CHAPTER 4 : RESEARCH DESIGN & METHODOLOGY

This chapter is divided into nine sections, starting with a brief overview of the research process and then describing the research instrument development and measurement development process. Sampling methodology is briefly discussed in the following section. In the next section, the rationale behind choosing partial least square path modelling, which is extensively used in this thesis, is described. After this, data analysis procedure adopted in this thesis is described with justification for the same. Finally, the analytical strategy of measurement is mentioned, after describing the data collection procedure.

4.1 Overview of Research Process

The research work presented in this thesis is primarily quantitative in nature. Partial Least Square Path modelling has been used throughout the research process. Two extensive surveys were conducted for the primary and the corollary study. The final model, as conceptualized for the primary study, is gradually built with a bottom-up approach. Thus, each building block related to antecedents of trust in OSMM is first examined. Finally, a comprehensive model is empirically evaluated with Hierarchical Component Modelling in order to find out the comparative effect of each building block on the outcomes of trust.

The items related to constructs tested in these studies have been chosen from highly cited earlier research works, which were then modified to suit the present context of OSMM. In both the studies, the data sets were checked to establish their suitability for analysis. Various processes which were used to examine these conformities are described briefly below.

4.2 Research Instrument Development

All items were measured with minor modifications from past research to suit the present context on a multi-item 5-point Likert scale in the range of 1 to 5, in which 1 denoted strong disagreement and 5 conveyed strong agreement. A five point Likert scale was selected to measure the construct items, as it balances parsimonious design with room for response. Although many scholars advocated the use of wider range of scales (such as 7 or 10), research showed that results obtained from these three scales showed similar characteristics in terms of mean, variance, skewness and kurtosis, on application of a simple transformation (Dawes, 2008). Moreover, phrases like “somewhat agree” and “somewhat disagree” does not offer any discernible psychometric advantages, since many respondents find them ambiguous. Besides this, the 5 point scale has an advantage in decreasing the central tendency bias, which is one form of response bias (Chengqi, Shim, & Otondo, 2010).

Constructs which are measured by items, that are not mutually interchangeable (Jarvis, MacKenzie, & Podsakoff, 2003), are a combination of indicators (Fornell & Bookstein, 1982) and represent consequences of the construct (Rossiter E, 2002), are treated as formative constructs. On the other hand, reflective constructs describe personality traits or attitudes (Haenlein & Kaplan, 2004).

4.3 Measurement Development

The questionnaire was divided into two major parts: (1) demographic variables and (2) construct items. The respondents were asked to choose one from a list of three Indian online fashion retailers with whom they were acquainted. 74.3% chose Myntra, 22.4% Jabong and 3.3% opted for Zovi. All participants were provided the URL of these online stores as well as link to their social networking pages on Facebook, Google Plus, Twitter and LinkedIn. They were requested to visit the website of their preferred online store and its page on their preferred online social networking site, and remember these while responding to the survey.

According to a study done by Indian Institute of e-Commerce, by 2020 India is expected to generate $100 billion online retail revenue out of which $35 billion will be through fashion e-Commerce (PTI, 2015). Another report claims that revenue generated from online retail is projected to grow to US$ 60 billion by 2020 (IBEF, 2017). Online apparel is one of the more popular verticals, which along with computers and consumer electronics make up 42% of the total retail e-commerce sales (Capital Market, 2014). Because of this emerging importance of online fashion retail, three online retail stores participating in OSMM were chosen for the purpose of the primary study of this thesis.

4.4 Pre-Test and Pilot Study

A pilot study of the questionnaire was conducted with an expert panel consisting of two faculty members, two research scholars and a middle level executive working in a social media consultancy firm, who are both heavy users of online social media and online shopping. They examined the exhaustiveness of the survey items and provided suggestions regarding the clarity and accuracy of the questionnaire items as well as the degree to which the questions were overlapped. Their suggestions were implemented before proceeding with the survey questionnaire for the primary study.

4.5 Sampling Methodology

Minimum sample size required for Effect Size $f^2 = 0.15$, Error Probability $\alpha = 0.05$, Power $(1-\beta) = 0.80$ with maximum of 25 predictors in the measurement and structural model is calculated to be 172 (Figure 4.1), using G*Power (Faul, Erdfelder, Lang, & Buchner, 2007). This was ensured during the final analysis for the primary study.

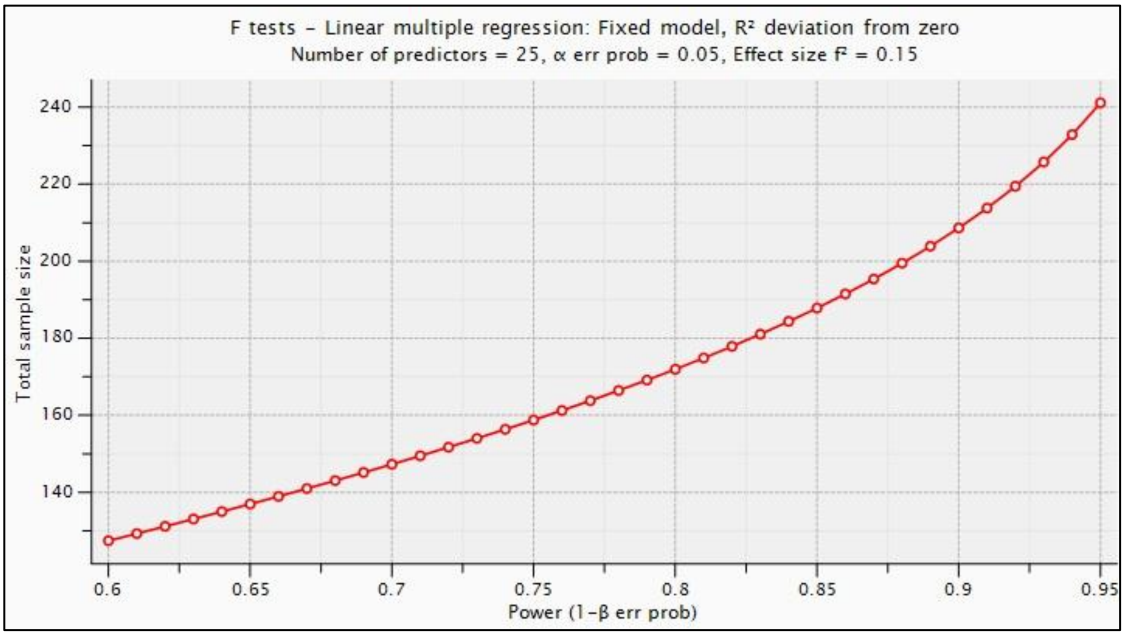

Figure 4.1: Sample size calculation using Power Plot from G*Power 3.0

4.6 Appropriateness of Statistical Method

4.6.1 Rationale behind Choosing Structural Equation Modelling

For more than a century statistical analysis has become an essential tool for researchers of social science. With the advent of computer and sophisticated software, applications of statistical methods have increased exponentially. Researchers have graduated from univariate and bivariate analysis to multivariate data analysis techniques for comprehension of more complex relationships by applying statistical methods that simultaneously analyse multiple variables.

Statistical techniques for data analysis may be broadly divided into first generation and second generation. Linear Regression, ANOVA, MANOVA, Principle Component Analysis, Discriminant Analysis and Multiple Regression are some examples of the first generation statistical techniques. Structural Equation Modelling techniques fall under second generation category.

Advantages offered by Structural Equation Modelling (SEM) make it the method of choice in analysing path diagrams when these involve latent variables with multiple indicators. These latent variables cannot be measured directly (e.g. beliefs, intentions, feelings etc.), but can be only gauged indirectly through characteristics attributed to them. Such latent variables should be based on relevant theory when they are expressed through measured variables like questionnaire scales (Churchill Jr., 1979).

SEM integrates the measurement model and the hypothesized structural model into a simultaneous assessment. It can be used to analyse many stages of independent and dependent variables and the error terms into a single unified model. This unified measurement and structural model is then estimated, either together as in Co-variance Based Structural Equation Modelling (CBSEM) or iteratively as in Partial Least Square (PLS) Structural Equation Modelling, and the results are presented as a single unified model in which the path estimates of both the measurement and the structural models are presented as a whole through a single, systematic and comprehensive analysis. This process allows a better estimation of both measurement and structural relationships in both CBSEM and PLS. Moreover, SEM allows creation and estimation of models with multiple dependent variables and their interconnections simultaneously, unlike linear regression. On the other hand, first generation statistical techniques like linear regression, ANOVA, MANOVA etc. can analyse only one layer of linkages between independent and dependent variables at a time. In addition, second generation techniques are better suited to handle moderation and mediation. Thus, the SEM estimates are better than those produced by linear regression, provided the distribution assumptions hold.

4.6.2 Brief Comparison of Covariance Based SEM and PLS SEM

The two most widely used types of SEM in social science research- PLS and CBSEM- are very different in their underlying philosophy, distributional assumptions, and estimation objectives (Gefen, Rigdon, & Straub, 2011). PLS has established its supremacy in exploratory research and shares the modest distributional and sample size requirements of ordinary least squares linear regression. However, since PLS does not allow the researcher to explicitly model the measurement error variance/covariance structure as in CBSEM, it yields biased parameter estimates (Chin, 1998a, 1998b, 2010).

On the other hand, CBSEM addresses the problem of measurement error by explicitly modelling measurement error variance/covariance structures and relying on a factor analytic measurement model for isolating random measurement error (unreliability). Systematic measurement error unique to individual observed variables is also separated from the latent variables, by defining the communalities of the observed variables (Jöreskog, 1979). Still, systematic measurement error shared across observed variables, arising through common method effects or use of otherwise invalid measures, may contaminate the latent variables and remains a potential confound.

PLS path modelling attempts to resolve the measurement error problem by optimizing proxies, consisting of weighted sum composites of the observed variables, for the latent variables to maximize the explained variance of dependent variables. Random measurement error being unpredictable, maximization of explained variance tends to minimize the presence of random measurement error in these latent variable proxies.

CBSEM's reliance on carefully developed measures based on strong theory marks it as a technique primarily used for confirmatory methodology. In spite of recent attempts by researchers to introduce more flexible measurement models, consistent with exploratory analysis, CBSEM's limitations as an exploratory method have long been noted (Spirtes, Scheines, & Glymour, 1990).

In contrast, PLS path modelling was initially envisioned to analyse data-rich by theory-primitive situations, characterised by emphasis on prediction of latent variables to account for the observed dependent variables. Lack of an overall inferential test statistic coupled with an ability to accommodate secondary data mark PLS as a tool well suited for exploratory research. However, Chin (2010) argues that PLS path modelling is also useful for confirmatory research.

4.6.3 Advantages of Partial Least Square Structural Equation Modelling

Wold's partial least squares structural equation modelling (PLS-SEM) approach (Wold, 1974, 1982) and the advanced PLS-SEM algorithms by Lohmoller (1989) have enjoyed steady popularity as a key multivariate analysis method for research in marketing (J. F. Hair, Sarstedt, Ringle, & Mena, 2012), strategic management (Joseph F. (Joseph F. Hair, Sarstedt, Pieper, & Ringle, 2012), accounting (Lee, Petter, Fayard, & Robinson, 2011), international marketing (Henseler, Ringle, & Sinkovics, 2009), management information systems (MIS) (Gefen et al., 2011) and operations management (Peng & Lai, 2012). Figure 4.2 below, taken from Hair et al. (Hair, Hult, Ringle, & Sarstedt, 2016), proves the almost exponential rise in popularity and use of PLS in leading journals of Management, Marketing as well as MIS Quarterly [Please refer to the *Appendix B: List of Journals Considered for Elaborating the Popularity of PLS-SEM* for a list of the journals which have been considered for this purpose].

Partial Least Square (PLS) path modelling belongs to a family of alternating least squares algorithms that extend Principal Component Analysis (PCA) and canonical correlation analysis to estimate (mainly linear) relationships between latent variables (Lohmoller, 1989). It is especially useful in case of:

- Small sample size
- Non-normal data
- Exploratory research objectives
- Use of formatively measured latent variables

PLS-SEM allows the use of both formative and reflective measurement models. The absence of error terms while measuring formative constructs may be difficult to defend as one cannot really be certain that all possible causes related to the latent variable are accounted for by the indicators (Diamantopoulos, 2006). This is overcome by establishing an acceptable level of measurement validity before analysis of the structural relationships (Chin, 1998b).

The factor analytic measurement model of CBSEM provides better protection from measurement error only if covariances among observed variables conform to a network of overlapping proportionality constraints for all pairs of reflective measures of each latent variable across all other observed variables in the model. Deviation from these overlapping proportionality constraints results in correlated measurement error. This requires strong and clear conceptualization of latent variables based on highly developed theory (Churchill Jr., 1979; Mackenzie, Podsakoff, & Podsakoff, 2011) and calls for multiple rounds of data collection, testing and refinement. On the other hand, PLS path modelling does not require measurement errors to be uncorrelated, because of its reliance on weighted composites.

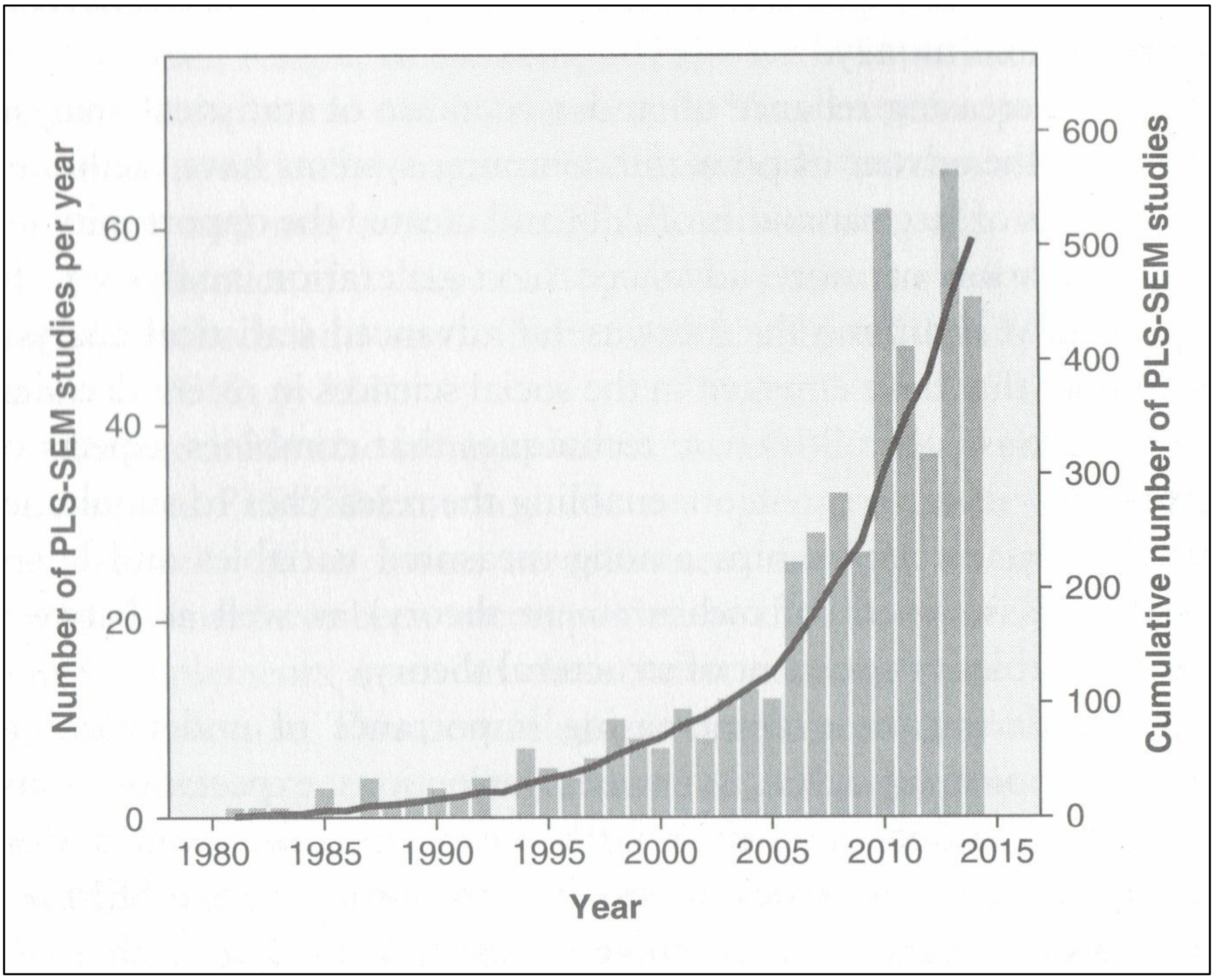

Figure 4.2: Number of PLS-SEM studies in management, marketing and MIS Quarterly

Since the data collected for both the primary and corollary study were found to violate multivariate normality, along with existence of both formative and reflective indicators, PLS Path Modelling was considered appropriate for data analysis.

4.7 Data Analysis Procedure

As a part of data cleansing, 12 responses were ignored for the analysis as these respondents took less than one-third of the median time of all respondents. Presence of junk data or apparent casual attitude toward some questions resulted in deletion of four more responses. Thus, 424 usable complete responses were acquired and used for the present analysis. The logic behind performing this procedure is briefly discussed in the following sub-sections.

4.7.1 Missing Data

As with other statistical analysis techniques, PLS also requires appropriate treatment of missing values. Missing data may arise when a respondent purposefully or inadvertently fails to answer one or more question(s) in a survey. A high proportion of missing data on a single data or more than 15% missing data on a questionnaire calls into question the validity of the data collected in a survey. This may require the entire survey or the construct in question to be removed from the questionnaire. Generally, a high proportion of missing data on a construct may indicate that the construct is perceived to be too sensitive by the respondents.

Missing data can be treated by considering any of mean replacement, expectation maximization algorithm, nearest neighbourhood, provided the missing value is below 5% per indicator (Hair, Hult, Ringle, & Sarstedt, 2014). Deleting all observations containing missing values may also be considered. But, doing so decreases variation in the data and may lead to bias, if certain groups of observations are deleted systematically.

The software primarily used for data analysis of this thesis- SmartPLS 3.0- offers two options to treat missing value: mean value replacement and case-wise deletion. Due to some technical glitch in the survey platform, a very small portion of data (4 indicator items from 27 respondents) was not recorded. Since this data does not correspond to any particular group of respondents and constitutes a very small proportion of the total data collected, mean value replacement algorithm was applied.

The demographic profile (age and gender) of the respondents with missing data was compared with that of the entire respondent profile. No significant difference in this regard was observed between these two groups ($p<0.05$).

4.7.2 Insufficient Effort Responding

Insufficient Effort Responding (IER) behaviour is generally caused by little or low motivation to comply with survey instructions, correctly interpret the content and provide accurate responses (Huang, Curran, Keeney, Poposki, & DeShon, 2012). This may seriously affect validity of the analysis and give rise to either Type-I or Type-II errors. Some of the approaches to deal with this issue are infrequency approach (asking the respondents to pick up an obvious choice), repeated item approach (asking the same question in different ways multiple times), inconsistency approach (checking response to highly correlated questions), response pattern approach (detection of suspicious response pattern across a series of items) and response time approach (checking for time taken by the respondent to complete the survey) (Liu, Bowling, Huang, & Kent, 2013).

In the surveys conducted, particular attention was given to this kind of responses and was tackled primarily with the help of repeated item approach, inconsistency approach, response pattern approach and response time approach. For example, in the first empirical study, respondents were asked to reveal on an average how long they were generally online and how long they used different Social Media Sites, namely Facebook, Google Plus, LinkedIn and Twitter. Anyone stating more time online in any of these OSM sites than the internet would be suspicious and removed from the data set collected. Similarly, they were asked the purpose behind their usage of these OSMs. A respondent who had earlier stated that (s)he did not use some of these sites, but later marked his (her) purpose behind using those sites would call for attention and that entire data set would be removed from the responses collected.

In another part of the survey respondents were also requested to reveal their likelihood of purchase from their preferred online store within the next 3 months, 6 months or during any time. An inconsistency in these responses have been dealt accordingly and removed from the dataset.

Straight-lining (respondent answers the same option for each item) and Christmas Tree Behaviour (picking up the options in a Christmas tree like pattern) were checked in the responses and were not found to be present.

Respondents who took less than one third of the median time taken by all respondents to finish the surveys had their responses removed from further analysis.

4.7.3 Outliers

Extreme response to a particular question or all questions constitutes outliers. Partial Least Square Structural Equation Modelling may be influenced by outliers as the OLS regression used in this technique is affected (Hair, Black, Babin, & Anderson, 2009). Generally any value that lies more than one and a half times the length of the box plot from either end of the box away is considered as an outlier (Tukey, 1977). But Hoaglin et al (Hoaglin, Iglewicz, & Tukey, 1986) suggested that the 1.5 multiplier was inaccurate 50% of the times, and suggested 2.2 as more valid multiplier in a lot of applied cases.

In the empirical studies conducted during this thesis work, responses related to constructs were collected on a Likert scale. Therefore, there was not much concern for outliers. Still, wherever applicable, data was cleansed depending on age, average duration of weekly internet usage, income and expenditure for online shopping.

4.7.4 Multivariate Normality

Most of the multivariate procedures and statistical tests assume multivariate normality. This indicates that each variable and all linear combinations of the variable are normally distributed (Tabachnick & Fidell, 2007). Statistical inferences become less robust as distributions deviate from normality. If the individual variables are not normally distributed, then that scenario indicates violation of multivariate normality assumption. Since it is difficult to test the huge number of linear combinations of variables, many researchers generally test the univariate normality as indicative of multivariate normality. The same has been followed in this thesis [Please refer to *Appendix C: Descriptive Statistics and Univariate Normality Assessment*].

In addition to this, a web-tool application based on the MVN package from R was utilized to assess multivariate normality (Korkmaz, Goksuluk, & Zararsiz, 2015) [Please refer to *Appendix D: Multivariate Normality Assessment (Primary Study)*]. Both the analyses found that the data collected for the study violated multivariate normality assumption.

4.7.5 Multicollinearity

Multicollinearity can be problematic from a methodological and interpretational standpoint in case of formative measurement models. The issue becomes even more severe when two or more formative indicators with exactly the same information in them are entered in the same block of indicators. This results in a singular matrix during the model estimation and PLS-SEM fails to estimate one of the two coefficients. Redundant indicators used as single items to measure two or more constructs may give rise to multicollinearity issue in the structural model. High levels of multicollinearity between formative indicators impact estimation of weights and their statistical significance. It boosts the standard errors, thereby reducing the ability to demonstrate that the estimated weights are significantly different from zero. Because of high multicollinearity, weights are incorrectly estimated and their signs may be reversed.

The level of collinearity can be assessed by Tolerance, which represents the amount of variance of one formative indicator not explained by other indicators in the same block. The square root of Variance Inflation Factor (VIF), which is the reciprocal of Tolerance, indicates the degree to which the standard error has been increased due to collinearity. To check for severe multicollinearity, formative indicators were assessed against Tolerance value of 0.2 or lower and a corresponding VIF value of 5 or higher respectively. The measurement values are reported during different sets of analyses conducted as a part of the thesis work.

4.7.6 Common Method Bias

Common method bias is a major threat to behavioural research. Self-reported measures are problematic as they are tied together in the minds of the respondents (Straub, Boudreau, & Gefen, 2004). Two approaches have been recommended to minimize the effect of common method bias: (i) a two-method comparative solution can be adopted wherein the actual behaviour of the respondents can be compared with their responses once they have completed the survey; (ii) a statistical standpoint can be taken by randomizing the order of items (Straub et al., 2004). Considering the time and cost involved in executing the first option, the second one was chosen to reduce common method bias.

4.7.7 Non-response Bias

Non-response bias is a major limitation of survey data collection method. It may arise because of various reasons like length of the survey, wording of the questionnaire etc. Presence of non-response bias may affect content validity. To minimize non-response bias, the questionnaire was kept as short as possible. This led to deletion of certain redundant items from established scale, as suggested by a 5 member expert panel, consisting of heavy users of social media and online shopping. Moreover, the respondents were assured of some gift for their effort and sincerity to complete the survey properly, besides some of them being randomly given more valuable surprise gifts. The online software platform- SurveyGizmo- used for conducting the survey also ensured that all necessary conditions for questionnaires were met.

Statistical procedure suggested by Hill et al (Hill, Roberts, Ewings, & Gunnell, 1997) to examine non-response bias was adopted. The respondents were divided into two groups based on the time of completion of the survey (early and late) to compare demographic data of these respondents for obtaining a perspective of data consistency. Consistent results indicate that the respondents are likely to be free from non-response bias in the sense of social background. Demographic details such as, age, gender, education level, average duration of internet usage etc. were checked using ANOVA and was found to be free from non-response bias.

4.7.8 Exploratory Factor Analysis

Researchers often use confirmatory factor analysis (CFA) before model evaluation using PLS-SEM. Proponents of this method suggest to avoid this practice and instead evaluate these measures via PLS-SEM statistics (Ringle, Sarstedt, & Straub, 2012). Therefore, Exploratory Factor Analysis was not conducted.

4.7.9 Heterogeneity

PLS path modelling assumes that the analysed data stem from a single population. But this assumption of homogeneity is unrealistic, since individuals are likely to be heterogeneous in their perception and evaluation of latent constructs (Jedidi & Jagpal, 1997; Sarstedt & Ringle, 2010). Two popular methods to estimate heterogeneity are Finite Mixture PLS (FIMIX-PLS) and PLS Prediction-Oriented Segmentation (PLS-POS).

FIMIX-PLS is regarded as the primary approach of all response based segmentation approaches to deal with unobserved heterogeneity (J. F. Hair et al., 2012; Sarstedt, 2008). Sarstedt introduced a non-parametric permutation based approach which utilise bootstrap confidence intervals for multi-group analysis. This maintains the family-wise error rate, does not rely to distributional assumptions and exhibits an acceptable level of statistical power (Sarstedt, Henseler, & Ringle, 2011).

On the other hand, PLS-POS is a distance based segmentation method that is appropriate for PLS path models with both reflective and formative measures and is able to uncover unobserved heterogeneity in formative measures. It uses an explicit PLS-specific objective criterion to form homogeneous groups and ensures continuous improvement of the objective criterion throughout the iterations of the algorithm (hill-climbing approach). This approach is found better than FIMIX-PLS as it overcomes the assumption of FIMIX-PLS that the endogenous latent variables in the structural model have multivariate normal distribution, and uses latent variable scores in the structural model based on the measurement model for the over-all sample, ignoring possible heterogeneity in the weights of the measurement mode (Becker, Rai, Ringle, & Völckner, 2013).

Considering implementation issues, Hair et al (Matthews, Sarstedt, Hair, & Ringle, 2016) suggests using a combination of FIMIX-PLS and PLS-POS. They suggest using FIMIX-PLS for providing segmentation retention criteria based on various Fit Indices, which would be taken as starting solution for running PLS-POS for improving upon it to discover heterogeneity.

The optimal solution during FIMIX-PLS is the number of segments with the lowest value, except in terms of Normed Entropy (EN), where a higher value indicates better separation of segments. If Akaike Information Criterion with factor 3 (AIC_3) and Consistent Akaike Information Criterion (CAIC) indicate the same number of segments, then the result likely points to the appropriate number of segments to be retained. AIC_4 and BIC have been found to perform well. AIC often over-estimates the number of segments, whereas Minimum Description Length 5 (MDL_5) shows pronounced underestimation tendencies. Thus, AIC and MDL_5 may be used as the range within which reasonable number of segments would lie. EN values above 0.5 indicate clear classification of data into the predefined number of segments (Ringle, Wende, & Will, 2010). Since missing values highly influence the outcome of heterogeneity analysis, case-wise deletion of records for missing value is suggested. Besides this, FIMIX-PLS should be run multiple times to avoid possible occurrence of a local optima. The segments thus generated should be substantial, differentiable and plausible. This needs to be checked by different heuristics processes, as there is no exact statistical test to accomplish this task (McLachlan & Peel, 2000). These suggestions have been followed during examination of heterogeneity.

4.7.10 Construct Validity

Factorial validity is important for establishing validity of latent constructs or latent variables, which represent research abstraction that cannot be measured directly (e.g. beliefs, perceptions etc.). Conventional research practice suggests measuring abstractions indirectly through several items in a research instrument (Churchill Jr., 1979). Each such measurement item is assumed to reflect only one latent variable. The property of each measurement item in a scale to relate better to it than any other is known as unidimensionality. In the context of PLS, unidimensionality cannot be measured, but is assumed to be there a priori (Gefen, 2003; Gerbing & Anderson, 1988).

Two elements of factorial validity of latent constructs are examined and measured in PLS (Churchill Jr., 1979; Gerbing & Anderson, 1988): (a) Convergent Validity and (b) Discriminant Validity. Together these two constitute Construct Validity (Straub et al., 2004).

Convergent validity ensures that each measurement item correlates strongly with its assumed theoretical construct. On the other hand, discriminant validity establishes that each measurement item correlates weakly with all other constructs.

Factorial validity is generally used with Exploratory Factor Analysis with the help of different estimation methods in first generation regression models. PLS, in contrast, performs Confirmatory Factor Analysis (CFA) (Gefen & Straub, 2005). Convergent validity is assumed when each measurement item loads with a significant t-value on its latent construct. Discriminant validity is ensured when

- The correlation of the latent variable scores with the measurement items load highly on their theoretically assigned factor and not highly on others
- The square root of every Average Variance Explained (AVE) is much larger than any correlation among any pair of latent constructs (Chin, 1998a).

AVE exhibits the ratio of the sum of the measurement item variance of each specific construct to the measurement error attributed to its items.

After critical examination, recent research has found some drawbacks associated with both cross-loading and Fornell – Larcker criteria for evaluation of discriminant validity. As a remedy, Henseler et al (Henseler, Ringle, & Sarstedt, 2014) proposed assessing the heterotrait-monotrait (HTMT) of the correlations. It is “the mean of all correlations of indicators across constructs measuring different constructs” (Hair et al., 2016). An HTMT value above 0.90 suggests a lack of discriminant validity. When constructs in the path model are conceptually distinct, a threshold value of 0.85 is acceptable (Henseler et al., 2014).

Content validity ensures that all legitimate measures of a construct are covered. To ensure this, an expert panel of two faculty members, two research scholars and an middle level executive working in a social media consultancy firm, who are both heavy users of online social media and online shopping, examined the exhaustiveness of the survey items. Besides examining the content validity, these experts also checked the clarity and accuracy of the questionnaire items and the degree to which the questions were overlapped. Following their suggestions, few modifications were made in the survey items.

4.7.11 Mediation Analysis

Mediation analysis is performed following categorization provided by Zhao et al. (Zhao, Lynch Jr., & Chen, 2010). The mediation analysis procedure is adapted from Preacher and Hayes (Preacher & Hayes, 2008). Since this process involves Bootstrapping procedure without any assumption about normality of distribution, this process is preferred to the more commonly used Sobel's test.

4.8 Data Collection Procedure

Self-administered online survey was conducted for the purpose of data collection. Considering the various technical abilities provided by SurveyGizmo (eg. branching, looping, randomizing, availability of various question types, security and data analysis), it was chosen as the platform for collecting responses through an online survey.

Proportion of data collected through online survey has now exceeded 60% in the USA and 50% in many other developed countries (Hair et al., 2014). Reduced cost, attention to comfort and privacy of the respondents, ability to verify some characteristics of data at the time of completion of the survey and possibility to reduce missing data have led to the growing popularity of online surveys. Moreover, online surveys can help to obtain a large sample, control question order and analyse non-response bias easily (Evans & Mathur, 2005). Access to good sample list from various institutes, where survey was conducted, also facilitated adoption of online survey for this thesis. As the studies conducted in this thesis are concerned with people's online behaviour, this form of data collection was found to be helpful. Reminders were sent periodically to respondents to complete the survey questionnaire.

Almost 28% of Indian population lies in the age group of 15-29 years (Ministry of Home Affairs Government of India, 2011). Since a large chunk of this age group comprises students and the tech-savvy new generation, who are the most active users of various OSM as well as consumers of online shopping, students of undergraduate and postgraduate levels in highly reputed Indian technical institutes were chosen as respondents for the survey of this study to empirically verify the proposed conceptual model.

For the purpose of the primary research, 9269 students pursuing graduate and post-graduate courses in reputed technical institutes (Indian Institutes of Technology and BITS Pilani) in different parts of India were invited through e-mails to take part in an online survey, powered by Surveygizmo. This included all e-mail IDs available online of the students of the selected institutes and hence may be considered as saturated sampling. The participants of the survey were provided 30 days to finish it, with option to pause and resume the survey at their will. This was done to minimize respondent fatigue, as the original survey would take approximately 30-35 minutes to be completed.

Data was collected online in two different ways. One set of respondents came to the survey venue and filled in the questionnaire online in the presence of the researcher. Another set of respondents filled the questionnaire from the comfort of their own place and time. Initially, the first method was adopted to ensure that respondents were able to clarify their doubts and they filled the survey sincerely. This led to collection of 115 responses. This stage helped in understanding the common doubts related to the survey and therefore, necessary modifications were done in the questionnaire. In order to collect more responses from different places of India, the modified questionnaire was sent to all Indian Institutes of Technology and BITS Pilani. This stage resulted in collection of 326 more responses.

Data collected through the two methods were compared with the help of t-Test on time taken for completion. No significant difference in this regard was observed between these two methods adopted.

Out of 728 students who expressed their willingness to participate in the survey, 440 completed it, resulting in 60.58% completion rate. Length of the survey, rapid proliferation of online surveys and infrequent use of e-mail IDs might have lowered the response rate. Non-response bias was assessed to verify that early and late respondents were not significantly different based on their socio-demographics. t-Tests between the means of the early (first 50) and late (last 50) respondents showed no significant differences ($p < 0.05$).

Although some researchers prefer to avoid student samples, this thesis work considers this sample appropriate for several reasons. Bello et al. (2009) suggest that research topics related to fundamental processes, structures and outcomes are concerned with the basic characteristics of human nature that are relatively independent of context and life experiences. This kind of research involves studying aspects of human nature and propensity that can explain specific phenomena, and are likely to generalize across diverse populations, thereby making the use of student samples legitimate. Researchers such as Kardes (1996) and Lucas (2003) have also argued that college students are appropriate research subjects when the research emphasis is on basic psychological processes or the theory tested links to human behaviours independent of sample characteristics. Thus, if the focus of research is theoretical, the makeup of a sample does not matter (Mook, 1983).

Besides this, Online Social Networks are highly popular among youngsters (Dasgupta, 2013). College students are among the most active users of various OSM sites and constitute major target for e-Commerce sites currently. They will transform to major target market for a lot of other online sellers in the next few years. They have tremendous purchase power and influence on other cohorts (Duffett, 2015). This also makes the students appropriate respondents for the surveys conducted in this thesis work (Megehee, 2009). Moreover, high degree of similarity on psychographic dimensions of these college students enhances research validity because of their apparent homogeneity (Aaker & Sengupta, 2000; Peterson & Merunka, 2014).

Bello et al. (2009) mention that the use of student samples may pose a threat to a study's internal validity if the students do not possess the requisite knowledge to respond adequately to the experimental treatments or survey questions.

Since the research undertaken during this thesis work is greatly related to fundamental processes, the student sample considered for the studies possess necessary knowledge and experience to respond properly and they constitute a major target market for a lot of online sellers, students were perceived to be appropriate respondents for the various surveys conducted.

4.9 Analytical Strategy of Measurement

Path Weighing Scheme was applied with an initial value of 1 for each of the outer weights, setting the stop criteria to 0.00001. Mean value replacement was chosen for dealing with missing values. Maximum iteration was limited to 300. But all calculations converged much before that. To adjust for biases and skewness in the bootstrap distribution, Bias-Corrected and Accelerated Bootstrapping was done for a two-tail test at significance level 0.05 with 1500 samples and construct level sign change option.

During analysis of the measurement models, reflective indicators with outer loadings below 0.4 were removed straight away. Reflective indicators with outer loading above 0.4 but below 0.7 were removed in cases where the removal resulted in increased composite reliability or AVE above the threshold value of 0.7 or 0.5 respectively. Discriminant validity was checked using Cross-loading, Fornell-Larcker criteria as well as HTMT criteria. Indicators of formative constructs with t-Statistics less than 1.96 (5% level of significance) and outer loading below 0.5 were considered for deletion from further analysis (Hair et al., 2016). Moreover, the formative indicators were checked with the help of VIF values, taking the threshold at 5.