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The Impact of Behavioral Biases including Salience Bias and Information Searches Effect on Investor Decision Mediated by Financial Wellbeing Using PLS SEM Modeling.

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Abstract: The present study investigate the effect of behavioral biases including salience bias and information searches on investor decision under the mediation of financial wellbeing in an emerging country like Pakistan. Prospect theory and efficient market hypothesis (EMH) theory provides the theoretical base of the study. The research is quantitative and taken sample of 450 individual investors. The study used SmartPLS 3.3.7. Data analysis is done through inner-model (measurement model), outer model (structural model) analysis, and mediation analysis. This study also illustrates the use of recent advances in PLS-SEM, designed to ensure the structural model results 'robustness in terms of non-linearity assessment – Ramsey RESET test, unobserved heterogeneity- by FIMIX-PLS and endogeneity assessment- by Gaussian Copula test in PLS-SEM framework. From the results, it is concluded that relationship between variables are significant under Ramsey RESET test. Whereas, no heterogeneity found in the variables. Also, no endogeneity issue seem in the study. The study provide the managerial implication for academic and practitioners. The study core purpose is to boost the regular use of these corresponding methods to accelerate methodological accuracy in the research field particularly in social sciences.

Keywords: Salience bias, Information searches, financial wellbeing, Investor decision, Ramsey RESET test, FIMI-PLS, Gaussian Copula test.

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1. Introduction

Investors mostly tried to tailor his/her need by investing in several funds to gain higher profits in future. Investors have a time limit to make their decision in right direction efficiently. It has been annually reported that individual investors' information and publicly traded firms demands for investment decisions

(Dang, Le, & Pham, 2020). Investors usually invest both in short term and long term period. Short term investment carried out for one year and long term investments results in huge returns on the basis of lots of fundS (Nia, 2020). Traditional finance theory conceptualized that finance representatives behaved realistically in making speculation about market and firm behavior pattern following over there. Agents at that time made rational choices which were based on rational economic expectation concept. Investors/agents followed profit maximization rule that uncovered their self-interest (Jain, Jain, & Jain, 2015).

All that movement made capital market more efficient and chance of irrationality did not existed over there. As a result, members/participants of the market become robust in making speculation about securities trading trends. Nevertheless, that traditional concept had its own flaws as it was unable to answer some critical points that remained uncovered. That unresolved areas were included why participants always remained below their expected gain? Why crises happened to market at the time of investment? Why members followed other members to take investment decisions? All those unanswered areas created revolution to emerge new area that cooperate and interlink with multiple paradigms. This area inter connected with other domains and make investors make rational decisions about investment (Nuzula, 2019). Advancements come in traditional area of finance in shaped of "behavioral" expanded robust. In the initial phase, behavioral biases were considered significantly liked why not investors gone for prescribed portfolio rather they hold portfolio that were under-diversified? Why most of investors remained at risker position longer than winning one? Why mostly agents/participants/members traded passively when active trading was available over there. Also, old studies just focused on economic costs of irrational decisions. If costs were more, members had seek to learn from their mistakes. Numerous literature review was highlighted the dilemma that for household market investors made decision based on their emotion, believes driven by social factors, as well as psychological factors whereas, the members behaved different in financial market decisions. This pinpoint the inequality gap between upper and lower socioeconomic groups respectively. Due to globalization, individuals in financial markets were in search of such investments that more fascinating and according to their participation in making investment decisions. By this, over the last three decades, trending towards investors had become increased on varied financial instruments employment. It was not necessary that all the investments that investors made would be profitable. Nearly, everyone could made investment but, it was not a game. Investing is a serious issue because, it put impact on future well-being of that particular investor (Rana, Baig, & Khan, 2014).

Over a decade and currently now, the emerging economy of Pakistan has to face a lot of uncertainty, and ups and downs. Many investors in Pakistan Stock market guilt that downfall they are facing is the result of big investors manipulations. It is become a necessity to develop and promote investment decisions made by individuals and adopt a proper financial policies and advisory services to build strong and protected financial system. Fewer previous studies are available describing how behavioral factors effect investment decisions made by individual investors by using regression analysis, discriminant analysis e.t.c. However, these studies did not explain the effect of behavioral factors including salience, information searches and financial wellbeing on investment decisions. Previous studies focused more on accounting information the factor of financial market along with behavioral biases. A need rises to study more and more behavioral factors in order to choose exact portfolio design for individual investors by the government and recommend some appropriate pathway for investments by the broker firms on the basis of investor's irrationality. Most of the prior literature focuses on North American, European, Middle East, and Asia and North African markets individually. The present research has analyzed the behavioral factors in emerging country. The present research is helpful to understand common behavioral patterns of investor in an emerging market to make a broad generalization of the findings.

The present study contributed to the existing body of knowledge about behavioral factors and their effect on investment behavior in an emerging country. The essence of this research is to identify behavioral factors and the literature related to them. The present highlighted the Investment decision-making behavior that is complicated concept and still under discussion. Such study is less widespread in economy ranging from emerging to develop. Thus, the present study generated interest to find out ways to overcome the effect of behavioral factors in decision-making. The present study thus has designed to provide ways such as: Does behavioral factors affect the investors in emerging economy? Do reverse causality exists between these factors and overall market? However, behavioral finance has in use less in emerging markets.

1.1 **Research question**

To what extent do the behavioral factors including salience bias, information searches, and financial wellbeing effect on individual investment decision?

1.2 Research objectives

The key objective of this study is to link the literature gap that author has been discussed in the preceding section on investor behavior in making investment decision i.e., investigating which factors are affecting the behavior of investor in making investment decision within the context of emerging country like Pakistan.

More specific and related objectives are listed as following for the purpose of current study is being conducted:

- Investigate, to what extent the variables salience bias, information searches, and financial wellbeing effect on the individual investment decision?
- Develop a theoretical framework for researchers to understand the phenomena how investors behave when make decisions.

2. Literature review

Investor decision is a becoming advance day by day. As it is growing extensively a need rise to shed light on all disciplines that are inter-related with one another. For this, the literature review is done with reference to various domains where the study variables are linked. Previously, traditional finance theories considered investment markets and its members are realistic and fascinating towards making more money to become rich. In many scenarios lot of factors including previous experience, emotions, beliefs effect investment decisions as well where investors became acted illogically and unexpectedly. With the passage of time economy grows and investors become more confident in making decision about investment in relevant areas. By having these modifications and advancements a new area become emerged named "behavioral finance". It ultimately combined with traditional approach to answer the unsolved questions in that area like why irregularities happen in making decision? Why risk become high day by day although advancements are there? e.t.c.

2.1. Prospect theory

Prospect theory is a vibrant behavioral theory indicated how people determine between alternatives that involved uncertainty and risk (e.g. % chance of losses/gains). It highlighted that people thought in term of current wealth rather than absolute outcomes. It was formulated by undeveloped risky adoption and pin-point towards people whom prefer to remain at uncertain side and had fear of loss. All these circumstances made prospect theory related to risk and unexpected return side (Kahneman & Tversky, 1979). The prospect theory support investor decisions, salience, information searches and tax incentives. It considered as a ground theory in behavioral finance that pin-point majority of variables in order to increase efficacy of firm.

2.2 Efficient market theory

It is commonly known as efficient market hypothesis. This theory reflect and elaborated why stock Behave in a manner they were expected to do. It holds information that underpin all the publicly available. Its three basic forms were considered functional, informational and allocative one. These three theories support the study variables firmly. Behavioral finance explained the irregularities in efficient market hypothesis (EMH) that further explained people behavior. Federal research division in its report said that the field of behavioral finance is multidisciplinary that relay on economic, psychology and other related areas respectively. The present study is based on EMH theory in order to investigate the effect of variables including information searches and tax incentive e.t.c.

All the above three theories are vital for the present study. These theories provides pathway for the variables that are under study to influence and result significantly. It also contributed to the existing body of knowledge.

2.3 Investment decision

Balqista, Nareswari, & Negoro, (2021) investigated the effect of behavioral factors including salience, overconfidence, sentiments, overreaction and herd behavior on investor decisions. Study used SmartPLS-SEM and concluded that study' behavioral factors have significant impact on investor decision making. Gill, M, & Ali, (2018) in their research found that investment has several meanings but the mostly used is to invest cash in any work for making extra revenue. Sometimes individual' participation in making decisions become fascinating. By analyzing these outcomes individuals can practice decision making effectively. Most of the time decisions are not properly driven by firm basic principles on the other hand driven by positive and negative attitudes developed for that particular corporation by itself (De, Erasmus, & Gerber, 2017). According to Social opinion, self-images of investors are mainly based on perception of group and in-group preferences. All these confirms the character of social identification in investment decisions (Borgers, Derwall, & Koedijk, 2015). Behavioral Finance undertakes that investment choices are grounded on irregularities (Ajmal, Mufti, & Shah, 2011), on essential heuristics (Baker & Nofsinger, 2010), on bounded rationality (Pompian, 2006; Park & Gupta, 2012), on psychological biases (Baker & Nofsinger, 2002), sometimes become irrational on the basis of incomplete information (Bikhchandani, Hirshleifer, & Welch, 1992). Besides all these, investor's mental status on account of psychology plays a havoc role in decision-making. Standard finance stated that people make rational decision by having complete information. Ideal and coherent decisions are depend on progressive financial knowledge (Merton, 1987).

2.4 Salience bias

Chaudhry, (2018) investigated the effect of salience bias on investment (long term- short term) by applied square-based structured equation modeling technique. Researcher concluded that salience effect investment in long term more than in short term. In addition to this, Yalcin, Tatoglu, & Zaim, (2016) determined the impact of heuristics on investment decision in USA. They used confirmatory factor analysis and structured equation modeling. They took small sample of 167 observations. Results showed that investment decision moderated the relationship and significantly affect heuristics/salience. Similarly, Riff & Yagil, (2016) did empirical study to examine salience effect on decisions in markets including bull, bear and normal. After analyzing researchers concluded that salience did exist in markets and effect decisions. On the other hand, Frydman & Camerer, (2017) investigated salience could affect information and investment side by side by applied natural experiment. Result indicated that no causality seemed between salience and information and investment. Also, there are some studies including Barber & Odean, (2005); Huberman, (2001); Jain & Wu, (2000) that showed salience was there to put impact on investment but, required optimism, control riskiness.

The above literature showed mixed effect of salience on investment decisions. These studies used old methods to examine the relationship. To fulfill the gap the present study used salience variable along with other behavioral factors to get accurate result and make research relevant.

H1: salience bias has a significant effect on investment decision.

2.5 Information searches

Sautma & Zeplin , (2022) conducted a study to investigate the effect of information and disposition effect on shifting investment decisions under the moderator "investor". The study concluded that information searches has significant effect on investment decision as it related to stock prices. Meder, Schwartz, & Young, (2019) investigated the two settings where the problem had to face due to interception of investment with information searches. The study setting was based on numerical illustration along with follow-ups. Study conducted to take lower NPV (net present value) in order to get more precise information. The study showed that long-term investment is critical when subjected to accounting where information issues related to it. In traditional context, it was driven by NPV. Study concluded that in many settings where information searches become critical factor NPV could not handle the situation. Besides, Eberhardt, Brüggen, Post, & Hoet, (2018) investigated the future framed by used investment and assurance settings to boost information searches retirement. The study had taken field experiment along with 7315 pension plan participants. The study analyzed how pension frame intervention encouraged pension planner to acquire information about income. Results showed that active involvement elucidated negative assessments. Similarly, Tseng, (2012) examined relationship of information searches and individual investment decision and taken income as moderator. Confirmatory factor analysis and hierarchical regression were applied. Results showed that significant relationship did exist. In contrast, Gill, M, & Ali, (2018) investigated investor behavior about decision by taken information searches as mediator variable. Lahore stock exchange and Faisalabad trading floor were taken as population. Data collected through questionnaire and regression (simple, multiple) analysis were applied. Result showed that partial mediation existed over there. Information searches did not significantly affect the relationship as a mediator. In addition to this, Rana, Baig, & Khan (2014) investigated relationship between investment behavior and earning and taken information searches as mediator variable. Questionnire survey was conducted to collect data from Pakistan stock exchange. Results showed that variables had positive effect on decisions.

In the above literature, studies including Meder, Schwartz, & Young (2019); Eberhardt et al. (2018); Tseng, (2012) showed that information searches influenced investment decisions effectively. While, studies including Gill et al. (2018); Rana, Baig, & Khan (2014) showed no significant relationship between information searches and investment decision. However, the previous studies used old approach and not proper measures. But, the present study will employ the new method to get clear picture of relationship.

H2: information searches has a significant effect on investor decision.

2.5 Financial wellbeing

Shah, Maqsood , & Mahmood, (2019) investigated framing effect and financial well-being by taken investment behavior as mediator. Structured Equation Modeling (SEM) technique was applied. Data collected from 344 business participants from Pakistan. Results of study showed that framing effect influenced financial well-being negatively and investment decision mediated the relationship. In addition to this, Strömbäck, Lind,, & Skagerlund, (2017) investigated the effect of self-control on financial wellbeing and financial behavior. A survey was conducted by taken sample of 2068 observations from Swedish population. Results showed that people with more self-control could save more money, payrolls e.t.c, and become more secured in taking financial decision and financial well-being. Similarly, Walstad & Allgood, (2016) determined the effects of perceived and actual financial literacy on financial behaviors of US. A combined measure of actual financial literacy and overall self-rating of financial literacy were employed. Data had been taken from US adults and households. Pobit analysis was used and researchers failed to identify the causal relationship between variables. Results showed that both literacies had impact on financial behavior. In addition to above citations, Tsai & Dwyer, (2016) investigated does financial assistance really assist? The Impact of debt on wellbeing, health behavior and self-concept in Taiwan. Study tested hypothesis by extended research into social contacts. Regression-estimation-with measurement modeling technique were employed to assess the impact of debt and unrealized loss (UL) in housing price on life situation. Results showed that positive investment lead to positive financial well-being. However, Gutter & Copur, (2011) examined financial behaviors and financial well-being of college students. Researchers took evidences from a National Survey. Data collected from 15 colleges' campus of US through online surveys. Regression test was applied and results showed that financial behaviors affect financial wellbeing significantly as it directly related to how much participants plan for saving for future and how much they spend.

In the above literature, Shah et al. (2019); Stromback et al. (2017); Walstad & Allgood (2016); Tsai & Dwyer (2016); and Gutter & Copur (2011) studies used old methods for investigation and their results generalizations were wreaked. Thus, it needs advancement to overcome this dilemma.

H3a: financial wellbeing mediating the effect of salience bias on investment decision significantly.
H3b: financial wellbeing mediating the effect of information searches on investment decision significantly.

In the below figure 1, Salience Bias (SB), and Information Searches (IS) both are independent (exogenous) variables that has influence on dependent (endogenous) variable named Investor Decision (ID). Whereas, Financial Wellbeing (FW) is a mediating (endogenous) variable of the study.

2.7 Conceptual framework

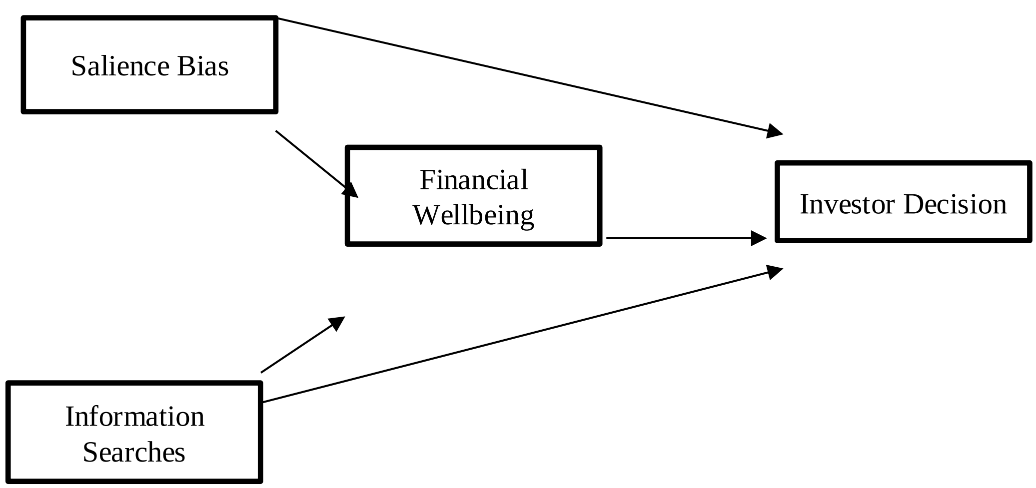


Figure 1: Model Proposed

3. Methodology

The study investigated the effect of behavioral biases including salience bias and information searches on investor decision under the mediating effect of financial wellbeing. The study was exploratory and a quantitative research. The target population had taken from Pakistan. The sampling frame were taken from IPOs, equity and bond market. The sampling method was simple random sampling by taken individual investors as a sampling unit. The sample size of the study was 450. Data was taken through survey questionnaire according to its cross-sectional nature. The questionnaire was developed on seven-point likert scale and item scales of variables were adapted from literature. Salience bias item scales were adapted from

Yalcin et al. (2016), information searches' item scales were adapted from Rana, Khan, & Baig, (2014), item scales of variable financial wellbeing were adapted from CFPB, (2017), and investor decision variable' item scale were adapted from Rana, Khan, & Baig, (2014).

For the data analysis purpose, SmartPLS 3.3.7 was used- a latest and prominent software application of Partial least squares structural equation modeling (PLS-SEM). It has become a standard tool to analyze complicated inter-relationships between observed and latent variables in social sciences along with number of studies conducted in fields included medicine and psychology (Menni et al., (2018)), field of scientific inquiry like engineering (Durdyev , Ihtiyar, & Banaitis, (2018)). PLS-SEM has advantages that subsidized towards its distribution and utilization over the last decade. PLS-SEM overcome the contradiction of academic research and prediction which were required to implement managerial consequences (Hair et al., 2019; Shmueli, Ray, & Velasquez , (2016)). Apart from debates, researchers identified some gaps/flaws in PLS-SEM, that later were filled by methodologist by developing improvements in methodological levels (Franke, & Sarstedt, 2019; Sharma et al., 2019b)

4. Results and discussion

Researcher focused on assessing the structural equation model along with robustness tests, which were of central concern when testing theoretical framework and deriving managerial recommendations. PLS-SEM is based on two subsets included inner model (structural model), and outer model (measurement model). Analysis also included problems related and approaches for handling non-linear effects, endogeneity, and unobserved heterogeneity in PLS-SEM framework.

4.1. Evaluation of measurement model (outer model)

The study is based on reflective measurement model and in order to access path coefficients in structural model, first examined the following a) indicator reliability, b) internal consistency, c) discriminant validity and d) convergent validity of the reflective measurement model to ensure that they are satisfactory (Wong, 2013). The table1 of the measurement model assessment mentioned below provide a clear picture of it. It include internal reliability (loadings of constructs), composite reliability, Cronbach's alpha, and Average Variance Extracted (AVE) and construct reliability measures along with mean, standard deviation, kurtosis and skewness.

The measurement model first subset named Internal Reliability and it is the condition for validity. Internal Reliability usually checked to confirm that associated indicators have much in common that is seen in latent construct. The study' latent constructs have loading ranging from 0.50-0.850. All constructs' outer loadings are satisfactory and resulting in increase of Average Variance Extracted (AVE) and composite reliability of their respective latent construct. Measurement model second characteristic is internal consistency reliability. In PLS-SEM, composite reliability is preferred over Cronbach's alpha to estimate the measurement model' internal consistency reliability. This is taken into consideration of different loadings of the indicators (Werts, Linn, & Joreskog, 1974). In the Table 1, the Composite Reliability of latent construct FW is 0.892, ID is 0.898, IS is 0.863, and S is 0.836. This show the high level of internal consistency in latent constructs. Whereas, the Cronbach's alpha of latent constructs (Financial wellbeing, investor decision, information searches and salience bias) are 0.866, 0.896, 0.818, and 0.756 respectively. The measurement model third characteristic is Convergent validity and it is refers to the model's ability to explain the indicator's variance. The AVE can provide evidence for convergent validity (Fornell & Larcker, 1981). The AVE for the latent construct named financial wellbeing, information searches, investor decision, and salience bias are 0.455, 0.476, and 0.596, and 0.508 respectively, well above the required minimum level of 0.50 (Bagozzi & Yi, 1988). Therefore, the measures of the two reflective constructs can be said to have high levels of convergent validity.

4.1.1. Discriminant validity

To access Discriminant validity there are three methods named; Fornell-Larcker Criterion (1981), Heterotrait-Monotrait Ratio (HTMT), and cross loading. Fornell-Larcker Criterion is a common and conservative approach. It is used in PLS-SEM. To examine this, square root of average variance extracted (AVE) of each latent variable should be larger than the latent variable correlations (LVC). The table 2 describe the discriminant validity, the measures of the three reflective constructs can be said to have high levels of discriminant validity by having LVC less than AVE. the LVC of FW, ID,IS, and S are 0.675, 0.772, 0.690, and 0.712 respectively.

Similarly, Heterotrait-Monotrait Ratio (HTMT) was developed by Henseler, Ringle , & Sarsted, (2015) when they used replication studies to recognize and prove that absence of discriminant validity could be better identified by Heterotrait-Monotrait Ratio (HTMT). It is a geometric of heterotrait heteromethod correlation divided by heterotrait monotrait ratio. In an extraordinary model, heterotrait correlations always be smaller than monotrait correlations. In the table 3, it can be viewed that latent construct HTMT are less than 1. HTMT of variables financial wellbeing, information searches, investor decision, and salience bias are below 1 (0.505, 0.356, 0.305 respectively). It indicates that discriminant validity has been established between given pair of reflective measure.

The net is cross loading. It is used to access discriminant validity of a reflective model. It is an alternative approach of AVE to access discriminant validity. In cross loading, no indicator variable should have higher association with other latent variable/construct than its own latent variable. In table 4, it can be seemed that variables financial wellbeing, information searches, investor decision, and salience bias have not higher correlation with another latent variable than its own latent variable. It determines that model is specified.

Table 1: Measurement model assessment

Latent construct and Indicator	**Loading**	**Mean**	**SD**	**Kurtosis**	**Skewness**	**CA**	**CR**	**AVE**	**rho_A**
						SI	SI	SI	SI
Salience Bias (Adapted from Yalcin et al. (2016)						0.756	0.836	0.508	0.779

SB1	0.742	4.1	1.265	1.147	-1.232				
SB2	0.81	4.12	0.876	0.994	-1.071				
SB3	0.746	4.129	0.898	1.749	-1.218				
SB4	0.608	3.98	1.01	1.218	-1.22				
SB5	0.630	4.044	0.967	1.253	-1.168				
Information Searches (Adapted from Rana, Khan, &Baig, (2014)						0.818	0.863	0.512	0.833
IS1	0.546	3.558	1.19	-0.786	-0.491				
IS2	0.750	3.838	0.932	0.914	-0.976				
IS3	0.742	3.867	1.026	0.692	-1.03				
IS4	0.749	3.822	1.121	0.471	-1.059				
IS5	0.703	3.824	0.977	0.482	-0.906				
IS6	0.714	3.653	1.06	0.109	-0.81				
IS7	0.595	3.751	1.029	0.464	-0.925				
Financial Wellbeing (Adapted from CFPB, (2017))						0.866	0.892	0.599	0.870
FW1	0.595	4.013	1.013	0.502	-1.043				
FW2	0.599	3.956	1.064	0.634	-1.067				
FW3	0.749	3.967	0.833	0.698	-0.839				
FW4	0.730	3.764	1.006	0.291	-0.83				
FW5	0.739	3.967	1.014	0.585	-0.986				
FW6	0.665	4.004	1.048	1.347	-1.323				
FW7	0.654	4.036	0.913	1.222	-1.089				

FW8	0.715	3.996	0.872	1.602	-1.102				
FW9	0.679	3.978	0.856	1.563	-1.024				
FW10	0.597	3.796	1.093	0.23	-0.911				
Investor Decision (Adapted from Rana, Khan, & Baig, (2014)						0.869	0.898	0.545	0.914
ID1	0.823	3.467	1.289	-0.721	-0.644				
ID2	0.849	3.522	1.108	-0.548	-0.489				
ID3	0.837	3.567	1.142	-0.421	-0.641				
ID4	0.710	3.709	1.082	-0.234	-0.668				
ID5	0.680	3.658	1.133	-0.426	-0.643				
ID6	0.715	3.711	1.114	-0.262	-0.747				

Note: CA: Cronbach's alpha; rho_A: construct reliability measure; CR: composite reliability; AVE: average variance extracted; SI: single item.

Table 2: Fornell-Larcker criterion- assessment of discriminant validity

	Latent Variable correlations (LVC)				**Discriminant Validity met?** (Square root of AVE>LVC?)
Latent Construct	Financial Wellbeing	Investor Decision	Information Searches	Salience Bias	
Financial Wellbeing	**0.675**				YES

Investor Decision	0.367	**0.772**			YES
Information Searches	0.454	0.369	**0.690**		YES
Salience Bias	0.536	0.315	0.652	**0.712**	YES

Table 3: Heterotrait-Monotrait Ratio (HTMT) - assessment of discriminant validity

	Financial Wellbeing	Information Searches	Investor Decision	Salience Bias
Financial Wellbeing				
Information Searches	0.505			
Investor Decision	0.421	0.356		
Salience Bias	0.649	0.815	0.336	

Note: HTMT: heterotrait-monotrait criterion

Figure 1: Heterotrait-Monotrait Ratio (HTMT)

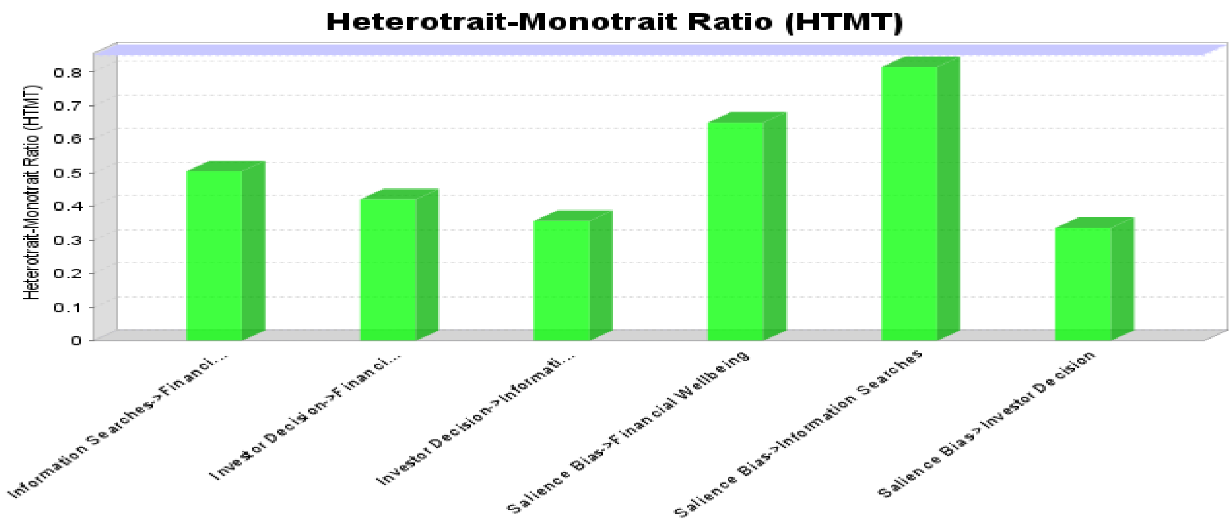


Table 4: Cross loadings- assessment of discriminant validity

	FW	ID	IS	SB
FW1	0.595	0.246	0.246	0.293
FW10	0.599	0.215	0.280	0.347
FW2	0.749	0.302	0.361	0.398
FW3	0.730	0.250	0.340	0.400
FW4	0.739	0.297	0.290	0.392
FW5	0.665	0.182	0.259	0.277
FW6	0.654	0.217	0.413	0.446
FW7	0.715	0.275	0.328	0.341
FW8	0.679	0.207	0.254	0.362
FW9	0.597	0.260	0.243	0.311
ID1	0.302	0.823	0.488	0.383
ID2	0.332	0.849	0.268	0.203
ID3	0.259	0.837	0.393	0.315

ID4	0.286	0.710	0.056	0.069
ID5	0.242	0.680	0.106	0.124
ID6	0.292	0.715	0.135	0.199
IS1	0.224	0.295	0.546	0.314
IS2	0.404	0.295	0.750	0.545
IS3	0.404	0.287	0.742	0.481
IS4	0.344	0.306	0.749	0.503
IS5	0.203	0.182	0.703	0.436
IS6	0.280	0.223	0.714	0.460
IS7	0.224	0.109	0.595	0.347
SB1	0.365	0.259	0.510	0.742
SB2	0.455	0.317	0.470	0.816
SB3	0.416	0.225	0.526	0.746
SB4	0.301	0.157	0.412	0.608
SB5	0.352	0.123	0.407	0.630

Note: FW is Financial Wellbeing, ID is Investor Decision, IS is Information Searches and SB is Salience Bias

4.2 Evaluation of structural model (inner model)

After accessing measurement model, the next subset is structural model has to be properly evaluated before drawing any conclusion. Structural model accessed through variance inflation factor (VIF), R-square, f-square, q-square, path model coefficients e.t.c. it also include robustness test including non-linearity assessment, unobserved heterogeneity, and endogeneity evaluation.

4.2.1 Variance inflation factor (VIF)

Collinearity is a key problem in PLS-SEM' inner model and estimated by variance inflation factor (VIF). The value of 5 or above normally specifies this problem (Hair , Ringle , & Sarstedt, (2011)). Since SmartPLS generate the VIF value, In PLS-SEM, both ID (Investor Decision) and FW (Financial Wellbeing) act as dependent/endogenous variables for this, the study need to run two different sets of linear regression to obtain their corresponding VIF values. For the first run of linear regression, ID is the dependent variable whereas information searches, salience bias, and financial wellbeing are serve as "Independent" variables (see in table 5). For the second run, FW is the dependent variable whereas information searches and salience bias, are serve as "Independent" variables. The both sets of regression showed a significant relationships of the constructs. As the VIF value of first set is 1.739 and for the second set it is 1.441, 1.787 and 1.991. All these values showed that no Collinearity problem is seemed in the data of the study.

Table 5: VIF values

	Financial Wellbeing	Investor Decision	Information Searches	Salience Bias
Financial Wellbeing		1.441		
Investor Decision				
Information Searches	1.739	1.787		
Salience Bias	1.739	1.991		

4. 2.2 Path coefficients

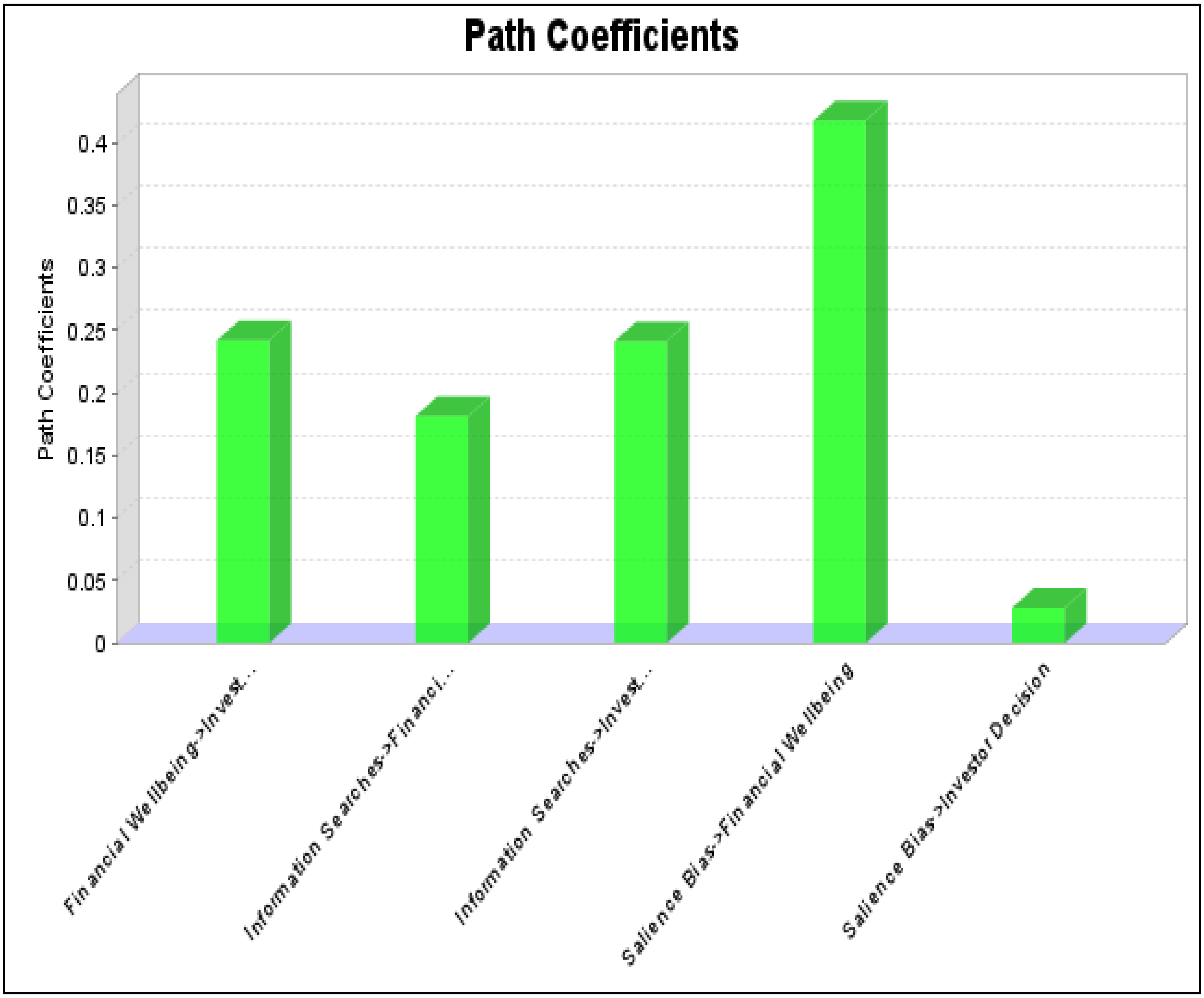
The next structural model assessment characteristic is given in table 6 of path coefficients/structural path coefficient (loadings) and are represented in the below figure 3(a, b). As the data is standardized and path loadings ranging 0-1. These loadings are significant (after using bootstrapping). The path coefficient of structural model resulted that except salience bias relationship with investor decision all other relationships are significant and supported hypotheses and relationships between variables.

Table 6: Path coefficients

Path	standard deviation (STDEV)	t Statistics (|O/STDEV|)	p-values	relationship
FW -> ID	0.070	3.324	0.001	significant
IS -> FW	0.049	7.975	0.000	significant
IS -> ID	0.071	3.968	0.000	significant
SB -> FW	0.056	5.724	0.000	significant

SB -> ID	0.078	0.024	0.981	insignificant

Figure 3a: path coefficient



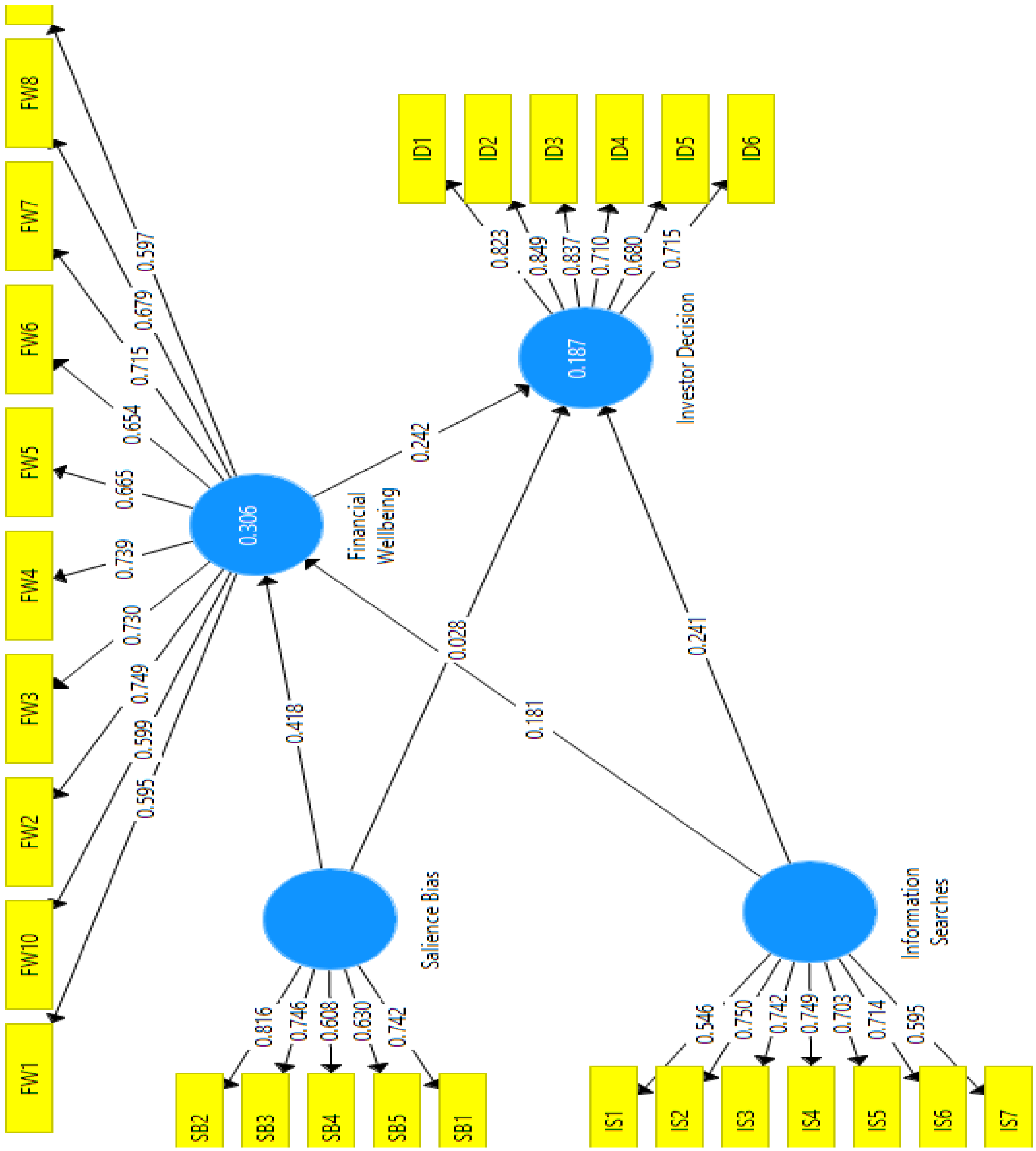


Figure 3b: Path model estimation

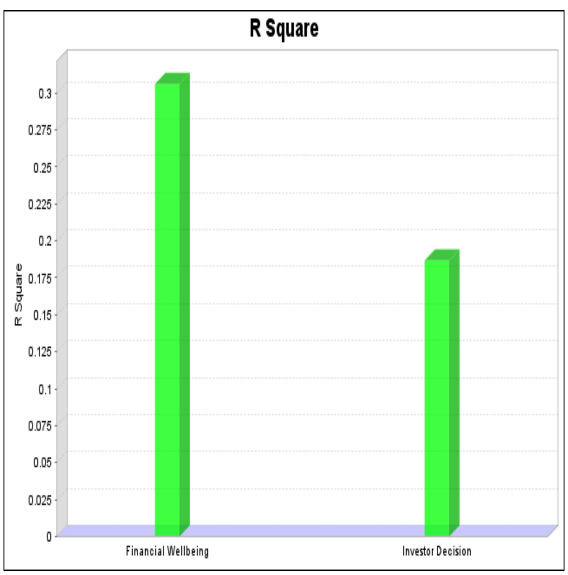
4.2.3 R-square

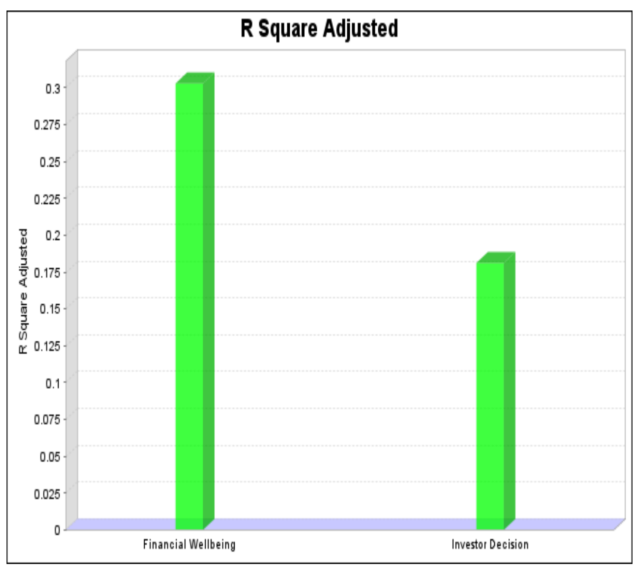
The next characteristic of structural model is R-square. It is also called coefficient of determination. It is supposed as an overall effect size degree of structural model (inner model) by Chin & Dibbern, (2010) describes results above the limits 0.67, 0.33 and 0.19 to be "substantial", "moderate" and "weak" respectively.in table 7, the r-square of financial wellbeing and investor decision are 0.306 and 0.187 showing that financial wellbeing r-square is moderate and investor decision r-square is weak. Whereas, the r-square adjusted of financial wellbeing and investor decision are 0.303 and 0.181 respectively. It has been indicted that adding predictor to regressor model not increase the r-square.

Table 7: Coefficient of determination (*R2*)

	R Square	R Square Adjusted
Financial Wellbeing	0.306	0.303
Investor Decision	0.187	0.181

Figure 4a: R-square **Figure 4b: R-square adjusted**





4.2.4 F-square

The next characteristic of structural model is assessing effect size "f-square". It is another name of r-square change effect. It expressed that how much r-square explained the unexplained variance proportion of R-square (Hair , Hult , & Ringle, (2017b)). According to Hart , Cohen, & Amant , (1994); Cohen, (1988) $\geq$ 0.2 signifies small f-square effect size, if f-square effect size is $\geq$.15 signifies medium effect size and f-square effect size $\geq$.35 signifies higher effect size. In the below table 8, reported that financial wellbeing and information searches has f-square 0.050 and 0.040 that has medium effect on investor decision. While, salience bias f-square is 0.000 which is very small effect size. On the other hand, information searches f-square is 0.027- a medium effect and salience bias has 0.145 a medium effect on investor decision.

Table 8: f Square

	Financial Wellbeing	Investor Decision	Information Searches	Salience Bias
Financial Wellbeing		0.050		
Investor Decision				
Information Searches	0.027	0.040		
Salience Bias	0.145	0.000		

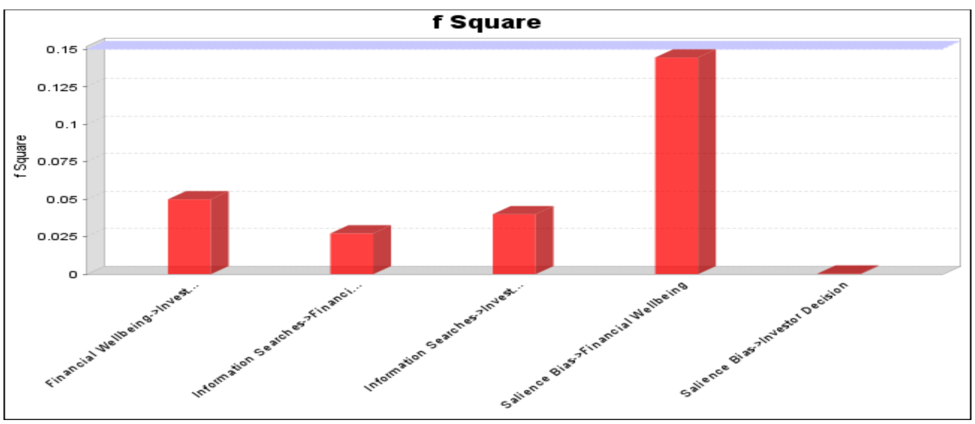


Figure 5: f-square

4.2.5 Q-square

Q-square is known as stone-geisser Q-square (Stone, 1974; Geisser, 1974; Chin, 1998; Ruiz et al., 2009: 546). It is estimated only for reflective model. If Q-square value is more than 0 it means that PLS-SEM model is analytical. According to Cohen (1988),$\geq$ 0.2 symbolizes small f-square effect size, $\geq$.15 signifies medium effect size and $\geq$.35 signifies higher effect size. Below in the table 9, endogenous variables including financial wellbeing and investor decision has 0.135 (medium) and 0.096 (medium). The table concluded that endogenous variable has predictive relevance in model.

Table 9: Q square

	SSO	SSE	Q^2 (=1-SSE/SSO)
Financial Wellbeing	4500.000	3892.801	0.135
Information Searches	3150.000	3150.000	
Investor Decision	2700.000	2440.361	0.096
Salience Bias	2250.000	2250.000	

4.2.6 Structural model robustness check of PLS-SEM

Numerous efforts have been taken in PLS-SEM based research to check the robustness of structural model constraints in form of either extending it or running complementary methods/approaches. The robustness check included non-linear assessment, checking endogeneity, and checking unobserved heterogeneity.

4.2.6.1 Non-linearity assessment

At the time of path estimation researchers assumed that linear relationship does exist between constructs. Linear relationship usually found between construct but, it is not necessarily found in several studies (Ahrholdt , Gudergan , & Ringle , (2019)). Several studies has taken interaction term in PLS path model to access non-linear effects. Several studies incorporated techniques included artificial neural networks, impact-asymmetry analysis, and at the second stage, neuro-fuzzy implication has taken. It has been seen whenever the association between variables become non-linear, the effect size not only depended on degree of change in independent variable but, also on its value (Hair , Sarstedt , & Ringle, (2018b)). In SmartPLS, non-linearity is check in terms of quadratic effect. Where linear relationship test between endogenous and exogenous constructs. If p-value goes above 0.05, it indicate the linear relationship between variables. On the other hand, In order to check whether a relationship is linear or not researchers highly recommended Ramsey, (1969) regression equation specification error test (RESET). The non-linearity analysis than estimate quadratic effects, which are common and by default it is cubic. The quadratic term is similar to interaction term. The interaction term (positive and negative), refers to the power of exogenous construct increase/decrease in exogenous construct's higher values. On the other hand, insignificant interaction term leads to linear effect robustness.

The study results supported the hypotheses H1: salience bias effect investor decision significantly- support literature studies (Chaudhry, (2018); Yalcin, Tatoglu, & Zaim, (2016); Similarly, Riff & Yagil, (2016)). H2:

information searches has significant effect on investor decision is in aligned of literature (studies including Meder, Schwartz, & Young (2019); Eberhardt et al. (2018); Tseng, (2012)) and supported them.

Table 10: Ramsey RESET test

Non-linear relationship	Coefficient	p-values	f^2 values	Ramsey' RESET
Salience bias*Salience bias->Financial wellbeing	0.019	0.436	0.001	F (3,387) =0.57, p =0.628
Information searches* Information searches -> financial wellbeing	0.051	0.251	0.005	
Salience bias*Salience bias ->Investor decision	0.029	0.439	0.006	F (3,399)= 1.52, p=0.201
financial wellbeing* financial wellbeing-> Investor decision	0.012	0.653	0.000	
Information searches* Information searches -> Investor decision	0.062	0.130	0.002	

In table 11 given above: Ramsey RESET test results are mentioned with the help of Rstudio. In Rstudio coding and commands are done to perform tests. The Ramsey RESET test has taken the latent scores of constructs and calculate the partial regression. It is conclude that no partial regression of financial wellbeing on salience bias, and information searches is seemed (F (3,387) ¼ 0.57, p ¼ 0.628) and also, partial regression of investor decision on financial wellbeing, salience bias, and information searches is seemed (F (3,399) ¼ 1.52, p ¼ 0.201). The whole relationship is subjected to non-linearity. Further, interaction terms included to calculate the quadratic effect of constructs. The table11 given below describes the quadratic effects between constructs. The quadratic effect between variables (FW->ID, S->FW, IS->ID, S->ID) are 0.654, 0.026, 0.262 and 0.324 respectively. All these effects showed that there exist linear relationship between variables. Thus, it is concluded that linear model is robust. As all p-values are above 0.05.

Table 11: Quadratic effect

Quadratic effect	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics	P Values
Quadratic Effect 1 FW -> ID	0.019	0.030	0.449	0.654
Quadratic Effect 2 IS-> FW	0.191	0.037	5.142	0.000
Quadratic Effect 3 S -> FW	-0.087	0.036	2.228	0.026
Quadratic Effect 4 IS -> ID	0.030	0.028	1.122	0.262
Quadratic Effect 5 S -> ID	-0.037	0.035	0.987	0.324

4.2.6.2 Unobserved heterogeneity assessment

The next test is to examine unobserved heterogeneity, this is an organized method in PLS-SEM model. This is done by applying FIMIX-PLS method. By following Matthews , Sarstedt, & Hair(2016), it is done through assuming a one segment solution by applying default setting for the stop criteria. The maximum no of iterations are 5000 and repetitions are 10. To calculate the maximum no. of segments firstly, calculated the minimum sample size need to calculate each segment (Sarstedt, Ringle, & Hair, (2017b)). G power is used to calculate the minimum sample size. In it, effect size should be taken 0.15 at a power level of 80%. After calculating segment/clusters, FIMIX-PLS for 2-10 segments/clusters used in initial analysis. AIC: Akaike's information criterion choose fewer clusters than indicated by AIC, MDL^5: minimum description length with factor 5 choose more clusters indicated by MDL^5. AIC3 and CAIC shown that if minimum values are in these cluster choose that clusters. Similarly, AIC^4 and BIC shown that if minimum values are in these cluster choose that clusters. The results of fit indices for 1-10 segments solutions are shown in table 12 given above. The min values of cluster are similar both in AIC^4 and BIC. Both criterion point towards 3 segment solutions. 3-segments solution indicated that min sample size requirements are meeting in it. MDL^5 pointing towards 1-segment solution. The results showed that analyses do not exactly point to a specific segment solution as, AIC^3 and CAIC point to different segments solutions and MDL^5 point to the same number of segments as AIC^{4} and BIC. It is therefore concluded that unobserved heterogeneity is not at a critical level, which actually supported the results of whole analysis.

Note: AIC: Akaike's information criterion; AIC3: modified AIC with factor 3; AIC4: modified AIC with factor 4; BIC: Bayesian information criteria; CAIC: consistent AIC; HQ: Hannan Quinn criterion; MDL5: minimum description length with factor 5; LnL: Log Likelihood; EN: entropy statistic; NFI: non-fuzzy index; NEC: normalized entropy criterion; na: not available; numbers in bold indicate the best outcome per segment retention criterion.

Table 12: FIMIX-PLS fit indices for 1-10 segments solutions

	1	2	3	4	5	6	7	8	9	10	Min
AIC (Akaike's Information Criterion)	2310.631	2188.97	2151.478	2141.893	2127.195	2114.645	2113.958	2099.503	2099.503	**2061.652**	2061.652
AIC3 (Modified AIC with Factor 3)	2317.631	2203.97	2174.478	2172.893	2166.195	2161.645	2168.958	2162.503	2162.503	**2140.652**	2140.652
AIC4 (Modified AIC with Factor 4)	2324.631	2218.97	**2197.478**	2203.893	2205.195	2208.645	2223.958	2225.503	2225.503	2219.652	2197.478
BIC (Bayesian Information Criteria)	2339.396	2250.609	**2245.991**	2269.28	2287.455	2307.78	2339.967	2358.385	2358.385	2386.283	2245.991

CAIC (Consistent AIC)	2346.396	**2265.609**	2268.991	2300.28	2326.455	2354.78	2394.967	2421.385	2421.385	2465.283	2265.609
HQ (Hannan Quinn Criterion)	2321.968	2213.264	**2188.729**	2192.101	2190.359	2190.767	2203.037	2201.538	2201.538	2189.601	2188.729
MDL5 (Minimum Description Length with Factor 5)	2510.499	2617.163	**2510.455**	3026.827	3240.498	3456.318	3684.001	3897.916	3897.916	4316.805	2510.455
LnL (LogLikelihood)	**-1148.32**	-1079.49	-1052.74	-1039.95	-1024.6	-1010.32	-1001.98	-986.751	-986.751	-951.826	-1148.32
EN (Entropy Statistic (Normed))		0.422	0.376	0.44	0.437	0.593	0.524	0.598	0.598	0.636	
NFI (Non-Fuzzy Index)		0.477	0.395	0.407	0.393	0.49	0.419	0.491	0.491	0.508	
NEC (Normalized Entropy Criterion)		260.098	280.809	251.997	253.347	182.95	214.042	180.722	180.722	163.785	

4.2.6.3 Endogeneity assessment

PLS-SEM structural model also included endogeneity assessment. It is follows by Hult , Hair , & Proksch, (2018) methodical process, which initiated first by Park and Gupta's (2012) with the name Gaussian Copula approach. It included latent variable' scores. First, verified whether variables/constructs are distributed ordinary to exhibit endogeneity? This is estimated by Kolmogorov–Smirnov test with Lilliefors correction (Sarstedt & Mooi , 2019) on the latent variable scores of information searches, financial wellbeing, salience bias, which serves as an independent variables in PLS path model estimation partial regression. It shows that none of latent scores of variables are normally distributed. It allows to perform

Gaussian copula approach. In the table 13, it is seemed clearly that none of the Gaussian copulas (IS, SB and FW) is significant at a p-value>0.05.

Table 13. Assessment of endogeneity test using the Gaussian copula approach.

Test	Construct	Coefficient	p-value
Gaussian copula of model 1 (endogenous variables; financial wellbeing FW)	FW	0.417	0.000
	IS	0.287	0.711
	SB	-0.013	0.000
	FW^C	0.007	0.771
Gaussian copula of model 2 (endogenous variables; Information searches IS)	FW	0.428	0.000
	IS	0.025	0.867
	SB	0.275	0.001
	IS^C	-0.040	0.813
Gaussian copula of model 3 (endogenous variables; Salience bias SB)	FW	0.414	0.000
	IS	-0.021	0.721
	SB	0.241	0.000
	SB^C	0.019	0.289
Gaussian copula of model 4 (endogenous variables; FW, IS)	FW	0.399	0.000
	IS	0.032	0.822
	SB	0.267	0.000
	FW^C	0.010	0.729
	IS^C	-0.050	0.762
Gaussian copula of model 5 (endogenous variables; IS, SB)	FW	0.399	0.000

	IS	0.032	0.822
	SB	0.267	0.000
	IS^C	0.010	0.756
	SB^C	-0.050	0.271
Gaussian copula of model 6 (endogenous variables; SB, FW)	FW	0.432	0.000
	IS	0.021	0.812
	SB	0.242	0.001
	FW^C	-0.019	0.738
	SB^C	0.017	0.265
Gaussian copula of model 7 (endogenous variables; FW, SB, and IS)	FW	0.432	0.000
	IS	0.021	0.812
	SB	0.231	0.010
	FW^C	-0.015	0.751
	SB^C	-0.047	0.811
	IS^c	0.021	0.312

Note: c is for copulas.

In the table 13, 7 models are developed for the study model. Where, all 3 independent variables financial wellbeing, information searches, and salience bias' copula are developed separately (model 1-3), than took 2 independent variables' copulas (model 4-6), and finally combined three independent variables all together in last model 7. In all models. The copula' p-values are seemed significant and above 0.05. It points towards no endogeneity issue is present in the data under study. The study results supported the hypotheses H1: salience bias effect investor decision significantly- support literature studies (Chaudhry, (2018); Yalcin, Tatoglu, & Zaim, (2016); Similarly, Riff & Yagil, (2016)). H2: information searches has significant effect on investor decision is in aligned of literature (studies including Meder, Schwartz, & Young (2019); Eberhardt et al. (2018); Tseng, (2012)) and supported them.

4.2.7 Mediation analysis in PLS-SEM

The relationships among the constructs are not always direct, they are indirect also. The study is included mediation between the relationship of constructs (salience bias, information searches) and investor decision. Mediation analysis is performed on the basis of Sarstedt, Ringle , & Hair (2017a). Which involves steps starting from calculating direct effect without mediators than, calculating indirect effect by including mediator. This is done through by taking PLS- algorithm and followed by bootstrapping. The path model estimation is given below in figure 6. Where salience bias t-statistic value is 2.587 towards investor decision. Information searches t-statistic value is 6.544 towards investor decision. This showed that significant relationship does exists between variables directly. It points towards presence of mediation in the relationship of constructs.

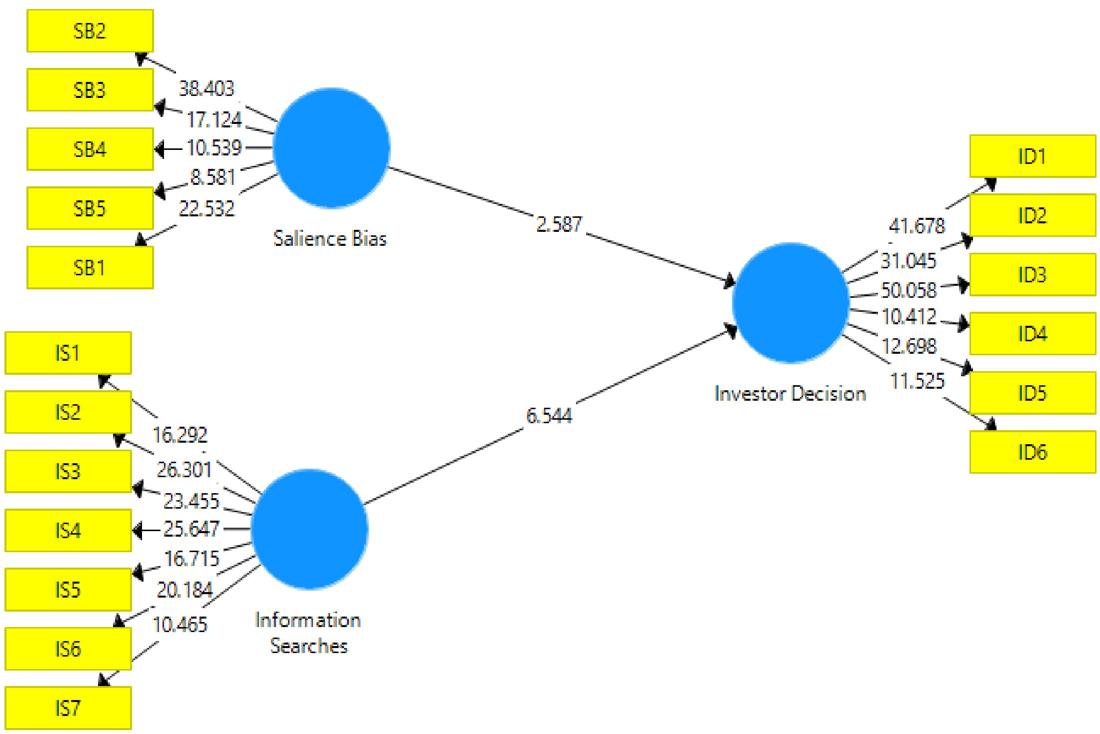


Figure 6: PLS-SEM direct effect

After calculating direct effect, next is to calculate the indirect effect. This is done by including mediator in the relationship between exogenous and endogenous variables. The path model is given below in figure 7 elaborating the indirect effect. The path model showed that after bootstrapping the salience bias t-statistic value is 0.480 towards investor decision and 7.338 towards financial wellbeing (mediator). Whereas, information searches t-statistic value is 4.59 towards investor decision in the presence of mediation (financial wellbeing- t-value: 2.557). This showed that complementary partial mediation does exists between constructs/variables.

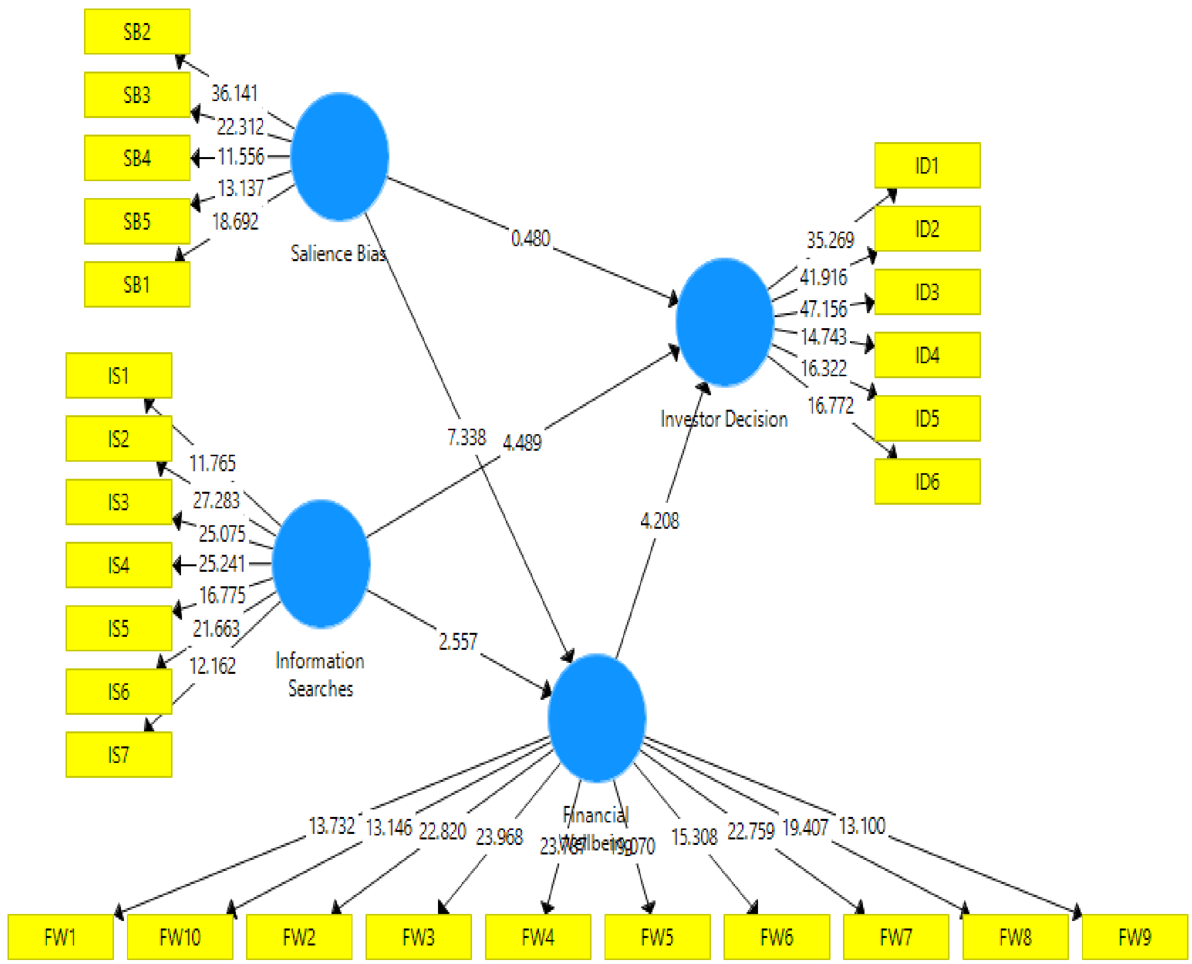


Figure 7: Path model estimation- indirect effect

Table 14: Mediation analysis results

Hypothesis	Procedure	Path	Path Coeff.	Indirect Effect	St. deviation	Total Effect	t-values	p-values	Hypothesis

H3a	**Step1: Direct Effect (without mediator)**	Salience bias->Investor decision	0.139	**n/a**			**2.649**	**0.008**	**Accepted/ Complementary Partial Mediation**
	Step2: Indirect Effect (with mediator)	Salience bias->Investor decision	0.028		0.053	0.129	**2.420**	**0.016**	
		Salience bias->financial wellbeing	0.418	**0.101**	0.060	0.418	**6.993**	**0.000**	
		financial wellbeing -> investor decision	0.242		0.053	2.420	**4.568**	**0.000**	
H3b	**Step1: Direct Effect (without mediator)**	Information searches-> investor decision	0.331	**n/a**			**6.458**	**0.000**	**Accepted/ Complementary Partial Mediation**
	Step2: Indirect Effect (with mediator)	Information searches-> investor decision	0.241	**0.0444**	0.049	0.285	**5.792**	**0.000**	
		Information searches-> financial wellbeing	0.181		0.074	0.181	**2.458**	**0.014**	
		financial wellbeing ->investor decision	0.242		0.053	0.242	**4.568**	**0.000**	

The above table 14: mediation analysis results are clearly stated that first performed PLS-algorithm and bootstrapping to calculate the direct effect of independent and dependent variables without considering mediation. The results of direct effect showed that Salience bias->Investor decision path coefficient is 0.139 at a p-value of 0.008. It seemed significant relationship between variables. Similarly, the results of direct effect showed that Information searches->Investor decision path coefficient is 0.331 at a p-value of 0.000. It point towards significant relationship between variables. The significant relationship showed that mediation does exist between constructs. In order to find out whether the mediation is partial, or full, indirect effect is used with the help of including mediator in relationship and again run PLS-algorithm, and bootstrapping. And researcher come to find out that path coefficients of indirect effect of salience bias > financial wellbeing > investor decision are 0.028, 0.418, and 0.242 at a p-value of 0.016, 0.000, and 0.000 respectively. Similarly, the path coefficients of indirect effect of information searches > financial wellbeing > investor decision are 0.241, 0.181, and 0.242 at a p-value of 0.000, 0.014, and 0.000. All these pointing towards complementary partial mediation presence in the relationship. This ultimately support the hypotheses 3a, and 3b. the previous literature shoed that studies of Shah et al. (2019); Stromback et al. (2017); Walstad & Allgood (2016); Tsai & Dwyer (2016); and Gutter & Copur (2011) studies used old methods for investigation and their results generalizations were wreaked. These studies needed advancement and the present study proved it by applied SmartPLS-SEM.

5. Conclusion

The present study investigate the effect of behavioral biases including salience bias and information searches on investor decision under the mediating effect of financial wellbeing in an emerging country like Pakistan. All that movement made capital market more efficient and chance of irrationality did not existed over there. As a result, members/participants of the market become robust in making speculation about securities trading trends. Nevertheless, that traditional concept had its own flaws as it was unable to answer some critical points that remained uncovered. All those unanswered areas created revolution to emerge new area that cooperate and interlink with multiple paradigms. This area inter connected with other domains and make investors make rational decisions about investment. Advancements come in traditional area of finance in shaped of "behavioral" expanded robust. . Prospect theory and efficient market hypothesis (EMH) theory provides the theoretical base of the study.

Researcher focused on assessing the structural equation model along with robustness tests by used SmartPLS-SEM. It is based on two subsets included inner model (structural model), and outer model (measurement model). The structural model also used advance techniques to access non-linearity, unobserved heterogeneity, and endogeneity issues related to the constructs under study. The study is based on reflective measurement model and in order to access path coefficients in structural model, first examined the following a) indicator reliability, b) internal consistency, c) discriminant validity and d) convergent validity of the reflective measurement model to ensure that the outer model is acceptable. . The study' latent constructs have loading ranging from 0.50-0.850. All constructs' outer loadings are satisfactory and resulting in increase of Average Variance Extracted (AVE) and composite reliability of their respective latent construct. In PLS-SEM, composite reliability is preferred over Cronbach's alpha to estimate the measurement model' internal consistency reliability. This is taken into consideration of different loadings of the indicators (Werts, Linn, & Joreskog, 1974). In the Table 1, the Composite Reliability of latent construct FW is 0.892, ID is 0.898, IS is 0.863, and S is 0.836. This show the high level of internal consistency in latent constructs.

The measurement model third characteristic is Convergent validity and it is refers to the model's ability to explain the indicator's variance. The AVE can provide evidence for convergent validity (Fornell & Larcker, 1981). The AVE for the latent construct named financial wellbeing, information searches, investor decision, and salience bias are 0.455, 0.476, and 0.596, and 0.508 respectively, well above the required minimum level of 0.50 (Bagozzi & Yi, 1988). Therefore, the measures of the two reflective constructs can be said to have high levels of convergent validity. To access Discriminant validity there are three methods named; Fornell-Larcker Criterion (1981), Heterotrait-Monotrait Ratio (HTMT), and cross loading.

The table 2 describe the discriminant validity, the measures of the three reflective constructs can be said to have high levels of discriminant validity by having LVC less than AVE. the LVC of FW, ID,IS, and S are 0.675, 0.772, 0.690, and 0.712 respectively. In the table 3, it can be viewed that latent construct HTMT are less than 1. HTMT of variables financial wellbeing, information searches, investor decision, and salience bias are below 1 (0.505, 0.356, 0.305 respectively). It indicates that discriminant validity has been established between given pair of reflective measure. The next is cross loading. It is used to access discriminant validity. It is an alternative of AVE to access discriminant validity of reflective model. In table 4, it can be seemed that variables financial wellbeing, information searches, investor decision, and salience bias have not higher correlation with another latent variable than its own latent variable. It concludes that that model is appropriately specified.

The next subset is structural model has to be properly evaluated before drawing any conclusion. Structural model accessed through variance inflation factor (VIF), R-square, f-square, q-square, path model coefficients e.t.c. it also include robustness test including non-linearity assessment, unobserved heterogeneity, and endogeneity evaluation. In table 5, two sets of linear regressions are generated for investor decision and for financial wellbeing. Both are significant. The next is determinant of coefficient (R^2) mentioned in table 7, the r-square of financial wellbeing and investor decision are 0.306 and 0.187 showing that financial wellbeing r-square is moderate and investor decision r-square is weak. Whereas, the r-square adjusted of financial wellbeing and investor decision are 0.303 and 0.181 respectively. It has been indicted that adding predictor to regressor model not increase the r-square. After R-square, the next is f-square calculation. In the table 8, it is reported that financial wellbeing and information searches has f-square 0.050 and 0.040 that has medium effect on investor decision. While, salience bias f-square is 0.000 which is very small effect size. On the other hand, information searches f-square is 0.027- a medium effect and salience bias has 0.145 a medium effect on investor decision. Further Q-square is calculated. The table 9, reported that endogenous variables including financial wellbeing and investor decision has 0.135 (medium) and 0.096 (medium). The table concluded that endogenous variable has predictive relevance in model.

The next included non-linearity assessment, unobserved heterogeneity assessment and endogeneity assessment. In table 11 given above: Ramsey RESET test results are mentioned with the help of Rstudio. It is conclude that no partial regression of financial wellbeing on salience bias, and information searches is seemed (F (3,387) ¼ 0.57, p ¼ 0.628) and also, partial regression of investor decision on financial wellbeing, salience bias, and information searches is seemed (F (3,399) ¼ 1.52, p ¼ 0.201). The whole relationship is subjected to non-linearity. Further, interaction terms included to calculate the quadratic effect of constructs. It is concluded that linearity existed in the model. The test accept the hypothesis of study H1: salience bias has significant effect on investor decision, and H2: information searches has significant effect on investor decision. After Ramsey RESET test, the next test is unobserved heterogeneity valuation with the help of FIMIX-PLS method. The table 12 showed the results. The min values of cluster are similar both in AIC^4 and BIC. Both criterion point towards 3 segment solutions. 3-segments solution indicated that min sample size requirements are meeting in it. MDL^5 pointing towards 1-segment solution. The results showed that analyses do not exactly point to a specific segment solution as, AIC^3 and CAIC point to different segments solutions and MDL^5 point to the same number of segments as AIC^4 and BIC. It is therefore concluded that unobserved heterogeneity is not at a critical level, which actually supported the results of whole analysis. The study results supported the hypotheses H1: salience bias effect investor decision significantly- support literature studies (Chaudhry, (2018); Yalcin, Tatoglu, & Zaim, (2016); Similarly, Riff & Yagil, (2016)). H2: information searches has significant effect on investor decision is in aligned of literature (studies including Meder, Schwartz, & Young (2019); Eberhardt et al. (2018); Tseng, (2012)) and supported them.

In the table 13, 7 models are developed for the study model. Where, all 3 independent variables financial wellbeing, information searches, and salience bias' copula are developed separately (model 1-3), than took 2 independent variables' copulas (model 4-6), and finally combined three independent variables all together in last model 7. In all models. The copula' p-values are seemed significant and above 0.05. It points towards no endogeneity issue is present in the data under study. The next, Mediation analysis is performed on the basis of Sarstedt, Ringle , & Hair (2017a). Which involves steps starting from calculating direct effect without mediators than, calculating indirect effect by including mediator. This is done through by taking PLS- algorithm and followed by bootstrapping. The path model estimation is given below in figure 6. Where salience bias t-statistic value is 2.587 towards investor decision. Information searches t-statistic value is 6.544 towards investor decision. This showed that significant relationship does exists between variables directly. It points towards presence of mediation in the relationship of constructs. Next is to calculate the indirect effect. This is done by including mediator in the relationship between exogenous and endogenous variables. The path model is given below in figure 7 elaborating the indirect effect. The path model showed that after bootstrapping the salience bias t-statistic value is 0.480 towards investor decision and 7.338 towards financial wellbeing (mediator). Whereas, information searches t-statistic value is 4.59 towards investor decision in the presence of mediation (financial wellbeing- t-value: 2.557). This showed that complementary partial mediation does exists between constructs/variables. This supported the hypothesis 3a, and 3b.

6 Implications

The study is rare in the field of social and behavioral sciences. The study provided the elaboration of behavioral factors including salience bias and information searches on the investor decision by taking financial wellbeing as mediator. The study not only contributing to the existing body of knowledge but, also contributed towards the usage of SmartPLS-SEM advance techniques which are still not applied yet. It contributed in for of theoretical, practical, managerial, investor, and social contribution.

6.1 Theoretical-practical implications

The study contributed to the theoretical background where, some researchers proved some disproved the relationship and not taking the mediation to make their studies justified. The study provides theoretical implications towards practitioners, and academics by the means of advance techniques used in the study. The prospect theory and efficient market hypothesis theory provided a framework to the researchers to extend their research studies in the field of behavioral and social sciences. The practitioners can also get advantage by practically applying these advance techniques in the field of social sciences. These techniques were used more in field other than behavioral sciences included medicine, and psychology, engineering, nursing e.t.c. in social science it seems new and demanding for the upcoming research areas that are uncover.

6.2 implication for investor

Investors have a time limit to make their decision in right direction efficiently. It has been annually reported that individual investors' information and publicly traded firms demands for investment decisions (Dang, Le, & Pham, 2020). Investors usually invest both in short term and long term period. Short term investment carried out for one year and long term investments results in huge returns on the basis of lots of fundS (Nia, 2020). Traditional finance theory conceptualized that finance representatives behaved realistically in making speculation about market and firm behavior pattern following over there. Agents at that time made rational choices which were based on rational economic expectation concept. Investors/agents followed profit maximization rule that uncovered their self-interest.

All that movement made capital market more efficient and chance of irrationality did not existed over there. As a result, members/participants of the market become robust in making speculation about securities trading trends. Nevertheless, that traditional concept had its own flaws as it was unable to answer some critical points that remained uncovered. That unresolved areas were included why participants always remained below their expected gain? Why crises happened to market at the time of investment? Why members followed other members to take investment decisions? All those unanswered areas created revolution to emerge new area that cooperate and interlink with multiple paradigms. This area inter connected with other domains and make investors make rational decisions about investment (Nuzula, 2019). Advancements come in traditional area of finance in shaped of "behavioral" expanded robust. In the initial phase, behavioral biases were considered significantly liked why not investors gone for prescribed portfolio rather they hold portfolio that were under-diversified? Why most of investors remained at risker position longer than winning one? Why mostly agents/participants/members traded passively when active trading was available over there

6.3 Social Implications

.Old studies just focused on economic costs of irrational decisions. If costs were more, members had seek to learn from their mistakes. Numerous literature review was highlighted the dilemma that for household market investors made decision based on their emotion, believes driven by social factors, as well as psychological factors whereas, the members behaved different in financial market decisions. This pinpoint the inequality gap between upper and lower socioeconomic groups respectively.

7. Limitations and future recommendations

The study is empirical in nature and little literature is available for it. A need rise to discover literature methodically. The study used adopted measures to calculate the results. There is a possibility to establish new measures for the study to contribute in the field. The study is conducted in Pakistan- an emerging, the results are according to its economic condition. It is recommended to apply the same study in developed country to take better comparison of two economies.

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