.000	1.202	1.762	0.185
Within Groups	289.180	424.000	0.682		
Total	290.382	425.000			

Although ANOVA results are insignificant, the mean difference between male and female investor's descriptive results is reported in Table 5-31. The results indicated that a male investor's mean score is (M=3.758, S.D=0.812), and the mean score of female investors is (M=3.581, S.D=0.943). The results are insignificant but indicate that the mean value

investor’s intuitive decision making for the male investor is slightly higher than female investors.

Table 5-31 - Mean Comparison (Gender)

	N	Mean	Std. Dev	Std. Error	Groups	Sig.
Male	383	3.758	0.812	0.041	-	-
Female	043	3.581	0.943	0.144	-	-

SMART-PLS also provides a way to analyze such data through dummy analysis by dividing data into two groups. The results from ANOVA analysis are insignificant to get further insight into the relationship. The analysis for gender is also conducted through SMART-PLS. The results are reported in Table 5-32, but the regression results against male investors and female investors' dummy variables are still insignificant. They do not indicate any impact hypothesis H6b is not supported.

Table 5-32 - Bootstrapping Results (Gender)

Relationship	B	std. β	Std. Error	t-stat.	p-value
Male -> Decision Making	-0.023	-0.023	0.042	0.539	0.590
Female -> Decision Making	0.023	0.023	0.043	0.537	0.591

5.2.10.3. Impact of age on decision-making style

To conduct a one-way ANOVA test for investor’s age, Levene’s and Welch's test results are reported in Table 5-33 below. The results of Levene’s test of homogeneity of variance are significant, indicating that equality of variance can’t be assumed or the variance is heterogeneous, and post hoc analysis techniques like Tukey's with the assumption of the equality of variance can’t be considered. In such a condition, the Welch test is considered and which is also reported in table 5-33. The Welch test results are significant, indicating that ANOVA analysis with post hoc tests without assuming the equality of variance like Games-Howell can be considered.

Table 5-33 - Homogeneity Test (Age)

	Statistic	df1	df2	Sig.
Levene	005.758	2.000	423.000	0.003
Welch	287.552	2.000	162.240	0.000

A one-way ANOVA analysis among investors is conducted to compare different age groups' effect on investors' intuitive decision-making style given the age group of 18-30, 31-50, and 51& above, respectively. The results of the ANOVA test are reported in table 5-34. The results indicate that there exists a highly significant impact of various age groups on

investor's intuitive decision-making style at a ($p<0.01$) for the three categories of 18-30, 31-50, and 51& above [$F(2,423) = 367.638$, $p=0.000$].

Table 5-34 - ANOVA (Age)

	Sum of Squares	Df	Mean2	F	Sig.
Between Groups	184.335	002.000	92.167	367.638	0.000
Within Groups	106.047	423.000	00.251		
Total	290.382	425.000			

The results of descriptive and post hoc analysis using the Games-Howell test are reported in table 5-35. The results indicated that the mean score of an investor between 18 to 30 years ($M=4.277$, $S.D=0.509$) is significantly different from the mean score of an investor between 30 to 50 years ($M=3.769$, $S.D=0.383$) at ($p<0.01$) and is also significantly different from the mean score of investors above 50 years ($M=2.303$, $S.D=0.557$) at ($p<0.01$). The results indicated that the mean score of 30 to 50 years ($M=4.318$, $S.D=0.575$) and investor of 51 years and above ($M=4.164$, $S.D=0.078$) is also significantly different; hence complete support for our hypothesis H6c is established.

Table 5-35 - Mean Comparison (Age)

	N	Mean	Std. Dev	Std. Error	Groups	Sig.
18-30	166	4.277	0.590	0.046	30-50	0.000
30-50	194	3.769	0.383	0.028	51 & Above	0.000
51 & Above	066	2.303	0.557	0.069	18-30	0.000

5.2.10.4. Impact of Investment experience on decision-making style

To conduct a one-way ANOVA test for investment experience, firstly, Levene's and Welch's test results are reported in Table 5-36 below. The results of Levene's test of homogeneity of variance are significant, indicating that equality of variance can't be assumed or the variance is heterogeneous, and post hoc analysis techniques like Tukey's with the assumption of the equality of variance can't be considered. In such a condition, the Welch test is considered and which is also reported in table 5-36. The Welch test results are significant, indicating that ANOVA analysis with post hoc tests without assuming the equality of variance like Games-Howell can be considered.

Table 5-36 - Homogeneity Test (Experience)

	Statistic	df1	df2	Sig.
Levene	005.226	2.000	423.000	0.006
Welch	364.945	2.000	143.883	0.000

A one-way ANOVA analysis through SPSS 20 is conducted among investors to compare different experience groups' effect on investors' intuitive decision-making style given the experience group of 00 to 05 years, 06 to 20 years, and 21 years & above, respectively. The results of the ANOVA test are reported in table 5-37. The results indicate that there exists a highly significant impact of various investment experience groups on investor's intuitive decision-making style at a ($p<0.01$) for all the three categories of 00 to 05 years of investment experience, 06 to 20 years of investment experience, and experience of 21 years & above with [$F(2,423) = 430.964$, $p=0.000$].

Table 5-37 - ANOVA (Experience)

	Sum of Squares	df	Mean^2	F	Sig.
Between Groups	194.788	002.000	97.394	430.964	0.000
Within Groups	095.594	423.000	00.226		
Total	290.382	425.000			

The results of descriptive and post hoc analysis using the Games-Howell test are reported in table 5-38. The results indicated that the mean score of an investor having experience between 00 to 05 years (M=4.183, S.D=0.493) is significantly different from the mean score of an investor having experience between 06 to 20 years (M=3.480, S.D=0.380) at ($p<0.01$) and is also significantly different from the mean score of investors above 20 years of investment experience (M=2.233, S.D=0.536) at ($p<0.01$). The results also indicated that the mean score of investors having 06 to 20 years of experience (M=4.318, S.D=0.575) and investors with investment experience of 21 years and above (M=4.164, S.D=0.078) is also significantly different; hence complete support for our hypothesis H6d is established.

Table 5-38 - Mean Comparison (Experience)

	N	Mean	Std. Dev	Std. Error	Groups	Sig.
0-5	264	4.183	0.493	0.030	6-20	0.000
6-20	102	3.480	0.380	0.038	21 & Above	0.000
21 & Above	060	2.233	0.536	0.069	0-5	0.000

5.2.10.5. Impact of qualification on decision-making style

To conduct a one-way ANOVA test for qualification, firstly, Levene's and Welch's test results are reported in Table 5-39 below. The results of Levene's test of homogeneity of variance are significant, indicating that equality of variance can't be assumed or the variance is heterogeneous, and post hoc analysis techniques like Tukey's with the assumption of the equality of variance can't be considered. In such a condition, the Welch test is considered and

which is also reported in table 39. The Welch test results are significant, indicating that ANOVA analysis with post hoc tests without assuming the equality of variance like Games-Howell can be considered.

Table 5-39 - Homogeneity Test (Qualification)

	Statistic	df1	df2	Sig.
Levene	033.164	6.000	419.000	0.000
Welch	535.625	6.000	065.754	0.000

A one-way ANOVA analysis through SPSS 20 is conducted among investors to compare the effect of different levels of educational qualification on investor's intuitive decision-making style. In contrast, the test is conducted to analyze the mean decision-making style of matriculating, intermediate, bachelor degree holder, master degree holder, MPhil degree holders, Ph.D. degree holders, and any other qualification groups of stock market investors. The results of the ANOVA test are reported in table 5-40. The results indicate that there exists a highly significant impact of various educational groups on investor's intuitive decision-making style at a ($p<0.01$) for all the seven categories of with matriculate, intermediate, bachelor degree holder, master degree holder, MPhil degree holders, Ph.D. degree holders and any other qualification groups of stock market investors [$F(6,419) = 186.093$, $p=0.000$].

Table 5-40 - ANOVA (Qualification)

	Sum of Squares	df	Mean^2	F	Sig.
Between Groups	211.147	006.000	35.191	186.093	0.000
Within Groups	079.235	419.000	00.189		
Total	290.382	425.000			

The descriptive and post hoc to analyze the mean difference between all the seven groups of qualifications using the Games-Howell test is reported in table 5-41. The results indicated that the mean score of an investor having matriculation level qualification ($M=4.760$, $S.D=0.167$) is significantly different from the mean score of the investor with intermediate ($M=4.600$, $S.D=0.383$) at ($p<0.01$), the mean score of the investor with bachelor's degree ($M=4.257$, $S.D=0.264$) at ($p<0.01$), the mean score of the investor with master's degree ($M=3.593$, $S.D=0.418$) at ($p<0.01$), the mean score of the investor with MPhil degree ($M=2.727$, $S.D=0.938$) at ($p<0.01$), the mean score of the investor with the Ph.D. degree ($M=1.345$, $S.D=0.270$) at ($p<0.01$) and the mean score of the investor with any other academic qualification ($M=2.610$, $S.D=0.465$) at ($p<0.01$).

The results also indicated that the mean score of an investor having intermediate level qualification (M=4.600, S.D=0.383) is significantly different from the mean score of the investor with a bachelor's degree (M=4.257, S.D=0.264) at (p<0.01), the mean score of the investor with master's degree (M=3.593, S.D=0.418) at (p<0.01), the mean score of the investor with MPhil degree (M=2.727, S.D=0.938) at (p<0.01), the mean score of the investor with the Ph.D. degree (M=1.345, S.D=0.270) at (p<0.01) and the mean score of the investor with any other academic qualification (M=2.610, S.D=0.465) at (p<0.01).

The mean score of an investor having a bachelor's degree (M=4.257, S.D=0.264) is significantly different from the mean score of the investor with a master's degree (M=3.593, S.D=0.418) at (p<0.01), the mean score of the investor with MPhil degree (M=2.727, S.D=0.938) at (p<0.01), the mean score of the investor with the Ph.D. degree (M=1.345, S.D=0.270) at (p<0.01) and the mean score of the investor with any other academic qualification (M=2.610, S.D=0.465) at (p<0.01).

Table 5-41 - Mean Comparison (Qualification)

	N	Mean	Std. Dev	Std. Error	Groups	Sig.
Matric	020	4.760	0.167	0.037	Inter	0.006
					Bachelor	0.000
					Masters	0.000
					M.Phil.	0.000
					Ph.D.	0.000
					Other	0.000
Inter	024	4.600	0.383	0.028	Bachelor	0.000
					Masters	0.000
					M.Phil.	0.000
					Ph.D.	0.000
					Other	0.000
Bachelor	143	4.257	0.264	0.022	Masters	0.000
					M.Phil.	0.000
					Ph.D.	0.000
					Other	0.000
Masters	167	3.593	0.418	0.032	M.Phil.	0.000
					Ph.D.	0.000
					Other	0.000
M.Phil.	041	2.727	0.938	0.146	Ph.D.	0.000
Ph.D.	011	1.345	0.270	0.081	Other	0.000
Other	020	2.610	0.456	0.102	M.Phil.	0.957

The mean score of an investor having a master's degree (M=3.593, S.D=0.418) is significantly different from the mean score of the investor with an MPhil degree (M=2.727, S.D=0.938) at (p<0.01), the mean score of the investor with the Ph.D. degree (M=1.345,

S.D=0.270) at (p<0.01) and the mean score of the investor with any other academic qualification (M=2.610, S.D=0.465) at (p<0.01), Also the mean score of the investor with MPhil degree (M=2.727, S.D=0.938) is significantly different from the mean score of the investor with the Ph.D. degree (M=1.345, S.D=0.270) at (p<0.01) but the mean score of the investor with any other academic qualification (M=2.610, S.D=0.465) is not statistically significant from the mean score of the investor with MPhil degree. Lastly, the mean score of Ph.D. degree (M=1.345, S.D=0.270) is significantly different from the mean score of the investor with any other academic qualification (M=2.610, S.D=0.465) at (p<0.01). Hence except for the impact between investors group with MPhil qualification and investor with any other qualification, all the intergroup mean behavior are statistically significant, indicating partial support for our hypothesis H6e.

5.2.10.6. Impact of the field of specialization on decision-making style

To conduct a one-way ANOVA test for field of specialization, firstly, Levene's and Welch's test results are reported in Table 5-42 below. The results of Levene's test of homogeneity of variance are significant, indicating that equality of variance can't be assumed or the variance is heterogeneous, and post hoc analysis techniques like Tukey's with the assumption of the equality of variance can't be considered. In such a condition, the Welch test is considered and which is also reported in table 5-42. The Welch test results are significant, indicating that ANOVA analysis with post hoc tests without assuming the equality of variance like Games-Howell can be considered. Our data include only two outcomes/groups, i.e., business-related qualification holders and others. Therefore, post hoc comparison between groups can't be calculated as in such conditions, and the overall results ANOVA model represents the same group's significance.

Table 5-42 - Homogeneity Test (Specialization)

	Statistic	df1	df2	Sig.
Levene	124.849	1.000	424.000	0.000
Welch	394.748	1.000	330.512	0.000

Although an independent sample t-test is usually conducted for such variables, having only two values and ANOVA is recommended for variables having three or more categories. However, ANOVA can still be used for such analysis (Moder, 2010). Resultantly ANOVA analysis among investors is conducted to compare the effect of investor's educational

specialization on their intuitive decision-making style given their specialization as business-related and others. The results of the ANOVA test are reported in table 5-43. The results indicate a significant impact of the educational field of specialization on investors' intuitive decision-making style for the two categories of business-related and others [F (1,424) =1.762, p=0.185].

Table 5-43 - ANOVA (Specialization)

	Sum of Squares	Df	Mean2	F	Sig.
Between Groups	124.929	1.000	124.929	320.151	0.000
Within Groups	165.453	424.000	0.390		
Total	290.382	425.000			

Hence, the ANOVA results are significant, and mean the difference between investors with business education background and investors with other educational specialization is reported in table 5-44. The results indicated that the mean score of investors with a business education background is (M=3.270, S.D=0.784), and the mean score of investors with other educational specialization is (M=4.364, S.D=0.303). The results are significant and indicate that the mean value of investor’s intuitive decision-making for investors with other educational specialization is significantly higher than investors with business education backgrounds. Hence complete support for our hypothesis H6f is established.

Table 5-44 - Mean Comparison (Specialization)

	N	Mean	Std. Dev	Std. Error	Groups	Sig.
Business Related	243.000	3.270	0.784	0.050	-	-
Other	183.000	4.364	0.303	0.022	-	-

As discussed earlier, during the analysis of investors' gender, SMART-PLS also provides a way to analyze such data with two outcomes through dummy analysis by dividing data into two groups. The results from ANOVA analysis are significant, but to get further insight into the relationship. The regression analysis for educational qualification is also conducted through SMART-PLS, and the results are reported in table 5-45. The regression results against the dummy variable of investors with business education background are negatively linked with investors' intuitive decision-making style. In contrast, in comparison, investors with other educational specialization are positively linked with investors' intuitive decision-making style by (β=0.266, $p<0.01$).

Table 5-45 - Bootstrapping Results (Specialization)

Relationship	B	std. β	Std. Error	t-stat.	p-value
Business Education -> Decision Making	-0.266	-0.265	0.033	8.183	0.000
Other Education -> Decision Making	0.266	0.265	0.033	8.118	0.000

5.2.10.7. Impact of investor location on decision-making style

To conduct a one-way ANOVA test for investor's location, firstly, Levene's, and Welch's test results are reported in Table 5-46 below. The results of Levene's test of homogeneity of variance are insignificant, indicating that equality of variance is assumed or the variance is homogeneous, and post hoc analysis techniques like Tukey's with the assumption of the equality of variance can be considered. There is no need to consider the Welch test in such a condition, which is also reported in table 5-46. The Welch test results are insignificant, indicating that ANOVA analysis with post hoc tests without assuming the equality of variance like Games-Howell can't be considered.

Table 5-46 - Homogeneity Test (Location)

	Statistic	df1	df2	Sig.
Levene	1.096	2.000	423.000	0.335
Welch	2.255	2.000	231.203	0.107

ANOVA analysis among investors is conducted to compare impact of investors' location on their intuitive decision-making style, given their location at Karachi, Lahore, and Islamabad. The results of the ANOVA test are reported in table 5-47. The results indicate an insignificant impact of location on an investor's intuitive decision-making style for all three categories of Karachi, Lahore, and Islamabad. [F (2,423) =2.232, p=0.109].

Table 5-47 - ANOVA (Location)

	Sum of Squares	Df	Mean^2	F	Sig.
Between Groups	003.032	002.000	1.516	2.232	0.109
Within Groups	287.349	423.000	0.679		
Total	290.382	425.000			

Now coming towards analyzing the difference between these three data collection locations, the results of descriptive and post hoc analysis using tukey's test are reported in table 5-48. The results indicated that the mean score of investors in Islamabad (M=3.654, S.D=0.868) is insignificantly different from the mean score of investors in Lahore (M=3.667, S.D=0.857) and is also indifferent from the mean score of investors at Karachi (M=3.830, S.D=0.779). Whereas the mean score of investors in Lahore (M=3.667, S.D=0.857) and

investors at Karachi (M=3.830, S.D=0.779) is also not significantly different; hence no support for our hypothesis H6g is found.

Table 5-48 - Mean Comparison (Location)

	N	Mean	Std. Dev	Std. Error	Groups	Sig.
Islamabad	103.000	3.654	0.868	0.086	Lahore	0.992
Lahore	125.000	3.667	0.857	0.077	Karachi	0.194
Karachi	198.000	3.830	0.779	0.055	Islamabad	0.185

6. Results and Discussion

This chapter aims to provide a summary of the results obtained through empirical analysis. Then the chapter will discuss these results given existing theories and literature on the matter. First, the results of hypothesis testing are reported in Table 6-1 below.

Table 6-1 - Hypothesis Results

Sr.	Hypothesis	Results
H_1	**Behavioral factors are significant determinants of return predictability in the Pakistan stock market.**	**Supported**
H_{1a}	Overconfidence is a significant determinant return predictability in the Pakistan stock market.	Supported
H_{1b}	Heuristics are a significant determinant of return predictability in the Pakistan stock market.	Supported
H_{1c}	Disposition effect is a significant determinant of return predictability in the Pakistan stock market.	Supported
H_2	**Behavioral factors are significantly and positively associated with the investor's intuitive decision-making.**	**Supported**
H_{2a}	Overconfidence is significantly and positively associated with the investors' intuitive decision-making.	Supported
H_{2b}	Availability heuristic is significantly and positively associated with Investors' intuitive decision-making.	Supported
H_{2c}	Representativeness heuristics is significantly and positively associated with Investors' intuitive Decision-Making.	Supported
H_{2d}	Disposition effect is significantly and positively associated with Investor's intuitive Decision-Making.	Supported
H_3	**Personality traits are significantly and positively associated with the Intuitive Decision-Making.**	**Supported**
H_{3a}	Agreeableness is significantly and positively associated with the Intuitive Decision-Making.	Supported
H_{3b}	Extroversion is significantly and positively associated with the Intuitive Decision-Making.	Supported
H_{3c}	Openness to experience is significantly and positively associated with the Intuitive Decision-Making.	Supported
H_4	**Personality traits are significantly and positively associated with Investor's biased behavior.**	**Supported**
H_{4a}	Agreeableness is significantly and positively associated with Investors' overconfidence behavior.	Supported
H_{4b}	Agreeableness is significantly and positively associated with Investors' availability heuristic.	Supported
H_{4c}	Agreeableness is significantly and positively associated with Investors' representativeness heuristic.	Supported
H_{4d}	Agreeableness is significantly and positively associated with	Supported

	Investors' disposition effect.	
H_4e	Extroversion is significantly and positively associated with Investors' overconfidence behavior.	Supported
H_4f	Extroversion is significantly and positively associated with Investors' availability heuristic.	Supported
H_4g	Extroversion is significantly and positively associated with Investors' representativeness heuristic.	Supported
H_4h	Extroversion is significantly and positively associated with Investors' disposition effect.	Supported
H_{4i}	Openness to experience is significantly and positively associated with Investors' overconfidence behavior.	Supported
H_{4j}	Openness to experience is significantly and positively associated with Investors' availability heuristic.	Supported
H_{4k}	Openness to experience is significantly and positively associated with Investors' representativeness heuristic.	Supported
H_{4l}	Openness to experience is significantly and positively associated with Investors' disposition effect.	Supported
H_5:	**Investor's biased behavior mediates the relationship between Personality traits (Agreeableness, Extroversion, and Openness to Experience) and Investor's intuitive decision-making.**	**Partially Supported**
H_{5a}	Overconfidence mediates the relationship between Personality traits (Agreeableness, Extroversion, and Openness to Experience) and investor's intuitive decision-making.	Partially Supported
H_{5b}	Availability mediates the relationship between Personality traits (Agreeableness, Extroversion, and Openness to Experience) and investor's intuitive decision-making.	Partially Supported
H_{5c}	Representativeness heuristic mediates the relationship between Personality traits (Agreeableness, Extroversion, and Openness to Experience) and investor's intuitive decision-making.	Partially Supported
H_{5d}	Disposition mediates the relationship between Personality traits (Agreeableness, Extroversion, Openness to Experience) and Investor's intuitive decision-making.	Partially Supported
H_6	**There is a significant difference in mean behavior of investors who are in different demographic groups.**	**Partially Supported**
H6a	There is a significant difference in mean behavior of investors who are in different marital status.	Partially Supported
H6b	There is a significant difference in mean behavior of investors who are in different gender group.	Not Supported
H6c	There is a significant difference in mean behavior of investors who are in different age group	Supported
H6d	There is a significant difference in mean behavior of investors who are in different experience group.	Supported
H6e	There is a significant difference in mean behavior of investors who are in different qualification group.	Partially Supported
H6f	There is a significant difference in mean behavior of investors who are in different field of specialization.	Supported
H6g	There is a significant difference in mean behavior of investors who are from different areas.	Not Supported

As can be observed, most of the study's hypotheses are supported by the empirical analysis. This section's prime focus is to explain the results by comparing and contrasting existing literature, especially with the studies utilized and discussed during the literature review, to establish the hypothesized linkages. The discussion and analysis of the results will be conducted based on the order established in hypothesis development.

The study's first hypothesis is related to the impact of behavioral biases on the stock market index. In an ideal world where efficient stock markets exist, stock markets are expected to follow a random walk, making them impossible to predict based on historical data, but this is not the case in the real world. This fact can be established through the autoregression of the stock market index. Still, the current study's focus through the first hypothesis is on establishing the influence of behavioral biases on the stock market index. This is done by creating a biased and unbiased threshold and then analyzing the autoregression pattern. In the prior section, empirically, there is a significant difference in autoregression coefficients in the presence and absence of behavioral biases. These results are in line with Olson's (2006) studies and Prechter's (2016) and the theory of social mood that Pakistan's stock market is not efficient and is influenced by social and cognitive factors in society. The stock market behaves differently during various phases (moods) in society due to herd behavior and interaction. A similar study by Xue and Zhang (2017) conducted a study on Chinese stock markets and established the impact of investor's sentiments on Chinese markets. This study posits and established that biased behavior at an individual investor's level leads to the overall market sentiments in accordance with the mechanism explained by theory of social mood. The overall investor sentiments than leads to over/under reaction in the stock market. Mumtaz et al. (2016) performed similar studies on the IPO's performance and established that investors overreact and underreact and cause securities to be overpriced and underpriced. Similarly, the bubbles and crashes in the overall market are also associated with this under/overreactions from investors' biased behavior. Overall the relationships established in the first hypothesis are in line with the studies of Mumtaz et al. (2016), Nofsinger (2005), Prechter (2016), and Xue and Zhang (2017).

After establishing the impact of behavioral factors on the functioning of the stock market in Pakistan, the study's second hypothesis focused on understanding the relationship between those behavioral factors and investors' decision-making style. The studies by Kudryavtsev et al. (2013) and Waweru et al. (2008) on investors indicated that these behavioral factors lead to irrational decision-making. Instead of relying on rational analysis, they rely on various shortcuts and habits to make financial decisions. These decisions are often suboptimal and deviate from the intrinsic value of the decision-making to over/under reaction to the relevant information. Instead of making rational analysis, they rely on their

sixth sense or intuition to make the decision. Hence, this linkage between biased behaviors, leading to intuitive decision-making is tested in the second hypothesis. It is established empirically in the prior chapter of the study that behavioral biases significantly impact investors' decision-making style to be intuitive instead of rational. These findings are also in line with the studies conducted by Anum (2017), Gul and Akhtar (2016), Sarwar et al. (2014), and Sheikh and Riaz (2012). They studied Pakistan stock market investors' behavior and concluded that investors in Pakistan are influenced by those behavioral factors significantly. Overall, the second hypothesis's findings are also in line with prospect theory presented by Kahneman and Tversky (1979), which established that individuals due behave differently to gains and losses due to cognitive factors.

The third hypothesis of this study further extends the model. After establishing and understanding through the first two hypotheses, the stock market in Pakistan is not efficient. It is also influenced by behavioral factors, which cause investor's decisions to be intuitive. The study furthers its reach to understand the dynamics of investors' behavior and what causes them to be biased. By deriving on to the trait theory, it is proposed and established empirically in the prior chapters that an investor's personality traits are also associated with investors' decision-making in Pakistan. However, there are very limited direct studies on the impact of personality traits on investors' decision making. The studies by Bortoli et al. (2019) and Sreedevi and Chitra (2012) examined the impact of investor's personality traits on investment choices. They concluded a significant difference in investors' choices and investment methods among investors with varying personality traits. Similarly, the studies of Davis et al. (2007) and Lauriola and Levin (2001) established in organizational settings that the personality traits of an individual are significantly linked with risky and poor decision making. Hence, the hypothesis's overall results regarding the linkage between individual investors' personality traits and economically suboptimal, poor or intuitive decision-making are in accordance with the existing literature.

The fourth hypothesis of the study focused on the relationship between personality traits and investors' biased behavior. The studies of Bashir et al. (2013), Gumus and Dayioglu (2015), and Nandan and Saurabh (2016) examined the relationship between personality traits and the biased behavior of investors. They concluded that personality traits do have a

significant impact on various biases. These studies derive the relationship based on the inference made by Maital et al. (1986) that their personality traits influence the behavior of an individual. Still, the prior studies' focus was only on the relationship between personality traits and different behavioral biases. They tested various personality models and interpreted the outcomes of the studies. The existing literature found mix results for this relationship, where some personality traits are found to be significantly impacting some biases. Still, this current study is focused on establishing a link between personality traits and behavioral biases in a causal manner. That's why only three personality traits of agreeableness, extraversion, and openness to experience are selected, given their nature to make an investor prone towards biased behavior. This link is discussed and established in the previous sections, as the empirical findings completely supported our hypothesis. These results concur with the trait theory of personality and the existing studies of Bashir et al. (2013) who studied investors in the Pakistan stock market and established links between personality traits and behavioral biases without proposing a causal relationship.

When the impact of behavioral biases with decision-making style is established and is supported by the studies of Hayat and Anwar (2016); Lin (2011), and Rasheed, Rafique, Zahid, and Akhtar (2018), etc. and given the impact of investors personality traits on both their decision-making style which also affirmed from the existing literature like Bortoli et al. (2019) and Sreedevi and Chitra (2012) and their relationship with biased behavior which is also supported by the studies of Bashir et al. (2013) and Sadi et al. (2011), etc. As explained by Baron and Kenny (1986) and Hayes (2017), all the basic requirements are present for the mediation of the behavioral biases between personality traits and the investor's decision-making style is fulfilled. Hence, the next hypothesis of the study further focused on this relationship by testing this mediating role. As discussed in the prior chapters, partial support for mediation is found for behavioral biases. To the best of our knowledge, this mediating relationship is not tested before. It hence is a contribution to the existing literature which needs further testing and exploration but in context of stock market investors in Pakistan partial mediation of behavioral biases is established, indicating that individual with the personality traits of agreeableness, extraversion, and openness to experience rely more on these biases to make investment decisions based on their intuition.

The study's last hypothesis focused on the impact of demographical variables on investor's decision-making style. Given the increased focus on contextualized research in management sciences, it's not a natural but social science. Within every context, various social variables change and resultantly varying the results. Therefore, to capture the impact of these social variables on the desired variable of interest, it is necessary to include these variables in the study to enhance the research study's generalizability. This study also considered various demographical characteristics, including marital status, gender, age, investment experience, qualification, specialization, and investor location. Numerous researches focus on the impact of demography in the field of behavioral finance, including but not limited to the studies of Bashir et al. (2013), Bengtsson et al. (2005), Graham et al. (2009), Gumus and Dayioglu (2015), Huang and Kisgen (2013), Lin (2011) and Zindel et al. (2010). These studies established an impact of various demographical variables on investors' behavior, including their decision-making style. This study also proposed and established the impact of investor's demographical characteristics on the investor's decision-making style empirically. The impact of gender and location on the decision-making style of investors can't be established. The results of gender analysis can be attributed to the lack of an appropriate sample for female investors and the indifference in behavior found among investors across the sample can be attributed to the fact that the data is collected from three major cities of Pakistan. These cities are financial hub of the country, where people from every ethnicity of Pakistan are residing hence due to this homogeneity among participants, no statistically significant difference can be established among the respondents of each city.

Combining the overall results of the hypothesis testing, including primary and secondary data-based models, it is established that the research outcomes are in accordance with the existing literature and inferred expectations. Although the study of impacts of behavioral biases is already established in Pakistan, there are still many dimensions of decision-making styles that need further exploration of their relationships. The current study is among the pioneer studies that analyze the impact of behavioral factors from each category and discuss its role in causing the decisions to be irrational or intuitive. The way forward for this relationship is to establish a link of behavioral factors on other dimensions of decision making while focusing on other behavioral factors. These linkages will further deepen our

understanding of investors' real-life behavior, which eventually impacts the overall stock market.

The second theoretical aspect of the study focused on the antecedents of biased behavior and decision-making styles. The existing literature pointed out that individuals' personality traits determine their behavioral outcomes and derive from the same logic. The behavioral outcomes of biased and intuitive behavior are linked with the personality traits of the investors. It was concluded that the select investor's personality traits cause investors' decisions to be irrational/intuitive, and behavioral biases mediate this relationship. Investors' particular personality traits make them rely on behavioral biases and reliance on these behavioral biases to lead to suboptimal/intuitive decision-making. This particular relationship is novel to this current study and particularly in the context of Pakistan. These findings have practical implications for researchers, brokers, and policymakers. This link needs to be studied further and established in various other behavioral biases and personality traits, further establishing its roots as a valid framework for the study of overall stock market behavior. Future researchers need to infer from this study to make some useful contributions in the context of Pakistani financial markets.

Table 6-2- Results Summary

Relationship	**Coefficients**	
Investors' Sentiments ----------> Market Return Predictability	0.136***	0.102***
Overconfidence Bias ----------> Market Return Predictability	0.016	0.331***
Heuristic Biases ----------> Market Return Predictability	-0.002	0.196***
Disposition Effect ----------> Market Return Predictability	-0.031	0.225***
Overconfidence Bias ---------> Intuitive Decision Making		0.243***
Availability Heuristic ---------> Intuitive Decision Making		0.232***
Representativeness Heuristic --------->Intuitive Decision Making		0.253***
Disposition Effect --------> Intuitive Decision Making		0.243***
Agreeableness ----------> Intuitive Decision Making		0.106**
Extraversion ----------> Intuitive Decision Making		0.115*
Openness to experience ----------> Intuitive Decision Making		0.216***
Agreeableness -------> Overconfidence Bias		0.355***
Agreeableness -------> Availability Heuristic		0.191***
Agreeableness -------> Representativeness Heuristic		0.315***
Agreeableness --------> Disposition Effect		0.215***
Extraversion ---------> Overconfidence Bias		0.430***
Extraversion ----------> Availability Heuristic		0.180***
Extraversion ---------> Representativeness Heuristic		0.351***
Extraversion ---------> Disposition Effect		0.170***
Openness to experience ----------> Overconfidence Bias		0.297***
Openness to experience ----------> Availability Heuristic		0.191***
Openness to experience ---------> Representativeness Heuristic		0.160***
Openness to experience ---------> Disposition Effect		0.366***
Agreeableness ---> Overconfidence Bias ---> Intuitive Decision Making		0.035**
Extraversion ---> Overconfidence Bias ---> Intuitive Decision Making		0.019*

Openness to experience ---> Overconfidence Bias ---> Intuitive Decision Making	0.031*
Agreeableness ---> Availability Heuristic ---> Intuitive Decision Making	0.023*
Extraversion ---> Availability Heuristic ---> Intuitive Decision Making	0.047*
Openness to experience---> Availability Heuristic ---> Intuitive Decision Making	0.019*
Agreeableness --> Representativeness --> Intuitive Decision Making	0.064***
Extraversion ---> Representativeness ---> Intuitive Decision Making	0.031**
Openness to experience ---> Representativeness ---> Intuitive Decision Making	0.054***
Agreeableness --> Disposition Effect --> Intuitive Decision Making	0.037**
Extraversion ---> Disposition Effect ---> Intuitive Decision Making	0.031**
Openness to experience ---> Disposition Effect ---> Intuitive Decision Making	0.069***

*=p<0.1, **=p<0.05, ***=p<0.001

Lastly the results summary of main models of this study are summarized in the table 6-2. Whereas in the context of demographical variables, there is a need to increase participation from the female part of the sample to have a comprehensive and generalizable framework in Pakistan's context. Apart from that, no significant evidence for the difference in behavior among investors operating in different cities can be established. All the other demographical variables are found to be significantly impacting the decision-making style. The difference between single individuals and individuals with any other marital status is also found to be insignificant. Similarly, the behavior of investors with MPhil degree and investors with any other qualification is also found to be insignificant.

7. Conclusion and Policy Implications

This section aims to explain and summarize the current study's inferences and provide implications of the current knowledge to all the stakeholders. This section will also enlist the possible future directions, delimitations, and limitations of the study for the future researchers to be overcome in the upcoming research studies.

7.1. Conclusions

The study concluded by answering the research questions that arise in the first chapter of the study. The study's focus is to understand and explain the behavior of the Pakistan stock market. The study focused on behavioral factors as a major cause for real-life inefficient behavior of the Pakistan stock market (PSX). Adopting the categorization of behavioral factors by Shefrin (2007). The four most common and significant behavioral biases from the literature are taken into account: overconfidence bias, availability heuristic, representativeness heuristic, and disposition effect covering every behavioral bias category. This study focused on the theory of social mood by Nofsinger (2005) and the socionomic

theory of finance by Prechter (2016) to propose a model for the real-life understanding of stock market behavior based on these behavioral biases. These theories posit that the overall market is influenced by individuals' moods, spread throughout the economy through social interactions. The behavioral biases that a single investor faces manifest themselves in the overall market through this process, making it deviate from the traditional random walk paradigm. This study found that prediction based on historical values exists in the Pakistan stock market. The hypothesis was affirmed by analyzing stock market behavior during bullish and bearish trends. It is established that predictability of current value based on historical data exists significantly during both phases of investor's sentiments, and there is no significant difference in the behavior between bullish and bearish trends. This finding indicates that determinants of investor’s behavior in both bullish and bearish trends are similar, and the current study believed those determinants to be the behavioral factors. This is also established for biases, heuristics and framing effects, and a dummy analysis utilizing the threshold regression model. It was established that the autoregression coefficients are found to be significant during the presence of these behavioral factors.

In contrast, in the absence of behavioral factors, the autoregression coefficient became insignificant. This indicates that for the Pakistan stock market (PSX), the influence of these behavioral factors is significant and is the cause of lack of market efficiency. The autoregression coefficient in presence and absence are also found to be significantly different from each other. Resultantly it is established that behavioral biases that impact a single individual manifest themselves onto the overall stock market in Pakistan through the mechanism established via the theory of social mood. To make markets more efficient, it is necessary to understand investors' behavior at an individual level and the factors that cause them to be irrational and biased. Only by addressing the issue at the individual level, efficient markets can be achieved.

In the second phase of this study, it focuses on this issue. By exploring the existing literature on the subject, the study came up with an extensive framework that tries to explain the underlying antecedents of biased behavior in an individual. The study utilizes the theory of personality traits and prospect theory. The first of which is of the view that any individual's behavioral outcomes can be determined through their personality traits and the later of both

established that cognitive and behavioral factors influence an individual's decision-making under uncertainty. Hence the study posits that biases and irrationality are linked with an investor's personality, and that biased behavior makes an investor intuitive or irrational. This irrationality of decisions is then depicted in the stock market when it fails to hold market efficiency via a random walk in the prices. In other words, an investor's biased behavior mediates the relationship between an investor's personality traits and decisional behavior at the Pakistan stock exchange (PSX). The study focused on individual investors in Pakistan to establish this framework through an adopted instrument. A pilot study before final data collection is conducted, and the reliability and validity are established. Apart from that, as another contribution to the existing literature, a translated version of the instrument is Urdu is also created. The instrument is then used to collect data through probability sampling utilizing services from a third party. The analysis of the collected data indicated that behavioral biases affect stock market investors in Pakistan. Investors' behavioral biases in the study, namely overconfidence, availability, representativeness, and disposition, significantly impact the investors' intuitive decision-making, which means that these biases cause investors' decisions to be based on their intuition rather than a rational analysis of available relevant information. As a result, the impact of the disposition effect on decision making is the highest. They are indicating that the most intuitive decision making is exhibited due the regret aversion. They hold the securities that are making losses for too long beyond rational behavior. This behavior from individual investors collectively impacts the overall stock market, creating market bubbles and crashes. The impact of overconfidence, availability, and representativeness is also significant and positive where overconfidence behavior of an investor causes intuitive decision making when an investor trade excessively beyond rational explanations, just relying on its gut feelings. The manifestation of which in the overall stock market is already established in the first model. Availability and representativeness bias is also associated with the existence of intuitive decision making. Due to the impact of availability bias, the Investors prefer to buy only those stocks for which more information available to them instead of doing a complete analysis of all the available information.

Due to the impact of representativeness bias, investors only invest only in stocks based on the similarity of their characteristics with their expected performance. That can lead to the bad performance of the market sometimes, especially when some people trick the

investors by spreading fake information to bend the trend of the stock market for their benefits hence explaining the behavior of investors that cause stock markets to deviate from the rational decision making and the stock market efficiency in Pakistan.

In the next phase of the investor's model, the study focused on the impact of personality traits and how they are linked with the behaviors related to biases and decision making of individual investors in Pakistan and once again, in line with the theory of social mood, it is proposed and established by the current study that the three personality traits of agreeableness, extraversion, and openness among a total of five from big five personality traits, which make an investor to be influenced by the surrounding environment and society. Investors with these personality traits will be more prone towards acceptance of biases derived behaviors circulating in the society and will follow the same path. Which collectively will impact the overall stock market, making it inefficient. The regression results for personality traits linkage with the decision-making style in Pakistan are significant and positive, which approve the preposition of the study that an investor with the personality trait of agreeableness will be prone to rely on intuition rather than a complete rational analysis. Such investors will agree and react to the recommendations, directions, and analysis provided to them through their social circle, including family, friends, and professional circle. Instead of analyzing the information fed to them by this circle, they will react to what they feel right and agreed to.

Similarly, extrovert investors, due to their outgoing nature and active participation in the community, will also get an impact from the baseless opinions and analysis circulating around them. This will also result in making their decisions derived from these interactions making them suboptimal or intuitive instead of analytical one. Lastly an investor with the personality trait of openness is innately prone to try new things and techniques in their everyday life they will grab on to every new information out there regardless of their authenticity or underlying logic and will act to the methods they feel new and got an appeal for them. This will also lead towards an irrational approach towards decision making. Conclusively all these personality traits are causing the stock market in Pakistan to be inefficient.

The study also focused on the relationship between personality traits and biased decision making of individual investors. As the biased behavior on the part of investors is also a behavioral outcome. In accordance with trait theory, every behavioral outcome can be explained through an individual's personality traits. This study utilized those there personality traits of agreeableness, extraversion and openness and posit that as these personality traits cause an investor's decision to be intuitive or irrational and behavioral biases also lead to intuitive decision-making. It is concluded that instead of a mere linkage between personality traits and biased behavior, there is a logical causal linkage between them, and these behavioral factors impact the decision-making style of an investor through these biases. These personality traits of agreeableness, extraversion, and openness make an investor prone to behavioral biases. Because of relying on these biases, an investor with these personality traits made decisions based on intuition rather than rational analysis. If the relationship is present, behavioral biases act as a mediator between personality traits and a stock market investor's decision-making style in Pakistan. The results indicated that these personality traits are linked positively and significantly with all four behavioral biases in the study, including overconfidence, availability, representativeness, and disposition effect. The highest value of the coefficient is for the relationship between extraversion and availability bias.

The lowest impact is also between openness and availability bias. These results indicate that availability bias is more sensitive to the trait of openness. The more a person is outgoing and social, the more his behavior will be driven by availability bias. This result is also in accordance with the underlying theories of this study. As availability refers to reliance on the most readily available information, the more a person plays an active role in society, the greater the new information he receives. The more his behavior will be in line with availability bias. The comparatively weak relationship between openness and availability can be explained as the stock market investors in Pakistan having personality trait of openness to new information is more expected to be linked more towards overconfidence behavior rather than availability bias driven behavior and it can be observed that among the highest impact of openness to new experiences is on overconfidence bias. As acting on new and novel information require overconfident behavior. In short, all three personality traits causing investors in Pakistan to be intuitive were also significantly and positively linked with underlying biases causing such intuitive behavior. After which, the mediating role of these

behavioral biases is tested, and partial support for mediation impact is established in the study. This support was in line with the expectation. The complementary mediation found in the study established that investors in Pakistan can use their personality traits to judge the degree of irrational decision making expected from them and the types of biases they are prone to. The dimensions they should carefully account for during the decision-making process.

Lastly, the impact of demographical variables on the decision-making style of investors is also considered. As discussed earlier, given the increased focus on contextualized research in management sciences, it's not a natural but social science. Within every context, various social variables change and resultantly varying the results. Therefore, to capture the impact of these social variables on the desired variable of interest, it is necessary to include these variables in the study to enhance the research study's generalizability. This study also considered various demographical characteristics, including marital status, gender, age, investment experience, qualification, specialization, and investor location. The demographical analysis results for marital status indicated that investors with single and any other marital status are more intuitive on average than married investors. This result can be attributed to the fact that after marriage, due to increase financial responsibilities, investors in Pakistan become more careful and cautious in their financial decisions, which results in having more calculated decisions instead of intuitive. The results for gender are not significant. These results can be attributed to the very low participation of females in Pakistan in the survey. Overall there is not a culture of women being stock market investors in Pakistan. Therefore based on these results, no meaningful interpretation can be made. Still, observing the mean behavior, it can be observed that male investors' mean score is slightly higher than the mean score of female investors. These results align with the existing evidence indicating that women are more conscious and careful in their decision-making than their male counterparts. Still, this impact is not significant in the case of Pakistan. The results for the impact of age and investment experience are all statistically significant among groups, indicating that with age and experience a stock market investor in Pakistan became more rational and relied less on their intuition. Hence young and less experienced investors need to take a step back and evaluate their decisions before making a final call. Otherwise, most of their decisions will be irrational and suboptimal, which will hurt them in the longer run.

Similarly the impact of various levels of educational qualification is also found to be significant, with lower education level associated with the higher mean value of intuitive decision making and higher education is associated with a lesser degree of intuitive decision making and more towards rational decision making. These results indicate the significance of education in the smooth functioning of a stock market. They indicate the significance of overall education to de-bias the decision making process of an investor, which will result in de-biasing the overall stock market in Pakistan. Still, any other qualification's mean behavior was found to be similar to the investors with MPhil qualification. This can be attributed to the fact that most of the investors having other qualifications in the sample are assumed to predominantly include professional business qualification like ACCA, CA, ICMAP, PIPA, etc. These investors with such qualifications are found to be financially literate, equivalent to investors with MPhil. Still, this relationship requires further exploration and other qualification requirements that need to be documented instead of just providing a simple other option. This study further explored the impact of business-related education or financial literacy on the investors' intuitive decision-making. It concluded that investors with business education are far less intuitive than non-business investors in Pakistan. This finding highlight the significance of financial literacy in the context of Pakistan. The higher the financial literacy among stock market investors in Pakistan, the less biased decision-making, and the stock market will be more efficient. Lastly, the impact of the investor’s location is analyzed. The data is collected from Karachi, Lahore, and Islamabad, but no significant difference in investors' mean behavior is established in the analysis. They are indicating that biases impact investors across Pakistan in the more or less same manner. A probable explanation for the results can be that the studies' target areas are federal and provincial capital and economic hubs of the whole of Pakistan, where people including investors from across every part of the country are located. This inclusive nature of the population in these cities makes their behavior similar, and no support for the proposition is found.

7.2. Theoretical Contribution

As far as the theoretical contribution is concerned of the current study is concerned, in Pakistan's stock market investors, behavioral finance is a relatively new field. Only a few studies are conducted about the factors impacting investors using behavioral finance. As per

the best of our knowledge, none of the previous studies conducted in Pakistan tested the effect of behavioral factors on investment decision making in such a comprehensive manner. Previous studies like studies by Zaidi and Tauni (2012), Bashir, Azam, Butt, Javed, and Tanvir (2013), Sarwar, Mansoor and Butt (2014), and Rasheed et al. (2018) were mainly focused on change on just one aspect of behavior, without linking it to the stock market. The study extended beyond this relationship and also included the personality antecedents that causes such behavior. The comprehensive nature of the framework is novel in its nature, especially in context of Pakistan and further need to be affirmed and tested.

With an increased focus on contextualized studies, culture's impact cannot be neglected while decision-making, especially in developing countries. In collectivist cultures like Pakistan, members are taught to value harmony and solidarity with others compared to European countries where they prefer individual interests (Markus & Kitayama, 1991). Values, norms, traditions, and family can also cause to deviate investors from rational decisions. How investors make decisions changes in collectivist cultures as compared to individualistic culture because the programming of the mind is different in each type of culture (Hofstede, 2006) hence it is important to study collectivist cultures like Pakistan where power distance is also high (Soares et al., 2007), to understand the difference in behavior across different cultures. Prior researchers conducted studies on the impact of behavioral factors on investment decisions primarily conducted in individualistic dominated cultures and the cultures where the power gap was low. This study will also fill this contextual gap in prior studies by exploring the differences among various groups of investors based on demographical characteristics.

7.3. Practical Contribution

This study has practical significance for all the investors, managers, financial planners, investment consultants, and policymakers in Pakistan. This study provides a comprehensive framework of stock market functioning. This knowledge provided stakeholders with a cause and effect mechanism. The policymakers can utilize this knowledge to understand the underlying reasons for the stock markets' inefficient working. The findings of the study related to financial literacy are also useful at a policy level. A higher level of financial literacy is associated with less biased decisions and a stable stock market.

This research provides insight into the behavioral factors that affect an investor's rational decision-making process by making it intuitive. This knowledge will help to understand the decision-making process in a much better way with empirical evidence. These findings will also help investors understand and overcome the irrational behavior and make financial decisions more efficient and rational, hence getting maximum value out of a financial decision. Financial advisors and planners can also use these findings to evaluate investors' type and the investment best suited for them. By analyzing the biasness profile of an investor, they will be better positioned to guide individual investors and make strategies by keeping in view these underlying biases.

The research also focused on personality antecedents that lead to biased behavior and influence the rational decision-making process. The results indicated that personality traits are a significant determinant of biased behavior and irrational decision making. These findings also have implications for all stakeholders. By identifying the personality traits associated with such behavior, policymakers can devise policies based on this framework to safeguard and protect investors' interests and ensure the smooth functioning of the Pakistan stock exchange (PSX). The professional consultants and analysts can use this knowledge to identify the types of investors based on their personality traits and their shortcomings in their decision-making. The individual investors can utilize this knowledge to overcome the irrational behavior based on the personality traits and de-bias there decision making.

7.4. Limitations

There are some limitations associated with the study that future researchers should address in future studies. The first limitation of the study is the sample size. It satisfies the basic requirements of statistical analysis, but the study can still be improved by gathering more data in primary data analysis and secondary data analysis. The secondary data analysis was limited to partial least squares. The deviation of data from normality techniques like simple regression and covariance-based structural equation modeling can’t be applied. Both primary and secondary data's reliability and validity can further be improved by increasing the sample size. In primary data, females' participation in the primary data sample is very low, due to which gender-based results can’t be calculated and compared. Another limitation is the provision of other qualifications section options, due to which no meaningful

comparison can be obtained. Instead of providing other category in the instrument, a place for the name of the particular qualification should be added to understand better and explain the results. In the second stage of sampling, convenience sampling can further be improved by introducing probability sampling in that phase. Apart from that, the research instrument is in English, which was pointed out by various respondents. As a contribution, the research study created a research instrument in Urdu by adopting all the psychological requirements for translation of instruments, which need to be tested in a Pakistani context to establish its validity further. The field of behavioral finance is new in comparison to the traditional views of finance. The field is particularly novel in the context of Pakistan. This framework, alongside the instruments, is also new, which needs to be implemented in various financial situations to establish and enhance results and measurements.

7.5. Delimitations

There are various delimitations associated with the study, which is due to limited time for the research, alongside constraint on the available resource and given the study's aim. Therefore, the current study's focus is limited to the stock exchange only and did not include other financial markets in Pakistan like Pakistan's mercantile exchange, property market, etc. Given the study's aim, the impact of behavioral biases on the stock market is tested through dummy variables only. In the second part, the study only focuses on individual investors, focusing on understanding individual investors' behavior. In contrast, institutional investors, like banks, mutual funds, securities companies, etc., are not part of this research. This research focuses only on intuitive investment decision-making styles among financial decisions and their relationship with behavioral factors. Other decision-making styles should also be considered in future studies. The studies only focus only on the categorization of Shefrin (2007) and selected only four out of those for this study. The impact of other behavioral factors and categorization also needed to be explored. The study focused on only a big five approach to personality traits and selected only three traits that are believed to be causing irrational behavior.

7.6. Future Directions

Future directions of every research originate from the limitations and delimitations of the study. As discussed earlier, behavioral finance is still a new field in Pakistan and is still evolving globally. Therefore, much work is needed in Pakistan to establish the inference and implications of the current study. Hence the first future direction is to further establish this framework's findings by utilizing other available primary data analysis methodologies that require normality of data, including least square regression and covariance-based structural equation modeling. The current findings also need to be established using the contextualized questionnaire proposed by this study. The study's secondary data-based model utilizes simple dummy variables to distinguish between behavior in the presence and absence of behavioral factors. It is further needed to be explored by applying proxies for behavioral biases that are advanced than simple dummy variable analysis further strengthen the final results. The secondary model can also incorporate stock markets worldwide to study and examine the underlying differences and their causes.

The existing framework can also be incorporated in the upcoming research by adding another dimension of decision making, behavioral biases, and personality traits. The extended framework can also provide additional aspects relating to reducing the impact of behavioral factors. Future studies can focus on identifying personality traits that increase inclination towards rational decision making. The moderating role of demographical variables can also be incorporated in the upcoming studies. This will provide a more comprehensive understanding of the behavior of individual investors with varying demographical characteristics.

Another issue regarding the study sample is that the current study focused only on the individual stock market investors in Pakistan. Future studies can focus on institutional investors and investors in various other sectors of Pakistan. With the inception of technology, there are a large number of investors that do operate online. They also needed to be incorporated in the upcoming studies as such investors are much more advanced than the traditional investors operating at brokerage directly, given their advanced knowledge of technology and its application. Their behavior may be substantially different due to the

difference in utilization and access to information from a traditional investor. The role of technology in this context is also needed to be studied.

Lastly, this current study only focused on investors self-reporting through the survey, which may not be an accurate picture of the actual behavior, and there is a chance of having unreliable results derived from misleading information; hence the finding of the current study is needed to be affirmed through a more controlled study like an experiment, in a controlled environment. Future studies can also focus on investors with portfolios diversified internationally and operating in different countries to further identify the underlying variables associated with different cultures' difference in behavior.

8. References

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9. Appendix

9.1. Sample Selection

Table 9-1-List of Brokers for Sample

Broker	Location	Sample
128 SECURITIES (PVT.) LTD.	Lahore	1
A. H. M. SECURITIES (PRIVATE) LIMITED	Karachi	1
A. I. SECURITIES (PRIVATE) LIMITED	Karachi	1
A.S. SECURITIES (PRIVATE) LIMITED *	Lahore	1
AAA SECURITIES (PRIVATE) LIMITED	Islamabad	1
ABA ALI HABIB SECURITIES (PVT) LIMITED	Karachi	0
ABBASI & COMPANY (PRIVATE) LIMITED	Lahore	1
ABBASI SECURITIES (PRIVATE) LIMITED	Karachi	1
ABM SECURITIES (PVT) LIMITED	Lahore	1
ACM GLOBAL (PVT.) LIMITED	Karachi	1
ADAM SECURITIES LTD.	Karachi	1
ADEEL & NADEEM SECURITIES (PVT) LTD.	Lahore	1
AHSAM SECURITIES (PVT.) LIMITED	Islamabad	1
AKD SECURITIES LIMITED	Karachi	1
AKHAI SECURITIES (PRIVATE) LIMITED	Karachi	0
AKY SECURITIES (PVT.) LTD.	Karachi	0
AL HABIB CAPITAL MARKETS (PRIVATE) LIMITED	Karachi	1
ALFA ADHI SECURITIES (PVT) LTD.	Karachi	1
ALFALAH SECURITIES (PRIVATE) LIMITED	Karachi	0
AL-HAQ SECURITIES (PVT) LTD.	Lahore	1
ALTAF ADAM SECURITIES (PVT) LTD.	Karachi	1
AMANAH INVESTMENTS LIMITED	Karachi	0
AMER SECURITIES (PRIVATE) LIMITED	Lahore	1

AMPLE SECURITIES (PRIVATE) LIMITED	Karachi	1
APEX CAPITAL SECURITIES (PVT) LIMITED	Karachi	1
ARCH CAPITAL SECURITIES (PVT.) LTD.	Lahore	0
ARIF HABIB 1857 (PRIVATE) LIMITED	Karachi	1
ARIF HABIB LIMITED	Karachi	1
ARIF LATIF SECURITIES (PVT) LTD.	Lahore	1
ASA STOCKS (PVT.) LIMITED	Lahore	0
ASAD MUSTAFA SECURITIES (PVT) LIMITED	Lahore	1
ASDA SECURITIES (PVT.) LTD.	Karachi	1
ASIAN SECURITIES LIMITED	Karachi	1
ASKARI SECURITIES LIMITED	Islamabad	1
AXIS GLOBAL LIMITED	Karachi	0
AYUB CHAUDHRY INVESTMENTS (PVT) LTD.	Lahore	0
AZEE SECURITIES (PRIVATE) LIMITED.	Karachi	0
B & B SECURITIES (PRIVATE) LIMITED	Karachi	1
BABA EQUITIES (PVT) LTD. *	Islamabad	1
BACKERS & PARTNERS (PRIVATE) LIMITED	Lahore	0
BAWA SECURITIES (PVT) LTD.	Karachi	1
BEST SECURITIES (PVT) LIMITED	Karachi	0
BHAYANI SECURITIES (PVT) LTD.	Karachi	1
BIPL SECURITIES LIMITED	Karachi	1
BISMILLAH SECURITIES (PVT.) LTD.	Lahore	0
BMA CAPITAL MANAGEMENT LTD.	Karachi	0
BRAINS SECURITIES (PVT.) LTD	Lahore	1
BRIDGE SECURITIES (PVT) LIMITED	Lahore	1
CAMCO (PVT.) LIMITED	Islamabad	0
CEDAR CAPITAL (PRIVATE) LIMITED	Karachi	1
CMA SECURITIES (PVT.) LIMITED $	Lahore	1
CONCORDIA SECURITIES (PVT) LIMITED	Karachi	0
CONTINENTAL CAPITAL MANAGEMENT (PVT) LTD	Karachi	1
CREATIVE CAPITAL SECURITIES (PVT) LTD.	Karachi	1
DALAL SECURITIES (PVT) LTD.	Karachi	1
DARSON SECURITIES (PVT) LIMITED	Karachi	1
DATTOO SECURITIES (PVT.) LTD.	Karachi	1
DAWOOD EQUITIES LTD.	Karachi	0
DAWOOD MOHAMMED SECURITIES (SMC-PVT.) LIMITED	Karachi	1
DIN CAPITAL LIMITED. *	Karachi	1
DIYANAH ISLAMIC FINANCIAL SERVICES (PRIVATE) LIMITED	Karachi	1
DJM SECURITIES (PRIVATE) LIMITED	Karachi	0
DOSSLANIS SECURITIES (PVT) LIMITED	Lahore	0
DR. ARSLAN RAZAQUE SECURITIES (PVT) LTD.	Lahore	0
EFG HERMES PAKISTAN LIMITED	Karachi	1
ELEVEN STARS SECURITIES (PVT) LTD	Karachi	1
ELIXIR SECURITIES PAKISTAN (PVT.) LTD.	Karachi	1
EQUITY MASTER SECURITIES (PVT.) LIMITED	Lahore	1
F. M. SECURITIES (PVT.) LTD. *	Lahore	1
FAIR EDGE SECURITIES (PRIVATE) LIMITED	Islamabad	1
FAIRTRADE CAPITAL SECURITIES (PVT.) LIMITED	Lahore	0
FAIRWAY SECURITIES (PVT) LIMITED	Lahore	1
FALKI CAPITAL (PRIVATE) LIMITED	Islamabad	1
FAWAD YUSUF SECURITIES (PVT.) LIMITED	Karachi	1
FDM CAPITAL SECURITIES (PVT) LIMITED	Karachi	0
FIKREES (PVT) LTD.	Karachi	0
FIRST CAPITAL EQUITIES LIMITED	Karachi	0

FIRST CHOICE SECURITIES LIMITED	Karachi	0
FIRST EQUITY MODARABA	Karachi	1
FIRST NATIONAL EQUITIES LIMITED	Lahore	1
FIRST STREET CAPITAL (PVT.) LTD.	Lahore	1
FLOAT SECURITIES (PVT) LIMITED	Karachi	0
FORTUNE SECURITIES LIMITED	Karachi	0
FOUNDATION SECURITIES (PRIVATE) LIMITED	Karachi	1
FRIENDLY SECURITIES (PVT) LTD.	Karachi	1
GALAXY CAPITAL SECURITIES (PVT) LIMITED	Islamabad	0
GAZIPURA SECURITIES & SERVICES (PRIVATE) LIMITED	Karachi	0
GENERAL INVEST. & SECURITIES (PVT) LTD.	Islamabad	1
GHANI OSMAN SECURITIES (PRIVATE) LIMITED	Karachi	1
GMI CAPITAL SECURITIES (PVT) LTD.	Karachi	1
GPH SECURITIES (PVT.) LTD.	Lahore	0
GROWTH SECURITIES (PVT) LTD.	Karachi	1
GUL DHAMI SECURITIES (PVT) LTD	Lahore	1
GULREZ SECURITIES (PRIVATE) LIMITED	Lahore	0
H. P. BYRAMJI & CO. (PVT) LIMITED	Karachi	0
H.M. IDREES H. ADAM (PVT.) LIMITED	Karachi	0
HABIB METROPOLITAN FINANCIAL SERVICES LIMITED	Karachi	1
HABIB ULLAH SHEIKH (PVT) LTD.	Lahore	1
HAMZA FARHAD SECURITIES (PVT.) LIMITED	Islamabad	1
HH MISBAH SECURITIES (PRIVATE) LIMITED	Karachi	0
HIGH LAND SECURITIES (PVT.) LIMITED	Lahore	1
HMC STOCKS (SMC-PVT.) LTD.	Lahore	1
HORIZON SECURITIES LIMITED	Lahore	1
HP SECURITIES (PRIVATE) LIMITED	Islamabad	0
IAK SECURITIES (PVT.) LIMITED	Lahore	1
ICON CAPITAL MANAGEMENT (PRIVATE) LIMITED	Karachi	0
IGI FINEX SECURITIES LIMITED	Karachi	0
INA SECURITIES (PVT.) LTD.	Lahore	1
INFINITE SECURITIES LIMITED	Lahore	0
INSIGHT SECURITIES (PVT.) LIMITED	Karachi	0
INTEGRATED EQUITIES LIMITED	Lahore	0
INTERACTIVE SECURITIES (PVT.) LIMITED	Karachi	1
INTERMARKET SECURITIES (PVT) LIMITED.	Karachi	0
INVESLINK CAPITAL (PVT.) LIMITED	Karachi	0
INVESTMENT MANAGERS SECURITIES (PVT.) LIMITED	Karachi	1
IQBAL USMAN KODVAVI SECURITIES (PVT) LTD	Karachi	1
IRFAN MAZHAR SECURITIES (PVT) LTD.	Karachi	1
ISMAIL IQBAL SECURITIES (PVT) LTD.	Karachi	1
JAVED IQBAL SECURITIES (PVT) LTD.	Lahore	1
JS GLOBAL CAPITAL LIMITED	Karachi	0
JSK SECURITIES LIMITED	Islamabad	0
K & I GLOBAL CAPITAL (PVT.) LTD.	Lahore	0
K.H.S. SECURITIES (PVT.) LIMITED.	Lahore	1
KHADIM ALI SHAH BUKHARI SECURITIES (PRIVATE) LIMITED	Lahore	1
KHANI SECURITIES (PVT.) LTD.	Karachi	0
KHAWAJA SECURITIES (PVT.) LIMITED	Lahore	1
KOSMOPOLITAN SECURITIES (PRIVATE) LIMITED	Karachi	0
KP SECURITIES (PRIVATE) LIMITED *	Islamabad	1
LAKHANI SECURITIES (PVT) LTD.	Karachi	1
M. J. MEMON SECURITIES (PVT) LIMITED.	Karachi	0
M. M. SECURITIES (PVT.) LIMITED	Karachi	1

MAAN SECURITIES (PRIVATE) LIMITED	Lahore	1
MANNOO CAPITAL (PRIVATE) LTD.	Karachi	0
MARGALLA FINANCIAL (PRIVATE) LIMITED	Islamabad	0
MARKET 786 (PRIVATE) LIMITED	Karachi	1
MAYARI SECURITIES (PVT) LIMITED	Karachi	0
MEMON SECURITIES (PVT.) LIMITED	Karachi	1
MERCHANT INVESTMENTS (PRIVATE) LIMITED	Karachi	1
MGM SECURITIES (PRIVATE) LIMITED	Lahore	1
MILLENNIUM BROKERAGE (PVT.) LTD.	Islamabad	1
MND INVESTMENT (PVT) LTD.	Lahore	1
MOHAMMAD MUNIR MOHAMMAD AHMED KHANANI SECURITIES (PVT.) LTD.	Karachi	0
MONEYLINE SECURITIES (PRIVATE) LIMITED	Lahore	0
MOONACO SECURITIES (PRIVATE) LIMITED	Karachi	0
MRA SECURITIES LIMITED	Karachi	1
MSD CAPITAL EQUITIES (PVT) LTD.	Lahore	1
MSMANIAR FINANCIALS (PVT) LTD.	Karachi	0
MUHAMMAD AMER RIAZ SECURITIES (PVT) LTD.	Lahore	0
MUHAMMAD ASHFAQ HUSSAIN SECURITIES (PVT) LTD	Karachi	1
MUHAMMAD HUSSAIN ISMAIL SECURITIES (PVT) LTD.	Karachi	1
MUHAMMAD SALIM KASMANI SECURITIES (PVT.) LTD.	Karachi	0
MUHAMMAD TARIQ MOTI SECURITIES (PVT) LTD.	Karachi	1
MULTILINE SECURITIES (PVT) LIMITED	Karachi	1
N.U.A SECURITIES (PRIVATE) LIMITED	Karachi	1
NAEL CAPITAL (PVT.) LIMITED	Karachi	1
NETWORTH SECURITIES LIMITED	Lahore	1
NEW PEAK SECURITIES (PVT.) LTD.	Lahore	1
NEXT CAPITAL LIMITED	Karachi	0
NINI SECURITIES (PRIVATE) LIMITED	Karachi	1
OPTIMUS CAPITAL MANAGEMENT (PRIVATE) LIMITED	Karachi	0
ORIENTAL SECURITIES (PVT) LTD.	Karachi	1
PASHA SECURITIES (PVT) LTD.	Islamabad	1
PATEL SECURITIES (PVT.) LTD.	Karachi	0
PEARL SECURITIES LIMITED	Karachi	0
PERVEZ AHMED CAPITAL (PVT.) LIMITED	Karachi	1
PINE SECURITIES (PRIVATE) LIMITED	Islamabad	1
PRIME SECURITIES (PRIVATE) LIMITED	Karachi	1
PROGRESSIVE INV. MANAGEMENT (PVT) LTD.	Islamabad	1
PROGRESSIVE SECURITIES (PRIVATE) LIMITED	Lahore	1
PUNJAB CAPITAL SECURITIES (PVT) LIMITED	Lahore	1
Q. AIN KHANANI SECURITIES (PRIVATE) LTD.	Karachi	1
R.T. SECURITIES (PVT) LIMITED	Karachi	1
RAFI SECURITIES (PRIVATE) LIMITED	Karachi	1
RAH SECURITIES (PVT.) LIMITED	Karachi	1
RAHAT SECURITIES LIMITED	Lahore	1
RELIANCE SECURITIES LIMITED	Karachi	0
RIAZ AHMED SECURITIES (PVT) LTD.	Islamabad	0
ROYAL SECURITIES (PVT) LIMITED	Karachi	1
RUC SECURITIES (PRIVATE) LIMITED *	Karachi	1
S.D. MIRZA SECURITIES (PVT) LTD.	Lahore	1
SAAO CAPITAL (PVT) LIMITED	Karachi	1
SAIMA QAISER SECURITIES (PVT) LIMITED	Lahore	1
SAKARWALA CAPITAL SECURITIES (PVT)LTD.	Karachi	1
SALIM SOZER SECURITIES (PVT.) LTD.	Karachi	0
SALMAN MAJEED SECURITIES (PVT) LIMITED	Lahore	0

SAYA SECURITIES (PRIVATE) LIMITED	Karachi	1
SAZ CAPITAL SECURITIES (PVT) LTD.	Karachi	1
SETHI SECURITIES (PVT) LTD	Lahore	1
SEVEN STAR SECURITIES (PVT.) LTD.	Karachi	1
SHAFFI SECURITIES (PVT) LIMITED	Lahore	0
SHAJAR CAPITAL PAKISTAN (PRIVATE) LTD.	Karachi	0
SHAJARPAK SECURITIES (PVT.) LIMITED	Lahore	0
SHERMAN SECURITIES (PRIVATE) LIMITED	Karachi	0
SPECTRUM SECURITIES LIMITED	Karachi	1
SPINZER EQUITIES (PRIVATE) LIMITED	Islamabad	0
STANDARD CAPITAL SECURITIES (PVT) LTD.	Karachi	1
STRONGMAN SECURITIES (PVT.) LIMITED	Lahore	0
SUMMIT CAPITAL (PRIVATE) LIMITED	Karachi	1
SURMAWALA SECURITIES (PRIVATE) LIMITED	Karachi	1
TANNU SECURITIES (PVT.) LIMITED	Karachi	1
TARIQ VOHRA SECURITIES (PVT) LIMITED	Karachi	1
TAURUS SECURITIES LIMITED	Karachi	1
TIME SECURITIES (PVT.) LTD.	Karachi	1
TOPLINE SECURITIES LIMITED	Karachi	0
TRUST SECURITIES & BROKERAGE LIMITED	Lahore	1
TS SECURITIES (PVT) LTD.	Karachi	1
UNEX SECURITIES (PVT) LIMITED.	Islamabad	1
VALUE STOCK AND COMMODITIES (PVT.) LTD.	Lahore	0
VECTOR SECURITIES (PVT.) LTD.	Karachi	1
VENUS SECURITIES (PVT.) LIMITED	Karachi	0
WE FINANCIAL SERVICES LIMITED	Karachi	0
XPERT SECURITIES (PRIVATE) LIMITED *	Islamabad	1
Y.H. SECURITIES (PVT.) LTD.	Karachi	0
YASIR MAHMOOD SECURITIES (PVT) LTD.	Lahore	0
Z.A. GHAFFAR SECURITIES (PRIVATE) LTD.	Karachi	0
ZAFAR MOTI CAPITAL SECURITIES (PVT) LTD.	Karachi	1
ZAFAR SECURITIES (PVT) LTD.	Lahore	1
ZAHID LATIF KHAN SECURITIES (PVT) LTD.	Islamabad	0
ZILLION CAPITAL SECURITIES (PVT) LTD. *	Karachi	0
0 = Excluded from sample	1 = Randomly selected	

9.2. Questionnaire (سوالنامہ)

Dear Respondent,

My name is Muhammad Haroon Rasheed. As a Ph.D. research scholar at NUML Islamabad, I am collecting data for my thesis, Title: Elucidating the Behavioral Factors Influencing Investors' Decision Making in Pakistan. It will take your 15-20 minutes to answer the questions and to provide valuable information. I assure you that data will be strictly kept confidential and will only be used for academic purposes. To ensure anonymity, your name or name of the organization is not asked, anywhere in the questionnaire.

Thanks a lot for your help and support!

Sincerely,

Muhammad Haroon Rasheed

Research Scholar, Ph.D. (Finance)

Department of Management Sciences

National University of Modern Languages, Islamabad

محترم جوابدہ ،

میرا نام محمد ہارون رشید ہے۔ بحیثیت پی ایچ ڈی ریسرچ اسکالر نمل اسلام آباد میں ، میں اپنے تھیسس کا ڈیٹا اکٹھا کر رہا ہوں ، عنوان: پاکستان میں سرمایہ کاروں کی فیصلہ سازی کو متاثر کرنے والے طرزعمل کے عوامل کی وضاحت کرنا۔ سوالات کے جوابات دینے اور قیمتی معلومات فراہم کرنے میں آپ کو 15-20 منٹ لگیں گے۔ میں آپ کو یقین دلاتا ہوں کہ ڈیٹا سختی سے خفیہ رکھا جائے گا اور اسے صرف تعلیمی مقاصد کے لئے استعمال کیا جائے گا۔ شناخت ظاہر نہ کرنے کے لئے ،

سوالنامے میں کہیں بھی آپ کا نام یا تنظیم کا نام نہیں پوچھا گیا ہے۔

آپ کی مدد اور تعاؤن کے لئے بہت بہت شکریہ!

مخلص،

محمد ہارون رشید

ریسرچ اسکالر ، پی ایچ ڈی (مالیات)

شعبہ مینجمنٹ سائنسز

نیشنل یونیورسٹی آف ماڈرن لینگویجز ، اسلام آباد

Section One								
Marital Status			Gender					
Married	Single	Other	Male		Female		Other	
Age	18 to 30		30 to 50		Above 50			
Investment Experience	0-5 Years		6-20 Years		21 Years & above			
Qualification	Matric	Inter	Bachelor	Masters	M.Phil.	PhD	Other	
Specialization	Business Related			Other				
Location	Islamabad		Lahore	Karachi				

Section Two								
How well do the following statements fit you?	**Strongly Disagree**	**Slightly Disagree**	**Neutral**	**Slightly Agree**	**Strongly Agree**			
(Please tick any one option)	**1**	**2**	**3**	**4**	**5**			
Extraversion:								
I really enjoy talking to people.	**1**	**2**	**3**	**4**	**5**			
I often feel as if I am bursting with energy.	**1**	**2**	**3**	**4**	**5**			
I am a cheerful, high-spirited person.	**1**	**2**	**3**	**4**	**5**			
I am a very active person.	**1**	**2**	**3**	**4**	**5**			
Agreeableness:								
I often get into arguments with my family and friends.*	**1**	**2**	**3**	**4**	**5**			
Some people think I am selfish and egotistical.*	**1**	**2**	**3**	**4**	**5**			
Some people think of me as cold and calculating.*	**1**	**2**	**3**	**4**	**5**			
I generally try to be thoughtful and considerate.	**1**	**2**	**3**	**4**	**5**			
Openness:								
I am intrigued by the patterns I find in art and nature.	**1**	**2**	**3**	**4**	**5**			
I often try new and foreign foods.	**1**	**2**	**3**	**4**	**5**			
I have little interest in speculating on the nature of the universe or the human condition.*	**1**	**2**	**3**	**4**	**5**			
I have a lot of intellectual curiosity.	**1**	**2**	**3**	**4**	**5**			
I often enjoy playing with theories or abstract ideas.	**1**	**2**	**3**	**4**	**5**			
Overconfidence Bias:								
I have earned better returns than other investors in the last year.	**1**	**2**	**3**	**4**	**5**			
I am better than fellow investors in choosing a good investment.	**1**	**2**	**3**	**4**	**5**			
Generally, I earn better returns on my portfolio than my fellow Investors.	**1**	**2**	**3**	**4**	**5**			
It seems to me that the prices of my portfolio of securities will increase more as compare to other stocks.	**1**	**2**	**3**	**4**	**5**			
My experience in making investment decisions is better than other fellow investors.	**1**	**2**	**3**	**4**	**5**			
My know-how of the stock market is better than at least 50% of the investors in the market.	**1**	**2**	**3**	**4**	**5**			
I have earned better returns than the overall returns of the KSE-100 Index in the last 12-months.	**1**	**2**	**3**	**4**	**5**			
I am confident that my portfolio will earn better returns than the overall returns of the KSE-100 Index in the next 12-months.	**1**	**2**	**3**	**4**	**5**			
Availability Bias:								
I prefer to sell stocks on the days when the value of the Stock Market Index decreases.	**1**	**2**	**3**	**4**	**5**			
I prefer to buy stocks on the days when the value of the Stock Market Index increases.	**1**	**2**	**3**	**4**	**5**			

I prefer to invest in local stocks than international stocks because the information on local stocks is more available.	**1**	**2**	**3**	**4**	**5**
I consider the information from my close friends and relatives as a reliable reference for my investment decisions.	**1**	**2**	**3**	**4**	**5**
I prefer to buy local stocks than trade-in international ones.	**1**	**2**	**3**	**4**	**5**
Representative Bias:					
I consider the past performance of the stocks before investing in it.	**1**	**2**	**3**	**4**	**5**
I believe that through a detailed analysis of past performance future value of a contract in the stock market can be determined	**1**	**2**	**3**	**4**	**5**
I avoid investments in stocks that have a history of poor earnings.	**1**	**2**	**3**	**4**	**5**
I buy 'hot' stocks which provided most return recently and avoid stocks that have performed poorly in the recent past	**1**	**2**	**3**	**4**	**5**
I use trend analysis to make investment decisions	**1**	**2**	**3**	**4**	**5**
Before investing I use trend analysis of some representative stocks to make investment decisions for all stocks.	**1**	**2**	**3**	**4**	**5**
Disposition Effect:					
I prefer to sell stocks whose prices has recently increased.	**1**	**2**	**3**	**4**	**5**
When I need cash I prefer to sell the stock which has increased in value.	**1**	**2**	**3**	**4**	**5**
I prefer to keep holding on stocks when their current price is lower than their purchase price.	**1**	**2**	**3**	**4**	**5**
When I need cash I sell securities that can give higher profits at that time.	**1**	**2**	**3**	**4**	**5**
When I need cash I prefer to sell the stock which has decreased in Value*	**1**	**2**	**3**	**4**	**5**
In case of loss positions in my portfolio, I generally wait for a price rebound instead of selling those securities.	**1**	**2**	**3**	**4**	**5**
Decision Making					
When making an Investment, I trust my inner feelings and reactions	**1**	**2**	**3**	**4**	**5**
I generally make Investments that feel right to me	**1**	**2**	**3**	**4**	**5**
When making Investments, I rely upon my instincts	**1**	**2**	**3**	**4**	**5**
When I invest, it is more important for me to feel the Investment is right than have a rational reason for it.	**1**	**2**	**3**	**4**	**5**
When I make Investment, I tend to rely on my intuition	**1**	**2**	**3**	**4**	**5**
****Reverse Questions***					

Any other comment/suggestion: _____

_____

_____

_____

_____

حصہ اول									
صنف				**ازدواجی حیثیت**					
مرد		عورت		دیگر		شادی شدہ		کنوارا		دیگر
عمر			**18 سے30**			**30 سے 50**			**50 سےاوپر**
سرمایہ کاری کا تجربہ			**0-5 سال**			**6-20 سال**			**21 سال اور زیادہ**
تعلیم	**میٹرک**		**انٹر**		**بیچلر**		**ماسٹرز**	**ایم فل**	**پی ایچ ڈی**	**دیگر**
تخصص				**کاروبار سے متعلق**					**دیگر**
مقام		**اسلام آباد**			**لاہور**				**کراچی**

حصہ دوئم						
درج ذیل بیانات آپ کو کتنا اچھا بیان کرتے ہیں؟	**شدید اختلاف**	**قدرے اختلاف**	**غیر جانبدار**	**قدرے متفق**	**شدید متفق**	
(براہ کرم کسی ایک آپشن پر نشان لگائیں)	**1**	**2**	**3**	**4**	**5**	
اکسٹراورژن						
مجھے لوگوں سے بات کرنے میں واقعی لطف آتا ہے۔	**1**	**2**	**3**	**4**	**5**	
مجھے اکثر ایسا لگتا ہے جیسے میں توانائی سے بھرپور ہوں۔	**1**	**2**	**3**	**4**	**5**	
میں ایک خوش مزاج ، حوصلہ مند شخص ہوں۔	**1**	**2**	**3**	**4**	**5**	
میں ایک بہت ہی سرگرم شخص ہوں۔	**1**	**2**	**3**	**4**	**5**	
ایگری ایبلنیس						
میں اکثر اپنے گھر والوں اور دوستوں سے بحث کرتا رہتا ہوں۔*	**1**	**2**	**3**	**4**	**5**	
کچھ لوگوں کا خیال ہے کہ میں خودغرض اور انا پرست ہوں۔*	**1**	**2**	**3**	**4**	**5**	
کچھ لوگ مجھے سردمہراور محتاط سمجھتے ہیں۔*	**1**	**2**	**3**	**4**	**5**	
میں عام طور پر بافکر اور بامروت رہنے کی کوشش کرتا ہوں۔	**1**	**2**	**3**	**4**	**5**	
اوپننیس						
میں فنون اور فطرت کے نمونوں سے دلچسپی رکھتا ہوں۔	**1**	**2**	**3**	**4**	**5**	
میں اکثر نئے اور غیر ملکی کھانے کھانے کی کوشش کرتا ہوں۔	**1**	**2**	**3**	**4**	**5**	
مجھے کائنات کی نوعیت یا انسانی حالت کے بارے میں قیاس آرائ کرنے میں کوئی خاص دلچسپی نہیں ہے۔*	**1**	**2**	**3**	**4**	**5**	
مجھ میں بہت فکری تجسس ہے۔	**1**	**2**	**3**	**4**	**5**	
مجھے اکثر نظریات یا تجریدی خیالات کا مشاہدہ کرنا پسند ہے۔	**1**	**2**	**3**	**4**	**5**	
اورکانفیڈینس بائس						
میں نے گذشتہ ایک سال کے دوران دوسرے سرمایہ کاروں کے مقابلے میں بہتر منافع حاصل کیا ہے۔	**1**	**2**	**3**	**4**	**5**	
میں اچھی سرمایہ کاری کے انتخاب میں ساتھی سرمایہ کاروں سے بہتر ہوں۔	**1**	**2**	**3**	**4**	**5**	
عام طور پر میں اپنے ساتھی سرمایہ کاروں کے مقابلے میں اپنے پورٹ فولیو پر بہتر منافع کماتا ہوں۔	**1**	**2**	**3**	**4**	**5**	
مجھے ایسا لگتا ہے کہ دوسرے شیئرز کے مقابلے میں میرے پورٹ فولیو کے شیئرز کی قیمتوں میں اور اضافہ ہوگا ۔	**1**	**2**	**3**	**4**	**5**	
سرمایہ کاری کے فیصلے کرنے میں میرا تجربہ دوسرے ساتھی سرمایہ کاروں سے بہتر ہے۔	**1**	**2**	**3**	**4**	**5**	
اسٹاک مارکیٹ کے بارے میں میرا علم اسٹاک مارکیٹ میں کم از کم 50% سرمایہ کاروں سے بہتر ہے۔	**1**	**2**	**3**	**4**	**5**	
میں نے گذشتہ 12 مہینوں میں کے ایس ای 100 انڈیکس کے مجموعی منافع سے بہتر منافع حاصل کیا ہے۔	**1**	**2**	**3**	**4**	**5**	
مجھے یقین ہے کہ میرا پورٹ فولیو آئندہ 12 ماہ میں کے ایس ای 100 انڈیکس کے مجموعی منافع سے بہتر منافع حاصل کرے گا۔	**1**	**2**	**3**	**4**	**5**	
اویلےبیلٹی بائس						
میں ان دنوں شیئرز فروخت کرنے کو ترجیح دیتا ہوں جب اسٹاک مارکیٹ انڈیکس کی	**1**	**2**	**3**	**4**	**5**	

قیمت کم ہوجاتی ہے۔					
میں ان دنوں شیئرز خریدنے کو ترجیح دیتا ہوں جب اسٹاک مارکیٹ انڈیکس کی قیمت میں اضافہ ہوتا ہے۔	**1**	**2**	**3**	**4**	**5**
میں بین الاقوامی شیئرز کے مقابلے میں مقامی شیئرز میں سرمایہ کاری کو ترجیح دوں گا کیونکہ مقامی اسٹاک کی معلومات زیادہ دستیاب ہے۔	**1**	**2**	**3**	**4**	**5**
میں اپنے قریبی دوستوں اور رشتہ داروں سے حاصل کردہ معلومات کو اپنے سرمایہ کاری کے فیصلوں کا قابل اعتماد حوالہ سمجھتا ہوں۔	**1**	**2**	**3**	**4**	**5**
میں بین الاقوامی شیئرز سے زیادہ مقامی شیئرز خریدنا پسند کرتا ہوں۔	**1**	**2**	**3**	**4**	**5**
ریپریزینٹےٹیونیس بائس					
میں سرمایہ کاری کرنے سے پہلے شیئرز کی ماضی کی کارکردگی پر غور کرتا ہوں۔	**1**	**2**	**3**	**4**	**5**
مجھے یقین ہے کہ ماضی کی کارکردگی کے تفصیلی تجزیہ کے ذریعے اسٹاک مارکیٹ میں کسی شیئر کی مستقبل کی قیمت کا تعین کیا جاسکتا ہے	**1**	**2**	**3**	**4**	**5**
میں ان شیئرز میں سرمایہ کاری سے گریز کرتا ہوں جن کی آمدن ماضی میں کم ہو۔	**1**	**2**	**3**	**4**	**5**
میں ایسے ’ فعال ‘شیئرز خریدتا ہوں جس نے حال ہی میں زیادہ منافع فراہم کیا ہو اور ان شیئرز سے گریز کیا جنہوں نے حالیہ عرصہ میں خراب کارکردگی کا مظاہرہ کیا ہے	**1**	**2**	**3**	**4**	**5**
میں سرمایہ کاری کے فیصلے کرنے کے لئے رجحان کا تجزیہ کرتا ہوں	**1**	**2**	**3**	**4**	**5**
میں تمام اسٹاک میں سرمایہ کاری کے فیصلے کرنے سے پہلے ، کچھ نمائندہ شیئرز کے رجحان کا تجزیہ استعمال کرتا ہوں۔	**1**	**2**	**3**	**4**	**5**
ڈسپوزیشن ایفکٹ					
میں ایسے شیئرز فروخت کرنے کو ترجیح دیتا ہوں جن کی قیمتوں میں حال ہی میں اضافہ ہوا ہے	**1**	**2**	**3**	**4**	**5**
جب مجھے نقد رقم کی ضرورت ہوتی ہے تو میں اس شیئرز کو فروخت کرنے کو ترجیح دیتا ہوں جس کی قیمت میں اضافہ ہوا ہے۔	**1**	**2**	**3**	**4**	**5**
میں شیئرز کواپنے پاس رکھنےکو ترجیح دیتا ہوں جب ان کی موجودہ قیمت ان کی قیمت خرید سے کم ہو۔	**1**	**2**	**3**	**4**	**5**
جب مجھے نقد رقم کی ضرورت ہوتی ہے تو میں ایسے شیئرز فروخت کرتا ہوں جو اس وقت زیادہ منافع دے سکیں۔	**1**	**2**	**3**	**4**	**5**
جب مجھے نقد رقم کی ضرورت ہو تو میں اس شیئر کو فروخت کرنے کو ترجیح دوں گا جس کی قیمت میں کمی واقع ہو.*	**1**	**2**	**3**	**4**	**5**
اپنے پورٹ فولیو میں نقصان کی صورت میں میں عام طور پر ان شیئرز کو فروخت کرنے کے بجائے قیمتوں میں اضافے کا انتظار کرتا ہوں۔	**1**	**2**	**3**	**4**	**5**
فیصلہ سازی					
سرمایہ کاری کرتے وقت ، مجھے اپنے اندرونی احساسات اور رد عمل پر اعتماد ہوتا ہے.	**1**	**2**	**3**	**4**	**5**
میں عام طور پر ایسی سرمایہ کاری کرتا ہوں جو مجھے صحیح محسوس ہوں.	**1**	**2**	**3**	**4**	**5**
سرمایہ کاری کرتے وقت ، میں اپنی جبلت پر بھروسہ کرتا ہوں	**1**	**2**	**3**	**4**	**5**
جب میں سرمایہ کاری کرتا ہوں تو ، اس کے لئے عقلی وجوہ کی بجائے یہ محسوس کرنا زیادہ ضروری ہوتا ہے کہ سرمایہ کاری مناسب ہے۔	**1**	**2**	**3**	**4**	**5**
جب میں سرمایہ کاری کرتا ہوں تو میں اپنی بدیہی/ اندازہ پر بھروسہ کرتا ہوں.	**1**	**2**	**3**	**4**	**5**
الٹ سوال*					

کوئی اور تبصرہ / مشورہ : _____

_____

_____

_____

_____

9.3. Tool for Validity Assessment

ASSESSMENT OF ADOPTED QUESTIONNAIRE FOR MEASUREMENT OF PERSONALITY TARITS, BIASES AND DECISION MAKINGSTYYLE OF INVESTORS IN PAKISTAN

Direction: the given tool asks for your evaluation of the provided questionnaire to be used in for the investigation from investors of stock markets of Pakistan, to establish its validity. You are requested to give your honest assessment using the criteria stated below; please check **(**√**)** only one from the selection.

Scale	**Interpretation**	**Description**
5	Very high valid	The questionnaire is valid and can provide unbiased data for the investigation, allowing 0-5% error
4	High valid	The questionnaire is valid and can provide unbiased data for the investigation, allowing 8-10% error
3	Valid	The questionnaire is valid and can provide unbiased data for the investigation, allowing 11-15% error
2	Less valid	The questionnaire is valid and can provide unbiased data for the investigation, allowing 16-20% error
1	Not valid at all	The questionnaire is valid and can provide unbiased data for the investigation, allowing 21-25% error

Validators' Questionnaire Assessment Indicators

The indicators in the questionnaire and its translation consistently and accurately measure each variables of the investigation.	**1**	**2**	**3**	**4**	**5**
The questionnaire and its translation fits with the variables under investigation, thus measuring what it tends to measure	**1**	**2**	**3**	**4**	**5**
The questionnaire and its translation has the capability to measure items of variables within a given time frame	**1**	**2**	**3**	**4**	**5**
The questionnaire and its translation has the ability to distinguish the characteristics or the properties of differing attributes of the subjects under study	**1**	**2**	**3**	**4**	**5**
The questionnaire and its translation has the ability to gather factual data, eliminating biases and subjectivity	**1**	**2**	**3**	**4**	**5**
Quick and complete data can be generated by the questionnaire and its translation within the time frame allowed to obtain the data	**1**	**2**	**3**	**4**	**5**
The questionnaire and its translation has no influence on the variables being measured	**1**	**2**	**3**	**4**	**5**
The questionnaire and its translation is framed in a clear, simple, in order to avoid risk of error	**1**	**2**	**3**	**4**	**5**
The questionnaire and its translation is capable of generating data that will be of value and practical use to the sectors concerned in the investigation.	**1**	**2**	**3**	**4**	**5**

Comments and Suggestions:

_____
_____
_____
_____

Date: _____

_____
Signature with named stamp of the validator

9.4. List of Validators

Subject Specialists (Management Sciences)	
Hammad Hassan Mirza Assistant Professor Noon Business School University of Sargodha Email: hammad.hassan@uos.edu.pk Cell # 0334-7550550	**Haroon Hussain** Assistant Professor Noon Business School University of Sargodha Email: DrHaroonHussain@uos.edu.pk Cell # 0345-4910678
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Individual Investors	
Umair Maqsood CDC AC # 04481-26849 DOSSLANI Securities ltd. Email: umairupap801@gamil.com Cell # 0300-7129638	**M. Shahid Rasheed** CDC AC # ---------- Foundation Securities ltd. Email: mshahid351@yahoo.com Cell # 0300-7968418
Institutional Investors	
Muhammad Luqman Zafar Mutual Fund Manager United Bank Limited Email: luqman.zafar@ublfunds.com Cell # 0341-5609977	

9.5. Pilot Study

https://docs.google.com/forms/d/e/1FAIpQLSdid9PCuXUPAhJMuiH6cm3zQGjSm75hCWo4l3o3NpoptRygoA/viewform

Table 9-2-Pilot Test Results

	Correlations								Cronbach's Alpha
	E	**A**	**O**	**OC**	**AB**	**RB**	**D.E**	**D.M**	
E	1	.377*	.723**	.650**	.747**	.607**	.648**	.684**	0.908
A		1	.420**	.512**	.386*	.418**	.662**	.570**	0.840
O			1	.648**	.869**	.531**	.735**	.622**	0.793
OC				1	.632**	.700**	.686**	.738**	0.874
AB					1	.478**	.723**	.646**	0.943
RB						1	.552**	.805**	0.893
DE							1	.806**	0.857
DM								1	0.872

E=Extraversion, A=Agreeableness, O= Openness, OC= Overconfidence, AB= Availability, RB= Representativeness, DE=Disposition, DM= Decision Making
*= Significant at p<0.05
**= Significant at p<0.01

https://docs.google.com/forms/d/e/1FAIpQLScf-TtGYNsFRlyeN5OfvKjdcaXeguNEn9oqMhK8LgPNm3s-Rw/viewform

Table 9-3 - Pilot Testing of Translated Instrument

	Correlations								Cronbach's Alpha
	E	**A**	**O**	**OC**	**AB**	**RB**	**D.E**	**D.M**	
E	1	.593*	.732**	.576**	.620**	.598**	.557**	.406*	0.905
A		1	.800**	.784**	.561*	.717**	.822**	.636**	0.877
O			1	.807**	.710**	.769**	.778**	.547**	0.858
OC				1	.530**	.920**	.880**	.664**	0.917
AB					1	.567**	.571**	.372*	0.856
RB						1	.854**	.747**	0.906
DE							1	.616**	0.903
DM								1	0.935

E=Extraversion, A=Agreeableness, O= Openness, OC= Overconfidence, AB= Availability, RB= Representativeness, DE=Disposition, DM= Decision Making
*= Significant at p<0.05
**= Significant at p<0.01

9.6. Instrument Translation

Table 9-4- Backward Translation Approach

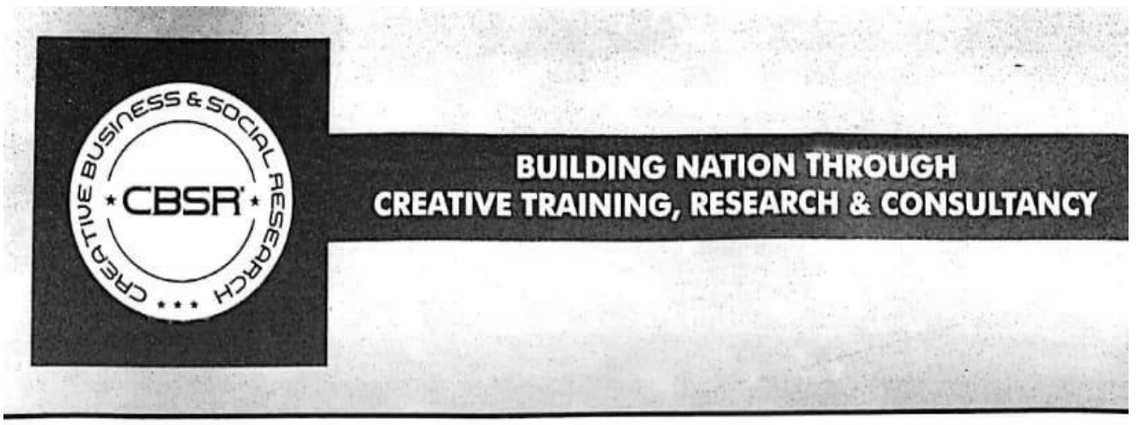
Sr.	Original	Forward	Backward
E1	I really enjoy talking to people.	مجھے لوگوں سے بات کرنے میں واقعی لطف آتا ہے۔	I really enjoy talking to people.
E2	I often feel as if I am bursting with energy.	مجھے اکثر ایسا لگتا ہے جیسے میں توانائی سے بھرپور ہوں۔	I often feel like I'm full of energy
E3	I am cheerful, high-spirited person.	میں ایک خوش مزاج ، حوصلہ مند شخص ہوں۔	I am a cheerful, enthusiastic person
E4	I am a very active person.	میں ایک بہت ہی سرگرم شخص ہوں۔	I am a very active person
A1	I often get into arguments with my family and friends.	میں اکثر اپنے گھر والوں اور دوستوں سے بحث کرتا رہتا ہوں۔	I often argue with my family and friends.
A2	Some people think I am selfish and egotistical.	کچھ لوگوں کا خیال ہے کہ میں خودغرض اور انا پرست ہوں۔	Some people think I'm selfish and egotistical.
A3	Some people think of me as cold and calculating.	کچھ لوگ مجھے سردمہر اور محتاط سمجھتے ہیں۔	Some people consider me cold and cautious.
A4	I generally try to be thoughtful and considerate.	میں عام طور پر بافکر اور بامروت رہنے کی کوشش کرتا ہوں۔	I usually try to be thoughtful and considerate.
O1	I am intrigued by the patterns I find in art and nature.	میں فنون اور فطرت کے نمونوں سے دلچسپی رکھتا ہوں۔	I'm interested in art and nature.
O2	I often try new and foreign foods.	میں اکثر نئے اور غیر ملکی کھانے کھانے کی کوشش کرتا ہوں۔	I often try new and exotic foods.
O3	I have little interest in speculating on the nature of the universe or the human condition.	مجھے کائنات کی نوعیت یا انسانی حالت کے بارے میں قیاس آرائ کرنے میں کوئی خاص دلچسپی نہیں ہے۔	I have little interest in speculating about the nature of the universe or the human condition.
O4	I have a lot of intellectual curiosity.	مجھ میں بہت فکری تجسس ہے۔	I have a great intellectual curiosity.
O5	I often enjoy playing with theories or abstract ideas.	مجھے اکثر نظریات یا تجریدی خیالات کا مشاہدہ کرنا پسند ہے.	I often like to observe theories or abstract ideas.
OC1	I have earned better returns than other investors in the last one year.	میں نے گذشتہ ایک سال کے دوران دوسرے سرمایہ کاروں کے مقابلے میں بہتر منافع حاصل کیا ہے۔	I have made better returns than any other investor in the last one year.
OC2	I am better than fellow investors in choosing good investment.	میں اچھی سرمایہ کاری کے انتخاب میں ساتھی سرمایہ کاروں سے بہتر ہوں۔	I am better than fellow investors in making good investment choices.
OC3	Generally I earn better returns on my portfolio than my fellow Investors.	عام طور پر میں اپنے ساتھی سرمایہ کاروں کے مقابلے میں اپنے پورٹ فولیو پر بہتر منافع	In general, I make better returns on my portfolio than my fellow investors

		کماتا ہوں۔	
OC4	It seems to me that the prices of my portfolio of securities will increase more as compare to other stocks.	مجھے ایسا لگتا ہے کہ دوسرے شیئرز کے مقابلے میں میرے پورٹ فولیو کے شیئرز کی قیمتوں میں اور اضافہ ہوگا ۔	I think my portfolio share price will increase more than other shares.
OC5	My experience at making investment decisions is better than other fellow investors.	سرمایہ کاری کے فیصلے کرنے میں میرا تجربہ دوسرے ساتھی سرمایہ کاروں سے بہتر ہے۔	My experience in making investment decisions is better than that of other fellow investors.
OC6	My know-how of stock market is better than at least 50% of the investors in the market.	اسٹاک مارکیٹ کے بارے میں میرا علم اسٹاک مارکیٹ میں کم از کم 50% سرمایہ کاروں سے بہتر ہے۔	My knowledge of the stock market is better than at least 50% of investors in the stock market
OC7	I have earned better returns than the overall returns of KSE-100 Index in last 12-months.	میں نے گذشتہ 12 مہینوں میں کے ایس ای 100 انڈیکس کے مجموعی منافع سے بہتر منافع حاصل کیا ہے۔	I have made a better profit than the overall profit of the KSE 100 Index in the last 12 months.
OC8	I am confident that my portfolio will earn better returns than the overall returns of KSE-100 Index in the next 12-months.	مجھے یقین ہے کہ میرا پورٹ فولیو آئندہ 12 ماہ میں کے ایس ای 100 انڈیکس کے مجموعی منافع سے بہتر منافع حاصل کرے گا۔	I am confident that my portfolio will outperform the KSE 100 Index over the next 12 months.
AB1	I prefer to sell stocks on the days when the value of the Stock Market Index decreases.	میں ان دنوں شیئرز فروخت کرنے کو ترجیح دیتا ہوں جب اسٹاک مارکیٹ انڈیکس کی قیمت کم ہوجاتی ہے۔	I prefer to sell shares on days when the stock market index falls.
AB2	I prefer to buy stocks on the days when the value of the Stock Market Index increases.	میں ان دنوں شیئرز خریدنے کو ترجیح دیتا ہوں جب اسٹاک مارکیٹ انڈیکس کی قیمت میں اضافہ ہوتا ہے۔	I prefer to buy shares on days when the stock market index rises in value.
AB3	I prefer to invest in local stocks than international stocks because the information of local stocks is more available.	میں بین الاقوامی شیئرز کے مقابلے میں مقامی شیئرز میں سرمایہ کاری کو ترجیح دوں گا کیونکہ مقامی اسٹاک کی معلومات زیادہ دستیاب ہے۔	I would prefer to invest in local shares over international shares as information of local stocks is more available.
AB4	I consider the information from my close friends and relatives as the reliable reference for my investment decisions.	میں اپنے قریبی دوستوں اور رشتہ داروں سے حاصل کردہ معلومات کو اپنے سرمایہ کاری کے فیصلوں کا قابل اعتماد حوالہ سمجھتا ہوں۔	I consider the information I receive from close friends and relatives to be a reliable reference for my investment decisions.
AB5	I prefer to buy local stocks than trade in international ones.	میں بین الاقوامی شیئرز سے زیادہ مقامی شیئرز خریدنا پسند کرتا ہوں۔	I prefer to buy local shares than international shares.
RB1	I consider the past performance of the stocks before investing in it.	میں سرمایہ کاری کرنے سے پہلے شیئرز کی ماضی کی کارکردگی پر غور کرتا ہوں۔	I consider the past performance of the shares before investing.
RB2	I believe that through detailed analysis of past performance future value	مجھے یقین ہے کہ ماضی کی کارکردگی کے تفصیلی تجزیہ کے ذریعے اسٹاک مارکیٹ میں	I believe that a detailed analysis of past performance can determine

	of a contract in stock market can be determined	کسی شیئر کی مستقبل کی قیمت کا تعین کیا جاسکتا ہے	the future value of a share in the stock market.
RB3	I avoid investments in stocks that have a history of poor earnings.	میں ان شیئرز میں سرمایہ کاری سے گریز کرتا ہوں جن کی آمدن ماضی میں کم ہو۔	I avoid investing in shares that have low returns in the past.
RB4	I buy 'hot' stocks which provided most return recently and avoid stocks that have performed poorly in the recent past	میں ایسے ' فعال 'شیئرز خریدتا ہوں جس نے حال ہی میں زیادہ منافع فراہم کیا ہو اور ان شیئرز سے گریز کیا جنہوں نے حالیہ عرصہ میں خراب کارکردگی کا مظاہرہ کیا ہے	I buy 'active' shares that have recently made higher profits and avoided shares that have performed poorly in recent times.
RB5	I use trend analysis to make investment decisions	میں سرمایہ کاری کے فیصلے کرنے کے لئے رجحان کا تجزیہ کرتا ہوں	I analyze the market tendency to make investment decisions.
RB6	Before investing I use trend analysis of some representative stocks to make investment decisions for all stocks.	میں تمام اسٹاک میں سرمایہ کاری کے فیصلے کرنے سے پہلے ، کچھ نمائندہ شیئرز کے رجحان کا تجزیہ استعمال کرتا ہوں۔	Before I make an investment decision in all stocks, I use a trend analysis of some representative shares.
DE1	I prefer to sell stocks whose prices has recently increased.	میں ایسے شیئرز فروخت کرنے کو ترجیح دیتا ہوں جن کی قیمتوں میں حال ہی میں اضافہ ہوا ہے	I prefer to sell shares that have recently risen in price.
DE2	When I need cash I prefer to sell the stock which has increased in value.	جب مجھے نقد رقم کی ضرورت ہوتی ہے تو میں اس شیئرز کو فروخت کرنے کو ترجیح دیتا ہوں جس کی قیمت میں اضافہ ہوا ہے۔	When I need cash, I prefer to sell shares that have risen in value.
DE3	I prefer to keep holding on stocks when their current price is lower than their purchase price.	میں شیئرز کواپنے پاس رکھنےکو ترجیح دیتا ہوں جب ان کی موجودہ قیمت ان کی قیمت خرید سے کم ہو۔	I prefer to keep the shares when their current price is less than their purchase price.
DE4	When I need cash I sell securities that can give higher profits at that time.	جب مجھے نقد رقم کی ضرورت ہوتی ہے تو میں ایسے شیئرز فروخت کرتا ہوں جو اس وقت زیادہ منافع دے سکیں۔	When I need cash, I sell shares that can make higher profits at that time.
DE5	When I need cash I prefer to sell the stock which has decreased in value	جب مجھے نقد رقم کی ضرورت ہو تو میں اس شیئر کو فروخت کرنے کو ترجیح دوں گا جس کی قیمت میں کمی واقع ہو۔	When I need cash, I would prefer to sell a share that has lost value.
DE6	In case of loss positions in my portfolio I generally wait for a price rebound instead of selling those securities.	اپنے پورٹ فولیو میں نقصان کی صورت میں میں عام طور پر ان شیئرز کو فروخت کرنے کے بجائے قیمتوں میں اضافے کا انتظار کرتا ہوں۔	In case of loss in my portfolio, I usually wait for the price to rise instead of selling these shares.
DM1	When making an Investment, I trust my inner feelings and reactions	سرمایہ کاری کرتے وقت ، مجھے اپنے اندرونی احساسات اور رد عمل پر اعتماد ہوتا ہے۔	When investing, I have confidence in my inner feelings and reactions.
DM2	I generally make	میں عام طور پر ایسی سرمایہ	I usually make investments

	Investments that feel right to me	کاری کرتا ہوں جو مجھے صحیح محسوس ہوں.	that I feel are right.
DM3	When making Investments, I rely upon my instincts	سرمایہ کاری کرتے وقت ، میں اپنی جبلت پر بھروسہ کرتا ہوں	When investing, I rely on my instincts
DM4	When I make an Investment, it is more important for me to feel the Investment is right than have a rational reason for it.	جب میں سرمایہ کاری کرتا ہوں تو ، اس کے لئے عقلی وجوہ کی بجائے یہ محسوس کرنا زیادہ ضروری ہوتا ہے کہ سرمایہ کاری مناسب ہے۔	When I invest, it's more important to realize that the investment is right, rather than rational.
DM5	When I make Investment, I tend to rely on my intuition	جب میں سرمایہ کاری کرتا ہوں تو میں اپنی بدیہی/ اندازہ پر بھروسہ کرتا ہوں.	When I invest, I rely on my intuition

9.7. Data Collection Certificate



Ref #: DCS/396/20

TO WHOM IT MAY CONCERN

This is to certify that Creative Business and Social Research (CBSR) has provided data collection services to Mr. Muhammad Haroon Rasheed, Ph.D. Scholar (Management Sciences) at the National University of Modern Languages (NUML) Islamabad, Pakistan.

Creative Business and Social Research (CBSR) has collected data on behalf of the said scholar from the stock market investors in Karachi, Lahore, and Islamabad. The data was collected by adhering to the study's requirements through the provided survey questionnaire.

Managing Director

CBSR

Date: 10/08/2020

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9.8. Results for Control variables

Table 9-5- Results for Sentiments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SENTIMENT < 1 – 1333 observations				
RETURN(-1)	0.136017	0.030396	4.474861	0.0000
RETURN(-2)	0.080842	0.029287	2.760356	0.0058
RETURN(-3)	-0.027215	0.0299S12	-0.909850	0.3630
RETURN(-4)	0.010477	0.027834	0.376404	0.7066
RETURN(-5)	-0.021796	0.027511	-0.792255	0.4283
RETURN(-6)	0.039825	0.027218	1.463178	0.1435
RETURN(-7)	-0.023131	0.027070	-0.854478	0.3929
RETURN(-8)	-0.068120	0.027190	-2.505299	0.0123
RETURN(-9)	-0.032860	0.027689	-1.186755	0.2354
RETURN(-10)	0.028333	0.027483	1.030941	0.3027
1 <= SENTIMENT – 1219 observations				
RETURN(-1)	0.101638	0.025971	3.913523	0.0001
RETURN(-2)	0.043380	0.027167	1.596809	0.1104
RETURN(-3)	0.005344	0.026787	0.199501	0.8419
RETURN(-4)	0.042471	0.028463	1.492122	0.1358
RETURN(-5)	0.018669	0.028833	0.647511	0.5174
RETURN(-6)	0.041701	0.029003	1.437804	0.1506
RETURN(-7)	0.042631	0.029005	1.469775	0.1417
RETURN(-8)	-0.016570	0.028819	-0.574988	0.5654
RETURN(-9)	0.008928	0.028345	0.314972	0.7528
RETURN(-10)	0.074573	0.028161	2.648073	0.0081
S.E. of regression	0.010245	Akaike info criterion		-6.315897
F-statistic	3.825903	Durbin-Watson stat		1.994183
Prob(F-statistic)	0.000000			

Table 9-6- Results for Biases

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BIASES < 1 -- 1902 observations				
RETURN(-1)	0.016010	0.023526	0.680524	0.4962
RETURN(-2)	0.074540	0.022447	3.320776	0.0009
RETURN(-3)	-0.029126	0.022490	-1.295047	0.1954
RETURN(-4)	0.032437	0.022504	1.441392	0.1496
RETURN(-5)	0.027566	0.022860	1.205894	0.2280
RETURN(-6)	0.003626	0.023005	0.157631	0.8748
RETURN(-7)	0.011562	0.022951	0.503753	0.6145
RETURN(-8)	-0.051931	0.022515	-2.306558	0.0212
RETURN(-9)	0.002358	0.022332	0.105608	0.9159
RETURN(-10)	0.067286	0.022548	2.984121	0.0029
1 <= BIASES -- 650 observation				
RETURN(-1)	0.331346	0.038069	8.703758	0.0000
RETURN(-2)	0.162685	0.044478	3.657636	0.0003
RETURN(-3)	0.101983	0.040271	2.532415	0.0114
RETURN(-4)	0.007321	0.040160	0.182285	0.8554
RETURN(-5)	-0.060438	0.038134	-1.584889	0.1131
RETURN(-6)	0.108013	0.037448	2.884331	0.0040
RETURN(-7)	0.007728	0.037616	0.205445	0.8372
RETURN(-8)	-0.015773	0.039369	-0.400657	0.6887
RETURN(-9)	-0.027550	0.041025	-0.671544	0.5019
RETURN(-10)	0.028723	0.038503	0.746008	0.4557
S.E. of regression	0.010131	Akaike info criterion		-6.338324
F-statistic	6.782794	Durbin-Watson stat		2.015437
Prob(F-statistic)	0.000000			

Table 9-7- Results for Heuristics

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HEURISTIC < 1 -- 1274 observations				
RETURN(-1)	-0.001933	0.029156	-0.066287	0.9472
RETURN(-2)	-0.024838	0.026143	-0.950059	0.3422
RETURN(-3)	-0.075195	0.027199	-2.764632	0.0057
RETURN(-4)	0.022340	0.027666	0.807465	0.4195
RETURN(-5)	0.002892	0.028508	0.101451	0.9192
RETURN(-6)	0.009217	0.028691	0.321255	0.7480
RETURN(-7)	0.001034	0.028384	0.036438	0.9709
RETURN(-8)	-0.052212	0.027720	-1.883522	0.0597
RETURN(-9)	-0.021802	0.027209	-0.801276	0.4230
RETURN(-10)	0.051444	0.028209	1.823678	0.0683
1 <= HEURISTIC -- 1278 observations				
RETURN(-1)	0.195520	0.026988	7.244675	0.0000
RETURN(-2)	0.062920	0.030204	2.083127	0.0373
RETURN(-3)	0.070515	0.028575	2.467738	0.0137
RETURN(-4)	0.042268	0.028196	1.499089	0.1340
RETURN(-5)	-0.005647	0.027166	-0.207863	0.8354
RETURN(-6)	0.058321	0.027241	2.140915	0.0324
RETURN(-7)	0.010030	0.027348	0.366736	0.7138
RETURN(-8)	-0.040837	0.027931	-1.462070	0.1438
RETURN(-9)	0.011345	0.028565	0.397175	0.6913
RETURN(-10)	0.047579	0.026931	1.766665	0.0774
S.E. of regression	0.010180	Akaike info criterion		-6.328502
Sum squared resid	0.262316	Schwarz criterion		-6.280408
F-statistic	5.479663	Durbin-Watson stat		2.005034
Prob(F-statistic)	0.000000			

Table 9-8- Results for Framing Effect

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FRAMING_EFFECT < 1 -- 1203 observations				
RETURN(-1)	-0.030555	0.028304	-1.079510	0.2805
RETURN(-2)	0.174246	0.027873	6.251457	0.0000
RETURN(-3)	-0.008894	0.028452	-0.312592	0.7546
RETURN(-4)	0.051361	0.027650	1.857585	0.0633
RETURN(-5)	0.034553	0.029180	1.184158	0.2365
RETURN(-6)	0.032772	0.028641	1.144248	0.2526
RETURN(-7)	0.007624	0.028926	0.263582	0.7921
RETU.RN(-8)	-0.053809	0.027870	-1.930708	0.0536
RETURN(-9)	0.032809	0.027529	1.191788	0.2335
RETURN(-10)	0.062642	0.027519	2.276279	0.0229
1 <= FRAMING_EFFECT -- 1349 observations				
RETURN(-1)	0.225031	0.026716	8.422986	0.0000
RETURN(-2)	0.133953	0.027423	4.884628	0.0000
RETURN(-3)	-0.000563	0.026721	-0.021069	0.9832
RETURN(-4)	-0.007048	0.027503	-0.256266	0.7978
RETURN(-5)	-0.019120	0.026122	-0.731943	0.4643
RETURN(-6)	0.047982	0.026561	1.806444	0.0710
RETURN(-7)	-0.006601	0.026283	-0.251167	0.8017
RETURN(-8)	-0.011546	0.027135	-0.425498	0.6705
RETURN(-9)	-0.048618	0.027675	-1.756735	0.0791
RETURN(-10)	0.044618	0.027144	1.643777	0.1003
S.E. of regression	0.010082	Akaike info criterion		-6.347861
Sum squared resid	0.257287	Schwarz criterion		-6.299767
F-statistic	8.060574	Durbin-Watson stat		2.006461
Prob(F-statistic)	0.000000			