CHAPTER – 3

RESEARCH OBJECTIVES AND METHODOLOGY

Preview

This chapter presents the research methodology, the study's objectives and hypotheses, along with sample size and data sources. In addition, this chapter provides specifics regarding the variables that were chosen and how those variables were operationalized. In addition to this, it covers the dependent factors, exploratory variables, and control variables that were selected for the analysis of the data that was collected. In addition to this, it includes specifics on the data description as well as checks of assumptions for the implementation of Structural Equation Modelling, Path Analysis, and Bootstrapping to carry out the analysis for this particular study.

3.1 Introduction

This chapter offers the objectives, statement of the problem, the hypothesis, the definition of the variables, the selection of the data, and the technique to determine the elements affecting the investment intention of the agrarian class from an Indian perspective. In the empirical study, a few different types of modelling, such as structural equation modelling and bootstrapping have been utilised. Also included are a number of different constructs. This chapter also includes information on the data that was gathered and utilised, the time period that the study covered, the databases that were chosen, and any additional sources of information that were used. As we move further into the chapter, we are presented with a description of the constructs, anexplanation of the SEM methodology, and a report of the fundamental statisticsregarding the data that was selected.

3.2 Statement of Problem as per research gaps

The revenue of farmers is significantly affected by livestock illnesses, poor weather circumstances such as flooding, thunderstorms, and heavy rains, among other things. The existing research has revealed that farmers are hesitant to make large-scale investments in such uncertain times. Many of the investment and livelihood possibilities available to farmers are characterized by unpredictability in terms of returns (Cadot, Dutoit, and Olarreaga, 2006). Furthermore, this study will attempt to close an existing gap in the literature by investigating the interaction effects of socio-demographic factors on the investing behavior of farmers. Previous study has lookedat the elements that influence the investing intentions of different types of investors (Sivaramakrishnan et al., 2017), (Sarkar & Sahu, 2018), (Sashikala & Chitramani, 2017), (Nugraha & Rahadi,2021), (Ejigu, 2020). Many variables influence farmers' investment behavior, although various literatures have differing viewpoints on the primary influencing elements that influence farmers' investment behavior. However, just a little amount of study has been done on the agrarian class's investing behavior in rural areas. The goal of this study was to add tothe subject of behavioral finance by looking at the investing intentions of agrarian class investors in rural regions. Furthermore, the study will investigate if socio-demographic characteristics influence the relationship between various behavioral elements and the farmers' investment decisions. Through the disclosure of the answer to this question, the study adds a new dimension to the existing literature and may be of assistance in the growing discussion on behavioral factors and the investment behavior of individual investors around the world, particularly in relation to theagrarian class of investors.

3.3 Objectives of the Study

The main objective is to study the investment pattern of agrarian in rural areas in Punjab. In the light of main objective, the following specific objectives have been formulated:

1. To understand the antecedents of investment intentions of the agrarian class
2. To examine the relationship between Financial Self efficacy, financial knowledge, social influence, Personal traits, and attitude towards investment intention of the agrarian Class
3. To examine the relationship between attitude towards financial risk propensity and financial planning with investment intention and investment behavior of the agrarian class.
4. To investigate the moderation effect of demographics on the investment intentions of the agrarian class

5. To suggest strategies for financial institutions to attract investment from agrarian class

3.4 Research Data and Sample Selection

The target respondents who were supposed to participate were all from the rural areas of Punjab. The sample size was obtained using a sample calculator, with a 95% confidence level, to provide a good representation of the population. On the basis of rural population (according to census 2011) four districts have been selected. (Gurdaspur, Hoshiarpur, Ludhiana and Ferozepur).

District	Rural Population
Gurdaspur	1643882
Ferozepur	1474592
Ludhiana	1425201
Hoshiarpur	1247969

Source: Census 2011

Further from each district four villages with population were selected. Final sample from each village was fixed at 25 sampling units.

	Gurdaspur		**Ferozepur**		**Ludhiana**		**Hoshiarpur**	
	Village	Population	Village	Population	Village	Population	Village	Population
1	Kalanaur	13,642	Mamdot Uttar	6,242	Dhandra	14,972	Bajwara	9,929
2	Awankha	9,722	RuknaMungla	5,764	Dad	9,932	Ahrana	5,495
3	Tibber	9,410	Jhok Harihar	5,441	Phullanwal	9,927	Janauri	5,248
4	Kahnuwan	8,972	Firozpur	5,293	Chhapar	7,974	Ajjowal	3,970

With a target of 500 sample units, we selected 120 units on pro rata basis from each district. Lastly, these 30 sampling units from each village were selected using snowball sampling on the reference of the sarpanch of the villages. Through surveys, the information was gathered from the intended respondents. In order to reach more target respondents, particularly those with limited English literacy, the surveys were translated into Punjabi and English. Additionally, it aids in accurately documenting the target respondents' fair responses in the regional tongue. A total of 500 people in rural areas were reached. Of the 445 respondents who were discovered to be from rural agrarian backgrounds (whose majorly income came from agriculture). To increase participation among people who don't know English, the questionnaire was available in both Punjabi and English. In addition, it facilitates local-language responses from the target respondent, which is important for the validation of the research. At this stage, the primary steps involved recording, editing, and coding the acquired research data, which was then ready for following stage of data analysis to ensure comprehensiveness, reliability, and readability (Lawrence, 2003). First, the collected data were recorded into SPSS 24. Afterward, coding was done to every individual question per its scaling measurement level. Only 45 responses (out of 445) were found as incomplete for majority of the questions by going through the cases. AsCreswell (2013) suggests, those respondents were removed from the data analysis because of their incompletion of survey. Thus, the study was limited to 400 valid responses.

3.5 Research Variables under Study

The current study seeks to determine how the following supporting variables relate to one another:

Investment Attitude: Investment attitudes are crucial for identifying novice investors who have not yet developed any investment-related behaviors or significant competence. The choice of sustainable investments is greatly influenced by the investors' own perspective. (Tang and Baumeister, 1984; Grant and Beck, 2008;Adam and Shauki, 2014). The following research variables are considered for the current study:

a) ***Financial risk propensity*** is an important factor for examine the investment behavior. It can be described as a person's willingness to accept additional risks that could reduce their prospective revenue. ***(Davies and Brooks, 2013; Sahi and Kalra, 2013).*** Risk propensity of investors is linked to their investment decisions and risk tolerance; for example, People with high risk tolerance (i.e., low aversion to risk) are more likely to invest, whereas those with low risk tolerance (i.e., high aversion to risk) are more likely to do the opposite. ***(Grable 2018***). The risk propensity of an investment is taken into consideration as an important aspect while making financial decisions**.** As a result of their financial wealth and risk tolerance, investors can reap big returns from their investments ***(Grable, 2017). Dulebohn and Murray (2007)*** conclude in the findings of their study that risk adverse individuals prefer to select investments with an overall lower risk level, and risk-taking investors prefer to choose overall higher risk level investments.

b) ***Investment Attitude is*** vital for the rookie investors who have not yet experienced the investment policy behavior. Affirmation or disapproval of a given investment option can be measured on a scale of good or poor, agreement or disagreement, and importance or not importance, depending on how strongly an investor feels about it ***(Ajzen, 1991).*** Attitudes successfully anticipate behavior when the goal of attitude and the behavioral option are closely aligned. Individual mindsets have a significant impact on long-term financial decisions. ***(Adam and Shauki, 2014; Grant and Beck, 2008; & Tang and Baumeister, 1984)***

c) ***Financial planning*** demonstrates how a person plans to handle their investments and current and future financial needs, as well as their efficient use of savings to build wealth (Malaysia Financial Planning Council, 2004). Investors plan their fixed income flow strategy based on their financial planning. Investors create their financial plans in order to reach their financial objectives, which in turn aids in determining their level of comfort with risk andhow they should act when investing.

d) ***Investment intention*** is demonstrated by a person's willingness to take specific steps in the direction of making an investment (Yadav and Pathak, 2017). Over the past ten years, academic studies on investor behavior and investing intentions have been published (Naveed et al., 2020; Deb and Singh, 2018; Sharif and Verma 2018). If all the elements of intention (attitude, subjective norms, and perceived behavioral control) are favorable, there is a strongprobability that a specific behavior will be carried out by a specific person.

e) ***Investment Behaviour-*** According to Hilgert and Hogart (2003), reliable financial behavior indicators can be found in an individual's attitude toward managing and planning finances. Akhtar and Das (2019) concluded that the intentions to invest influences individual investors’ investment behavior. More specifically, while determining the behavior of individual investors, investment behavior examines an association among demographic factors, financial awareness, and perceived risk attitudes (Sarkar and Sahu, 2018). In their study, Wiedemann et al. (2009) explored the possible mediator part of investment planning in analyzing the bonding between the investment intention and the behavior of potential investors.

3.6 Research Hypothesis

In order to study the impact of financial self-efficacy, financial knowledge, social influence and personal traits on attitude towards investment, PLS SEM bootstrapping results gave the path coefficients along with T values and respective p values. The hypothesis for the above-mentioned objectives is as follows:

H_1: There exists a significant positive relationship between financial self-efficacy and attitude towards investment.

H_2: There exists a significant positive relationship between financial knowledge and attitude towards investment.

H_3: There exists a significant positive relationship between social influence and attitude towards investment.

H4: There exists a significant positive relationship between personal traits and attitude towards investment.

To investigate the final dependent variable, Investment behavior, the impact of attitude, financial risk propensity and financial knowledge is examined on investment intention first then further leading to investment behavior. So, the following hypothesis is made:

H_5: There exists a significant positive relationship between attitude towards investment and
financial risk propensity.

H_6: There exists a significant positive relationship between attitude towards investment and financial planning.

H_7: There exists a significant positive relationship between attitude towards investment and investment Intention.

H_8: There exists a significant positive relationship between investment intention and investment behavior.

H_9: There exists a significant positive relationship between financial risk propensity and investment intention.

H_{10}: There exists a significant positive relationship between financial planning and Investment intention.

3.7 Research Model

Icek Ajzen (1985, 1991) propounded the theory of planned behavior (TPB) model which explained and used to predict the behavior that posits the behavior that is determined by intention and in few instances, perceived control behavior. According to Ajzen, 1985 the intention is developed by three factors predominantly, that is attitude, subjective norms and perceived behavioral control. Studies have shown that incase an individual develop positive attitude towards specific behavior then they generally develop positive intention to carry out that behavior (Gopi and Ramayah, 2007; O'Connor and White, 2010; Phan and Zhou, 2014).

In accordance with this concept, an explicit behavior may be visualized in significant subparts; investor's attitude and investor's intention are identified. Based on research in previous literature on behavior and related theories on environment psychology like TPB theory, the present study adopts the concept of TPB and put forward the hypothesis relating to attitude of agrarian class investors in India towards the intentionto invest.

Therefore, our research study presumes that behavioral beliefs and control which are traits of attitudinal behavior that have a fundamental functionality in determining the future intention of agrarian investors in India. The present study therefore attempts to make use of TPB as groundwork. The Theory of Planned Behavior (TPB) looked into a number of background variables (personality, sex, socioeconomic status, age, education, ethnicity and prior experiences) that may have an impact on people's behavioral views and, consequently, their viewpoint on behavior and intention. (Ajzen, 1985, 1991). Recent studies have discovered that attitude, perceived control behavior, and subjective norms influence an investor's intention to invest (Luky, 2016; Phan & Zhou, 2014). There is a wealth of materialthat demonstrates the impact of emotional and psychological factors on investors' choice of investments (Griffith, Najand, & Shen 2020; Lo, Repin, &Steenbarger, 2005). It has been suggested that the Theory of Planned Behavior (Ajzen 1985; 1991) is an extension of these findings.

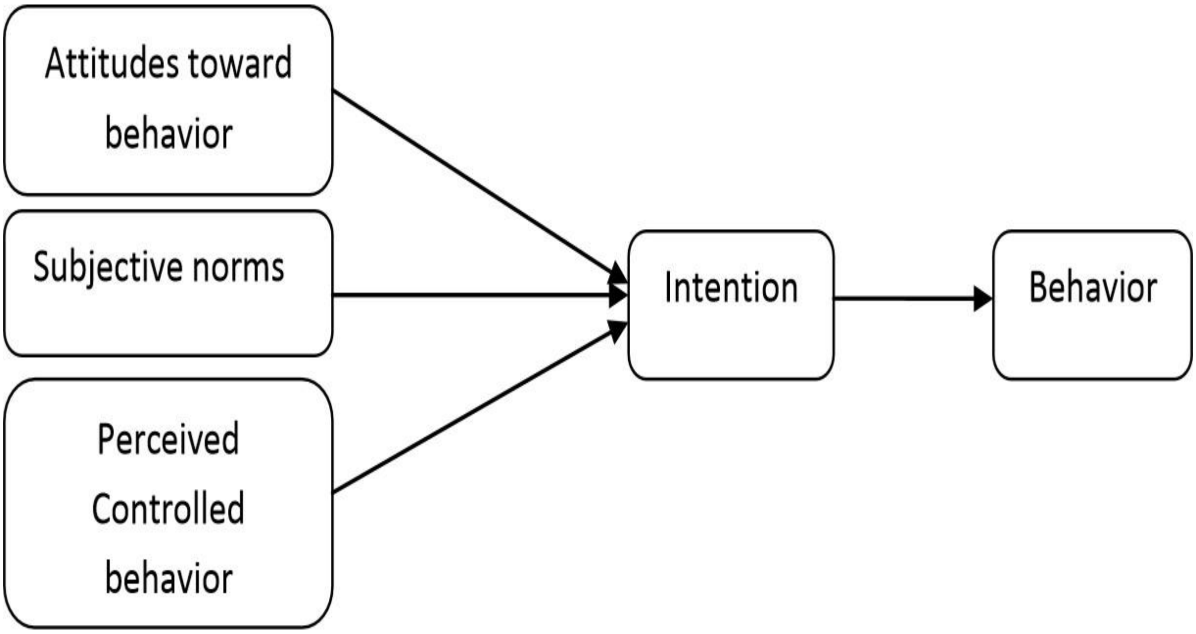


Figure 3.1: Theory of Planned Behavior (Ajzen, 1985)

3.8 Statistical Techniques

3.8.1 Structural Equation Modelling (SEM)

The research model was confirmed using the structural equation modeling (SEM) method. "A variety of statistical models that depicts the association between distinct variables" is the most common definition of SEM. Hair Jr. et al., 2017).

Marketing research frequently employs structural equation modeling (SEM), a method for second-generation multivariate data analysis, because it enables the theoretically justified testing of additive and linear causal models (Chin, 1996; 2004;

Haenlein and Kaplan, 2013). The simultaneous evaluation of the measurement model and the structural model is made possible by SEM, which makes exploratory factor analysis and structural route analysis two effective statistical methods. SEM also has a better ability to explain variance in the dependent variable(s) than multiple regression because it takes into account both direct and indirect effects (Lee et al., 2011) In recent years, structural equation modeling (SEM) applications have grown significantly (Matthews et al., 2016b; Rutherford et al., 2011, 2012). This is primarily because the method is now better able to evaluate the validity and reliability of multi-item construct measurements and examine relationships between structural model assumptions (Bollen, 1989; Hair et al., 2012b).

A structural equation model is made up of two sub models: the inner model, which describes the connections between the independent and dependent latent variables, and the outer model, which describes the connections between the latent variables and their observable indicators. In SEM, a variable may be either endogenous or exogenous. The opposite direction is indicated by all path arrows pointing at an external variable. An endogenous variable has at least one path to it (s) and represents the effects of other variables. Independent variables are also referred to as exogenous latent variables because they "cause" changes in the values of other latent variables in the model. Endogenous latent variables are affected either directly or indirectly by exogenous variables that the model classifies as dependent variables. A model that represents both the relationships between the latent variables and their observable measurements is referred to as a "full" or "complete" model.

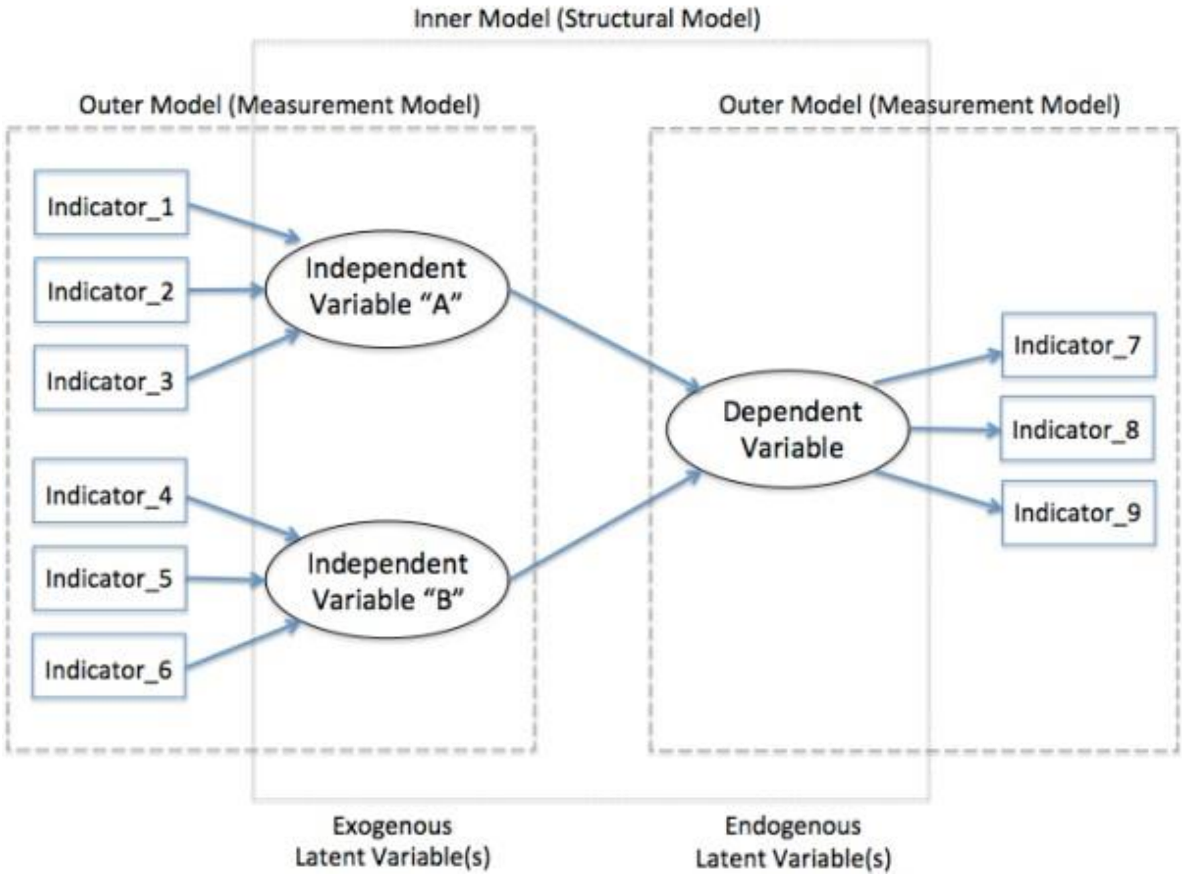


Figure 3.2 Inner vs. Outer Model in a SEM Diagram

Researchers can choose between variance-based partial least squares (PLS-SEM; Lohmöller, 1989; Wold, 1982) and covariance-based SEM (CB-SEM; Jöreskog, 1978, 1993).

The following provides a description of the aforementioned two structural equation modelling methods:

3.8.2 Covariance–Based Structural Equation Modelling (CB-SEM)

The objective of CB-primary SEM is to back up accepted hypotheses (i.e., explanation). CB-SEM has been extensively used in social science over the past few decades to test hypotheses to either support or refute theories. It is still the method of choice today, particularly when the sample size is large, the data are normally distributed, and, most importantly, the model is accurately described. To put it anotherway, the appropriate variables are selected and coupled together when developing a theory-based structural equation model (Hair, Ringle, & Smarted, 2011). However, a lot of industry and academic experts say that it can be hard to find a data set that meets these requirements. In addition, the research objective may be exploratory, so we don't know much about how the variables relate to one another. In this situation, marketers might want to think about CB-SEM. CB-SEM is utilized for:

• The objective is the evaluation of competing theories, theory testing, or theory validation.

• Error words require additional conditions, like the co variation.

• The structural model contains circular links.

• The study requires a universal goodness-of-fit criterion.

3.8.3 Partial Least Square Structural Equation Modelling (PLS-SEM)

Although PLS is a prediction-focused SEM method that works best for exploratory research (Sarstedt et al.,), it can be used for confirmatory research. 2014a). Researchers who employ PLS-SEM anticipate that their model will have high prediction accuracy while also being based on complicated causal explanations, thereby resolving the apparent conflict between confirmatory and predictive research (Sarstedt et al., 2018). PLS is a soft modeling technique, in contrast to SEM, which relies on presumptions regarding the data distribution (Vinzi et al., 2010). PLS-SEMis a viable alternative to CB-SEM in the following circumstances: Wong, 2010;Hwang and other, 2010; Bacon, 1999).

• Key "driver" structures or forecasting key target structures are the goals. • The structural model includes structures that can be measured in some way. Understanding that CB-SEM can also be used with formative assessments is essential, but doing so requires changing the description of the construct (for example, the construct must include both formative and reflective indicators to meet identification requirements).

• A complicated structural model with numerous constructs and indicators

• The sample size is too small or the data are not distributed properly.

• Scores for latent variables will be used in subsequent research.

It's important to keep in mind that not all statistical analyses can be done using PLS-SEM. Marketers should also be aware of PLS weaknesses, SEM's which include:

- If the sample size is small, high-valued structural route coefficients are required.
- Multi-collinearity issue, if properly addressed.
- It cannot explain undirected correlation since arrows are always single-headed.
- Biased component estimation, loadings, and path coefficients may be the result of scores on latent variables that may not be completely consistent.
- It could result in significant mean square errors when estimating the loading of the route coefficient.

Despite these flaws, PLS is useful for structural equation modeling in real-world research projects, especially when there are few participants and skewed data distributions, like in surveys of female senior executives or CEOs of multinational corporations (Wong, 2011). PLS-SEM has been used in a variety of fields, including the behavioral sciences (e.g., Bass et al., 2003), structure (such as Sosik et al., Marketing (for instance, Henseler et al., 2009), an information management system (such as Chin et al., 2003), and the company's strategy. For instance, Hulland, 1999)

3.8.4 Justification for PLS SEM.

The following are the most prominent justifications for the utilization of PLS- SEM:

The following ideas are discussed: (i) non-normal data; (ii) small sample sizes; and (iii) constructs that are formatted.

(1) Unusual data: Multivariate normal distributions typically do not apply to data from social science studies. When attempting to analyze a path model using CB-SEM, non-normal data may result in understated standard errors and overestimated goodness-of-fit metrics (Lei and Lomax, 2005). Because it interprets non-normal data in accordance with the central limit theorem, PLS- SEM can handle non-normal data more freely. (Cassel et al., 1999; Beebe et al., 1998).

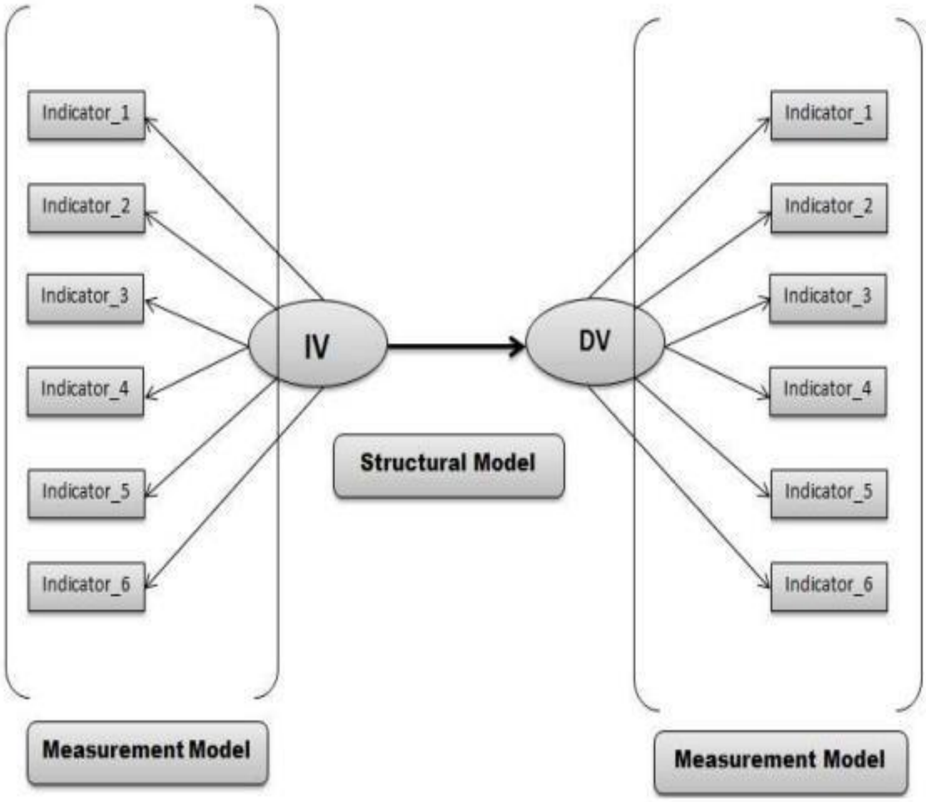
(2) The sample size is small: In SEM, parameter estimations, model fit, and statistical power are all affected by sample size (Shah and Goldstein, 2006). PLS-SEM, in contrast to CB-SEM, allows for much smaller sample sizes, even for

models that are extremely complex. In these situations, PLS-SEM frequently performs better than CB-SEM in terms of statistical power and convergence behavior.

(3) Indicators of form: Formative measurements illustrate situations in which the indicators create the construct, in contrast to reflecting indicators, which are created by the construct rather than the other way around (i.e., the arrows point from the construct to the indicators). Although PLS-SEM and CB-SEM both have the ability to estimate models using formative indicators, PLS-SEM has received a lot of support as the method that should be used (Hair et al., 2014). Researchers usually prefer PLS-SEM because CB-SEM studies of formative indicators frequently have problems identifying those (Jarvis et al., 2003). Due to earlier PLS-SEM review studies (Hair et al., 2012), researchers should use the most recent set of assessment criteria when evaluating the validity of formatively assessed components, pointed out that formative indicators were handledcarelessly. (Hair et al., 2014)

3.8.5 PLS-SEM Characteristics

PLS-SEM has gone through two steps. The validity and reliability of the measurement models are first evaluated in line with a list of requirements for formative and reflective measurement models. The second phase is the examination of the structural model estimates (Hair, Ringle, & Sarstedt, 2011). The latent variables are defined by the measurement model. (LVs) that are used, and for each LV, a set of observed variables, or indicators, are provided. It makes an effort to ascertain whether the theoretical elements are accurately reflected in the observable variables. The hypothesized links between the constructs are evaluated for relevance and significancein order to assess the structural model.



Source: Hair *et al.* (2014) A primer on partial least squares. *Sage.*

Figure: 3.3 Measurement Model and Structural Model Source: Hair et al. (2014) A primer on partial least squares.

3.8.6 Measurement Model Assessment

Model assessment (structural model) provides actual measurements of the associations between the constructs and indicators (measurement models) as well as between the constructs. Because of the empirical measurements, we are able to compare the representation of reality in the sample data with theoretically established measurement and structural models. To put it another way, we could look at how well the theory makes sense of the data (Hair et al., 2014). The discriminant validity, internal consistency, average variance extraction analysis, and construct reliability of each item are examined in this study to assess the measuring model.

3.8.7 Composite Reliability

Continuity within Most of the time, dependability is evaluated first. Cronbach's alpha, a well-known internal consistency metric, is used to evaluate the reliability based on the correlations between the observed indicator variables. Cronbach's alpha states that all indicators have equal credibility—that is, they have equal outer loadings on the construct. However, PLS-SEM ranks indicators according to their individualreliability. Additionally, the reliability of internal consistency is frequently understated by Cronbach's alpha due to its sensitivity to the number of items on the scale (Hair et al., 2014). A different internal consistency reliability measurement, composite reliability, ought to be used in place of Cronbach alpha due to the population's limits. The composite dependability serves the same purpose as Cronbach's alpha as an indicator of internal consistency. Higher numbers on the composite dependability scale, which ranges from 0 to 1, indicate greater levels of dependability. In most cases, it has the same meaning as Cronbach's alpha. For instance, values of composite reliability between 0.60 and 0.70 are acceptable in exploratory research, while values between 0.70 and 0.90 can be considered satisfactory in later stages of the investigation (Hair et al., 2014).

3.8.8 Convergent Validity

Convergent validity is the degree to which a measure correlates well with other measures of the same construct. As a result, the concept and the things that serve as its indicators or measures ought to share a significant amount of variation. The indicators' external loadings were taken into account to establish convergent validity. A construct's high outer loading indicates that the associated indicators are wellrepresented by the construct and share numerous characteristics. As a general rule, a latent variable should typically account for at least 50% of the volatility of each indicator. Since 0.708 squared = 0.50, an indicator's outer loading should be greater than 0.708, indicating that the measurement error variance is less than the variance shared by the concept and its indicator. It is generally accepted because 0.70 is sufficiently close to 0.708 (Hair et al., 2014). The dependability of each individual item was evaluated by examining the loadings, or straightforward correlations, of the indicators with the associated latent variables.

3.8.9Average Variance Extracted (AVE)

A typical metric to demonstrate convergent validity at the construct level (AVE) is the average variance extracted. This criterion is calculated by multiplying the sum of the squared loadings divided by the number of construct-related indicators by the grand mean value. As a result, a building's communality is equivalent to the AVE. It is necessary to account for at least half of the indicator's volatility if the average values are greater than 0. However, an AVE of less than 0.50 indicates that the items still typically have a greater degree of inaccuracy than the construct can account for (Hair et al., 2014).

3.8.10 Discriminant Validity

The degree to which a construct actually differs from other constructs is measured by its discriminant validity in terms of empirical criteria. As a result, demonstrating discriminant validity demonstrates that a construct is distinct and covers situations that are not covered by other model constructs. The Fornell-Larcker criteria were usedto evaluate discriminant validity. This approach enables comparison of the AVEsquare root values and the latent variable's correlations. Each concept's AVE ought to have a square root that is greater than the highest correlation it has with any other construct in order to demonstrate discriminant validity. The idea that a construct differs more from other constructs in terms of variance from its associated indicators than from other constructs is the basis for the justification of this methodology (Hairet al., 2014).

3.8.11 Bootstrapping

PLS-SEM cannot be used to evaluate the significance of coefficients like outer weights, outer loadings, and path coefficients because it does not assume that the data are normally distributed. PLS-SEM, on the other hand, employs a nonparametric bootstrap method to determine the significance of coefficients (Davison & Hinkley, 1997; Efron and Tibshirani ,1986). During bootstrapping, the initial sample is subdivided into a number of subsamples, which are also referred to as bootstrap samples. The method is referred to as replacement when an observation that was selected at random from the sampling population is reintroduced into the population (i.e., the population from which the observations are drawn always contains all of the same elements). Bootstrap samples are created by resampling (with replacement) from the sample data that is already available in order to approximate the sampling distribution of a statistic. Because they are created from a large number of distinctdata points, these samples are referred to as "phantom samples." The number of bootstrap samples should be substantial, but it must be greater than or equal to the total number of valid observations in the data collection. According to Hair et al., (2014) 500 bootstrap samples are usually recommended.

3.9 Statistical Software

Different software programmes were available in addition to SPSS Version 20 for path modelling. Smart PLS (Version 3.2.3) is used in this work to create the measurement and structural models. In addition to SPSS and SmartPLS-3, Microsoft Excel 2010 was used to display the empirical scores graphically.

3.10 Data Description

Descriptive Statistics

The descriptive statistics for each variable taken into account in the current study are reported in this subsection. If the respondents are a key source of data for the research, the demographic profile is essential. The age, gender, and income of the individuals in the sample serve as indicators of the demographics of the population. The profile of our research sample as a whole is illustrated in Table.

Demographic Profile

Measure	Items	Frequency	Percentage
Gender	Male	242	61
	Female	158	39
Age	Less than 25 years	73	18
	26-35 years	163	41
	36-45 years	93	23
	46 – 55 years	45	11
	55 years and above	26	7
Marital Status	Single/Unmarried	141	35
	Married	259	65
Qualification	High School (10^{th})	117	29
	Senior Secondary School (10+2/Diploma)	89	22
	Graduate	102	26
	Post Graduate	82	21
	Doctorate	10	3

	Others	0	0
Income from Agriculture	Less than 5 Lakh	88	22
	5-10 Lakh	196	49
	10-15 Lakh	80	20
	15-20 Lakh	19	5
	20 Lakh and above	17	4
Income from Non-Agriculture	Less than 5 Lakh	206	52
	5-10 Lakh	84	21
	10-15 Lakh	58	15
	15-20 Lakh	37	9
	20 Lakh and above	15	4
House ownership	Own	344	86
	Rented	56	14
Financial Products awareness	Bank deposits	275	69
	Postal savings	46	12
	Insurance	54	14
	Bonds/Debentures	5	1
	Mutual funds	6	2
	Share market	3	1
	Pension Schemes	10	3
	Commodities	1	0
Current financial investments	Bank Deposits	265	66
	Equity (Shares)	12	3
	Mutual Funds	10	3
	Postal Savings	44	11
	Life Insurance	51	13
	Chit funds (specify)	0	0
	Bonds/Debentures	7	2
	Provident fund	11	3
Financial advice taken before	Family members	241	60
	Friends	54	14

investment	Colleagues	40	10
	Financial Advisors	37	9
	Media (Business Channels/ Newspapers)	28	7

References

Adam, A. A., & Shauki, E. R. (2014). Socially responsible investment in Malaysia: Behavioral framework in evaluating investors' decision-making process. *Journal of Cleaner Production*, *80*, 224–240. https://doi.org/10.1016/j.jclepro.2014.05.075

Akhtar, F., & Das, N. (2019). Predictors of investment intention in Indian stock markets: Extending the theory of planned behaviour. *International Journal of Bank Marketing*, *37*(1), 97–119. https://doi.org/10.1108/IJBM-08-2017-0167

Ajzen, I. and Fishbein, M. (1977). Attitude-behavior relations: Theoretical analysis and review of empirical research. *Psychological Bulletin, 84, 888-918.*

Ajzen I. (1991). The Theory of planned behaviour. *Organizational Behaviour and Human Decision Processes, 50, 179–211.*

Ajzen I. The Theory of planned behaviour', *Organizational Behaviour and Human Decision Processes*, 199150 179–211.

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In J. Kuhl & J. Beckman (Eds.), Action control: From cognition to behavior *(pp. 11–39). Heidelberg: Springer*.

Beebe, K.R., Pell, R.J. and Seasholtz, M.B. (1998), Chemometrics: A Practical Guide, *Wiley, New York, NY*

Bollen, K.A. (1989) Structural Equations with Latent Variables, *Wiley, New York*

B. Efron, R. Tibshirani(1986) Bootstrap Methods for Standard Errors, Confidence Intervals, and Other Measures of Statistical Accuracy.*Statist. Sci. 1(1): 54-75. DOI: 10.1214/ss/1177013815*

Cassel, C., Hackl, P. and Westlund, A.H. (1999), "Robustness of partial least-squares method for estimating latent variable quality structures", *Journal of Applied Statistics, Vol. 26 No. 4, pp. 435-446*

Chin, W.W. (1998) 'The partial least squares approach to structural equation modeling', in Marcoulides, *G. (Ed.): Modern Methods for Business Research, pp.295–358, Erlbaum, Mahwah, NJ.*

Chin, W. W., Marcolin, B. L., & Newsted, P. R (2003). A Partial Least Squares Latent Variable Modeling Approach For Measuring Interaction Effects: Results From A Monte Carlo Simulation Study And Electronic Mail Emotion/Adoption Study, *Information Systems Research, 14(2), 189-217*

Davies, G.B.,& Brooks,P (2014)Risk Tolerance: Essential, behavioural and misunderstood*https://www.researchgate.net/publication/258378890_.*

Davison .A.C, Hinkley D. V. (1997) Bootstrap Methods and Their Application. *Technometrics.94(445) DOI:10.2307/1271471*

Deb, S.; Singh, R. (2018) Dynamics of Risk Perception Towards Mutual Fund Investment Decisions. *Iranian Journal of Management Studies,* 11, 407-424

Dulebohn, J. H.; Murray, B. (2007) Retirement Savings Behavior of Higher Education Employees. Research in Higher Education, 48 *(5) 545–582. doi:10.1007/s11162-006-9038-z*

Ejigu, S. N. (2020). Determinants of Investment Intention in Micro and Small Enterprises Among Business College Students in East Gojjam Zone. *Research Journal of Finance and Accounting, 11*(3), 12–22. https://doi.org/10.7176/rjfa/11-3-02

Fishbein, M., & Ajzen, I. (1975). Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research. *Reading, MA: Addison-Wesley.*

Grable (2018) Another Look at Risk-Profiling *Journal of Financial Service Professionals*, 2018 72 18-21.

Gopi, M.; Ramayah T. (2007) Applicability of theory of planned behavior in predicting intention to trade online: Some evidence from a developing country. *International Journal of Emerging Markets,2,* 348–360

Grant, P. M.; Beck, A. T. (2008) Defeatist beliefs as a mediator of cognitive impairment, negative symptoms, and functioning in schizophrenia. *Schizophr, Bull*. 35, 798–806. doi: 10.1093/schbul/sbn008

Gopi, M. & Ramayah, T. (2007). Applicability of theory of planned behavior in predicting intention to trade online: Some evidence from a developing country. *International Journal of Emerging Markets, 2(4). 348-360.*

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: a review of four recent studies. *Strategic Management Journal,20(2), 195–204.*

Hwang, H., Malhotra, N. K., Kim, Y., Tomiuk, M. A., & Hong, S. (2010). A comparative study on parameter recovery of three approaches to structural equation modeling. *Journal of Marketing Research, 47 (Aug), 699-712.*

Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. (2014), A Primer on Partial Least Squares Structural Equation Modeling, *Sage, Thousand Oaks, CA.*

Hair, J.F., Sarstedt, M., Pieper, T.M. and Ringle, C.M. (2012a), "The use of partial least squares structural equation modeling in strategic management research: areview of past practices and recommendations for future applications", *Long Range Planning, Vol. 5 Nos 5/6, pp. 320-340.*

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2011), "PLS-SEM: indeed a silver bullet", *Journal of Marketing Theory and Practice*, *Vol. 19 No. 2*, *pp. 139-151*

Hilgert, M. A., Hogarth, J. M., & Beverly, S. G. (2003). Household financial management: The connection between knowledge and behavior. *Fed. Res.Bull.*, *89*, 309.

Hair Jr, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107-123.

Hair, J.F., Sarstedt, M., Ringle, C.M. and Mena, J.A. (2012b) 'An assessment of the use of partial least squares structural equation modeling in marketing research', *Journal of the Academy of Marketing Science, Vol. 40, No. 3,pp.414–433.*

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2011) 'PLS-SEM: indeed, a silver bullet', *The Journal of Marketing Theory and Practice, Vol. 19, No. 2, pp.139–152.*

Haenlein, M., & Kaplan, A. M. (2004). A beginner's guide to partial least squares analysis. *Understanding statistics*, *3*(4), 283-297.

Henseler, J. and Fassott, G. (2010), “Testing moderating effects in PLS path models: an illustration of available procedures”, in Esposito, V.V., Chin, W.W., Henseler, J. and Wang, H. (Eds), *Handbook of Partial Least Squares: Concepts, Methods and Applications, Springer, Berlin, pp. 713-735.*

Henseler, J., Ringle, C., & Sinkovics, R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing, 20(2009), 277–320.*

Jöreskog, K.G. (1978) ‘Structural analysis of covariance and correlation matrices’, *Psychometrika, Vol. 43, No. 4, pp.443–477.*

Jöreskog, K.G. (1993) ‘Testing structural equation models’, in Bollen, K.A. andLong, J.S.(Eds.): Testing Structural Equation Models, *pp.294–316, Sage, Newbury Park.*

Jarvis, C.B., Mackenzie, S.B., Podsakoff, P.M., Mick, D.G. and Bearden, W.O. (2003), “A and critical review of construct indicators and measurement model misspecification in marketing consumer research”, *Journal of Consumer Research, Vol. 30 No. 2, pp. 199-218*

Kalra S. S., & Arora, A. P. (2012). Individual investor biases: a segmentation analysis. *Qualitative Research in Financial Markets*, 4(1), 6–25.

Lei, M. and Lomax, R.G. (2005), “The effect of varying degrees of nonnormality in structural equation modeling”, *Structural Equation Modeling, Vol. 12 No. 1, pp. 1-27.*

Lo, A. W., Repin, D. V., & Steenbarger, B. N. (2005). Fear and greed in financial markets: A clinical study of day-traders. *Social Science Research Network, 1-27. https://papers.ssrn.com/abstract=697168*

Lohmöller, J-B. (1989) Latent Variable Path Modeling with Partial Least Squares, *Physica, Heidelberg*

Luky, M. R. (2016). Minat berinvestasi di pasar modal: Aplikasi theory of planned behavior serta persepsi berinvestasi di kalangan mahasiswa. *Jurnal Ilmiah Mahasiswa. FEB, 4(2), 20.* *https://jimfeb.ub.ac.id/index.php/jimfeb/article/view/3245*

Lee, L., Petter, S., Fayard, D. and Robinson, S. (2011) 'On the use of partial least squares path modeling in accounting research', *International Journal of Accounting Information Systems, Vol. 12, No. 4, pp.305–328*.

Matthews, L.M., Sarstedt, M., Ringle, C.M. and Hair, J.F. (2016a) 'Identifying and treating unobserved heterogeneity with FIMIX-PLS: Part II – case study', *European Business Review, Vol. 28, No. 2, pp.208–224.*

Matthews, L.M., Zablah, A.R., Hair, J.F. and Marshall, G.W. (2016b) 'Increased engagement or reduced exhaustion: which accounts for the effect of job resources on salesperson job outcomes?', *Journal Of Marketing Theory & Practice, Vol. 24, No. 3, pp.249–264*.

Malaysia Financial Planning Council, M. F. P. C. (2004). RFP Module 1- Fundamentals of Financial Planning, MFPC, Kuala Lumpur. Int. *Journal of Economics and Management*, *5*(1), 149-168.

Naveed M.; Ali. S.; Iqba, K.; Sohail, M. K. (2020) Role of financial and non-financial information in determining individual investor investment decision: a signaling perspective *South Asian Journal of Business Studies*. 9, 261-278.

Nugraha, B. A., & Rahadi, R. A. (2021). Analysis of Young Generations toward Stock Investment Intention: A Preliminary Study in an Emerging Market. *Journal of Accounting and Investment*, *22*(1), 80–103. https://doi.org/10.18196/jai.v22i1.9606

O'Connor, E.L. and White, K.M. (2010), "Willingness to trial functional foods and vitamin supplements: the role of attitudes, subjective norms, and dread of risks", *Food Quality and Preference, Vol. 21 No. 1, pp. 75-81*

Olarreaga, M., Cadot, O., & Dutoit, L. (2006). How costly is it for poor farmers to lift themselves out of poverty? *Policy Research Working Paper Series* No 3881. https://elibrary.worldbank.org/doi/abs/10.1596/1813-9450-3881

Phan K.C.; Zhou J.(2012)Factors Influencing Individual Investor Behavior: An Empirical Study of the Vietnamese Stock Market.*American Journal of Business and Management,*3, 77-94

Reinartz, W., Haenlein, M. and Henseler, J. (2009), "An empirical comparison of the efficacy of covariance-based and variance-based SEM", *International Journal of Research in Marketing, Vol. 26 No. 4, pp. 332-344*

Rutherford, B.N., Wei, Y., Park, J. and Hur, W-M. (2012) 'Increasing job performance and reducing turnover: an examination of female Chinese salespeople', *The Journal of Marketing Theory and Practice, Vol. 20, No. 4, pp.423–436.*

Shah, R. and Goldstein, S.M. (2006), "Use of structural equation modeling in operations management research: looking back and forward", *Journal of Operations Management, Vol. 24 No. 2, pp. 148-169*

Sharif, M.; Verma O. P.(2019) Saving and Investment Pattern of Rural Households of Himachal Pradesh *Pragati: Journal of Indian Economy*,5,75-86 https://doi.org/10.17492/pragati.v5i2.14377

Sosik J J, Kahai S S, Piovoso M J (2009) Silver bullet or voodoo statistics? A primer for using the partial least squares data analytic technique in group and organization research. *Emerald Management Reviews: Group & Organization Management, 34(1), 5-36*

Statsoft (2013). Structural Equation Modeling, Statsoft Electronic Statistics Textbook. *http://www.statsoft.com/textbook/structural-equation-modeling/*

Sivaramakrishnan, S., Srivastava, M., & Rastogi, A. (2017). Attitudinal factors, financial literacy, and stock market participation. *International Journal ofBank Marketing*, *35*(5), 818–841. https://doi.org/10.1108/IJBM-01-2016-0012

Sarkar, A. K., & Sahu, T. N. (2018). Analysis of Investment Behaviour of Individual Investors of Stock Market: A Study in Selected Districts of West Bengal. *Pacific Business Review International*, *10*(7), 7–17. www.pbr.co.in

Sashikala, V., & Chitramani, P. (2017). Impact of Investment Bias on Investment Intention. *International Journal of Engineering Technology, Management and Applied Sciences*, *5*(5), 411–418.

Sarstedt, M., Ringle, C.M., Henseler, J. and Hair, J.F. (2014a) 'On the emancipation of PLS-SEM: a commentary on Rigdon 2012', *Long Range Planning, Vol. 47, No. 3, pp.154–160.*

Sarstedt, M., Hair, J.F., Ringle, C. and Hair, J.F. (2018) 'Partial least squares structural equation modeling', Homburg, C., Klarman, M. and Vomberg, *A. (Eds.): Handbook of Market Research, Springer, Germany, In Press.*

Tang, T. L., & Baumeister, R. F. (1984). Effects of personal values, perceived surveillance, and task labels on task preference: The ideology of turning play into work. *Journal of Applied Psychology, 69*(1), 99– 105. https://doi.org/10.1037/0021-9010.69.1.99

Wiedemann, A. U., Schu¨z, B., Sniehotta, F., Scholz, U., & Schwarzer, R. (2009). Disentangling the relation between intentions, planning, and behaviour: A moderated mediation analysis. *Psychol- ogy & Health, 24, 67–79*

Wong, K. K. (2010). Handling small survey sample size and skewed dataset with partial least square path modelling. Vue: *The Magazine of the MarketingResearch and Intelligence Association, November, 20-23*

Wong, K. K. (2011). Review of the book Handbook of Partial Least Squares: Concepts, Methods and Applications, by V. Esposito Vinzi, W.W. Chin, J. Henseler & H. Wang (Eds*). International Journal of Business Science &Applied Management. 6 (2), 52-54.*

Wold, H. (1982) 'Soft Modeling: the basic design and some extentions', in Jöreskog, K.G. and Wold, H. (Eds.): Systems Under Indirect Observations: Part II*, pp.1–54, North-Holland, Amsterdam.*

Yadav, R.; Pathak, G.S. (2016) Intention to purchase organic food among young consumers: evidences from a developing nation. *Appetite*, 96, 122-128