CHAPTER 4
METHODOLOGY

This chapter discusses the methodology used to investigate the constructs and relationships that define the hypothetical model on service quality, customer satisfaction and behavioural intentions. The research design of the study was executed in two phases. The first phase focused on development and refinement of the scales used to measure service quality. Phase II involved the actual testing of the developed perceived quality instrument and the model. A discussion of phase II of the research addresses sampling design, questionnaire development, and data collection. Chapter 4 concludes with a review of the statistical analysis used to test the hypotheses.

4.1 Research design

An exploratory research design was used to determine the dimensions of perceived service quality, as the purpose was to explore new insights into understanding the concept. Further, this study utilizes a cross-sectional research design to evaluate customer expectations and perceptions of service quality in banking and insurance sector. Based on the literature review, it is found out that the disconfirmation measure (P-E) of service quality provide richer information than the performance – based measures and have greater diagnostic value for managerial intervention. Hence perceived service quality is measured as a disconfirmation measure. But when the relationship between perceived service quality, customer satisfaction and behavioural intentions is studied, “perception only score” is used, as suggested by Parasuraman et al. (1993). This research further measured the customer satisfaction and behavioural intentions.
The Intent of this study is to develop a reliable and valid instrument based on the original ten dimensions of service Quality as proposed by Parasuraman et al. (1985). As there is lack of consensus in the existing literature on the issue of scales used to measure perceived service quality.
4.1.1 Domain specification

The ten determinants of service quality (Parasuraman et al.1985), that included tangibles, reliability, responsiveness, competence, courtesy, credibility, security, access, communication and understanding the customer and their descriptions served as the basic structure of the service quality domain from which items were derived for the development of measurement scale. In the literature review, the concept of service quality is discussed in detail.

4.1.2 Item generation

The initial pool of items, were developed from the inferences obtained by the review of the subject and from experience surveys. A semi-structured interview format was used whereby all interviewees were initially asked the same open-ended question. Based upon their responses, further questions were formulated to completely understand the interviewee's comments. As far as the required number of respondents is concerned, qualitative methodology indicates that subjects are interviewed until no new information is being revealed; that serves as an indication that sufficient research has been conducted (Berg 1998). In this case ten customers and three service providers each of banking and insurance services were selected for the Experience Survey. Some would argue that only the service providers can identify the dimensions of service quality; others would argue that only customer’s opinion matters. This study adopts both the perspective, as it is believed that both the groups will have valuable insights about perceived service quality.

The Interviews focused on –

- How customers evaluate service quality in banking and insurance industry?
- What are the key factors influencing the customer’s perceptions of service quality?

4.1.3 Preliminary scale development

Based on literature review and experience surveys with customers and service providers, an initial pool of fifty four items were derived. The initial scale was tested for content
validity by a panel of three academicians. The panel evaluated how well the content of a scale represents the measurements task at hand and based on their recommendations a final structure of ten dimensional forty nine item scale was developed.

4.1.4 Scale administration

Data for the initial refinement of the 49-item instrument were gathered from a sample of 200 customers. The sample size of 200 was chosen because other scale developers in the marketing area had used similar sample sizes to purify initial instrument (Churchill et al. 1974; Parasuraman et al. 1988). The respondents were distributed equally in service categories- insurance and banking. To qualify for the study, the respondents should be an adult, who had used the services for at least one year. The sampling technique used is purposive sampling. Each item in the initial instrument was used to collect two sets of information—one is the expectation about the firms in general in each service category and other is about the perception of a particular firm whose service quality was being assessed. A seven point scale ranging from “Strongly Agree” (7) to “Strongly Disagree” (1) with no verbal labels for scale ranging from 2 to 6, accompanied each statement.

4.1.5 Scale purification

The instrument was refined by analyzing the pooled data. The pooling was appropriate, as the basic purpose of this research was to develop an instrument that would be meaningful and reliable in assessing quality in banking and insurance sector. The process of purification of the scale began with reliability analysis. The coefficient alpha is computed for each of the ten dimensions. The criterion used to decide, whether to delete a particular item was the item’s corrected item-to-total correlation. The next stage of scale purification was examining the dimensionality of the reduced scale and was done using exploratory factor analysis.
PHASE II

Phase II involved the administration and testing of the perceived service quality instrument that was developed in phase I. This phase also involves the testing of model relating service quality, customer satisfaction and behavioural Intentions.

4.1.6 Questionnaire Design

Measurement of research constructs

After the process of scale purification the reduced scale was used for data collection in Phase II. In chapter two, literatures survey is done related to our research problem to identify suitable definition for each of the concept or constructs. In this stage, all constructs were defined clearly in to dimensions and items. There are three main constructs in the questionnaire. They are service quality, customer satisfaction and guest behavioral intentions. An introduction of the questionnaire stated the aim of this research and declared that all the information provided will be confidential and used for this study only. The questionnaire is composed of four major parts-

Part I : Consumer behaviour

This section comprised of information related to consumer’s behaviour, and their preferences. For eg.

- Which is your most preferred way for utilizing banking services?
- Which attribute of the bank do you value the most?
- How frequently do you visit the bank for transactions?

Part II : Service quality

The study of Parasuraman, et al., 1985 on determinants of service quality served as the foundation for the development of the initial research instrument. Quality is defined as an attitude, a multi-dimensional construct composed of differences between perceptions and
expectations. Phase I of this study purified the initial instrument and this reduced scale was used in this part of the questionnaire. While each statement is divided into two column statement, the format generates separate ratings for expected and perceived quality with two identical side by side scales. A seven point Likert scale ranging from “Strongly Agree” (7) to “Strongly Disagree” is used to measure the rating on customer’s expectations and perception of service quality. For e.g.:

<table>
<thead>
<tr>
<th>Statement - Service quality</th>
<th>Banks should possess the given feature</th>
<th>Your opinion on whether your bank possess a feature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employees giving personalized attention</td>
<td>1  2  3  4  5  6  7</td>
<td>1  2  3  4  5  6  7</td>
</tr>
</tbody>
</table>

Part III Overall quality and Customer satisfaction

This part has one item related to overall quality rating of the firm, and four items on overall satisfaction/dissatisfaction. A seven point scale ranging from “Excellent” (7) to “poor” (1) with no labels for scale ranging from 2 to 6, accompanied the statement on overall quality. To measure satisfaction, a seven point Likert scale ranging from “Extremely Satisfied” (7) to “Extremely Dissatisfied” (1) with no labels for scale ranging from 2 to 6, was used.

Table 4.1 Customer Satisfaction- Statements and Source

<table>
<thead>
<tr>
<th>Construct</th>
<th>Statement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customer Satisfaction</td>
<td>• I feel satisfied with the decision to choose this bank</td>
</tr>
<tr>
<td>Adapted from Westbrook &amp; Oliver (1991)</td>
<td>• My choice of this bank is a wise one</td>
</tr>
<tr>
<td></td>
<td>• I enjoy the experience with this bank</td>
</tr>
<tr>
<td></td>
<td>• I feel satisfied with overall services of this bank</td>
</tr>
</tbody>
</table>
Part IV: Behavioural Intentions

This part includes measuring consumer's behavioral intentions by asking possible actions they might take in future based on their overall experience. Again a seven point Likert scale ranging from “Extremely Likely” (7) to “Not at all likely” (1) with no labels for scale ranging from 2 to 6, accompanied each statement.

Table 4.2 Behavioural Intentions- Statements and Source

<table>
<thead>
<tr>
<th>Construct</th>
<th>Statement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Behavioural Intentions</td>
<td>• I would say positive things about bank to other people</td>
</tr>
<tr>
<td>(Adapted from Parasuraman et al. (1996))</td>
<td>• I would recommend this bank to my friends, relatives etc.</td>
</tr>
<tr>
<td></td>
<td>• I would continue using the services of this bank.</td>
</tr>
<tr>
<td></td>
<td>• I consider this bank as first choice on my list.</td>
</tr>
<tr>
<td></td>
<td>• I would continue using services of this bank, even if the charges are higher</td>
</tr>
</tbody>
</table>

Part V: Demographic details

This part would like to find out the respondents personal background in order to analyze the results of this research on the basis of this demographic data. The background information of the respondents includes - Gender, income, level of education, age, and occupation.

Pre-testing of Questionnaire

A pre-test of the questionnaire was conducted to assess the reliability of the items used in the survey (Cooper & Schindler, 2006). The purpose of a pre-test was to obtain feedback from customers to test the readability, comprehensibility, wording, order effects, and ambiguity of the question and to expose any other weaknesses in the questionnaire design and instrumentation (Hair et al. 1998). During the pre-test procedure, respondents were
encouraged to comment on any questions that they thought were unclear, ambiguous, or that they were unable to answer. Following this process, some minor changes were made to the survey questions. The final version of the questionnaire is in Appendix 2 and 3.

4.1.7 Sampling design

To qualify for the study, the respondents should be an adult, who had used the services for at least one year. The final data collection was done from a sample of 500 each for customers of insurance and banking services. The sampling technique used for this study is quota sampling. As the population in Gujarat State does not constitute a homogeneous group, quota sampling is used so as to obtain a representative sample. The classification variable used for purpose of this study was geographical region, where leading cities of Gujarat were included, namely Ahmedabad, Baroda, Surat, Rajkot and Bhavnagar. Further, to obtain a better representation of the population, the selected sample consists of respondents from different age groups, income levels and education levels.

Sample size estimation

Based on maximum likely hood principle for Proportion, sample size is estimated. The population proportion was assumed at p=0.5 and q=0.5, so as to generate largest possible numerator in the given formula for a given level of precision. At 95 percent level of significance and desired precision level of 5 percent, the sample size for the study was estimated by the formula:

\[ N = \frac{(p*q*z^2)}{D^2} \]

Where, p and q = 0.5 Therefore the estimated sample size of households for the study was 385 \([(0.50*0.50*(1.96)^2)/(0.05)^2\)] numbers of respondents.

Around 500 questionnaires each of banking and insurance were used to collect the required data, out of which 488 of banking and 479 questionnaire of insurance were complete in all respects. These questionnaires were used for further analysis.
4.1.8 Data collection procedures

The data collection for phase II of this study was gathered from questionnaires which were circulated to 500 customers each of banking and insurance sector. The respondents were assured confidentiality. Screened and qualified respondents were instructed to indicate two levels of service- first the level of service that should be offered by firms within the service category in question and second the perceptions about the firm, they had used and with which they were most familiar.

4.2 Data analysis procedures

The data was analyzed using SPSS software Version 17 and AMOS 18, once all the usable responses from the questionnaires were recorded and coded. Summary statistics was used to describe all sample characteristics, service quality items and items on customer satisfaction and behavioural intentions. Correlation statistics and regression analysis were used to study the relationship between different variables. To identify differences between two groups, independent t test was used.

The data was further assessed using statistical techniques- factor analysis, Structural Equation Modeling (SEM) and analysis of variance (ANOVA). Exploratory factor analysis was used to examine the underlying factors that make up the sub-dimension, SEM was used to test the hypothetical model, and analysis of variance was used to compare the results based on the demographic variables.

4.2.1 Descriptive statistic analysis

To better understand the characteristic of each variable for e.g. gender, age, education etc, descriptive statistic analysis has been applied to illustrate the mean, median, standard deviation of each research variable.

4.2.2 Scale Evaluation Techniques

A multi-item scale should be evaluated for accuracy and applicability. This involves an assessment of reliability and validity of the scale.
Reliability of the Measurement Scale

Reliability is the extent to which a scale produces consistent results if repeated measurements are made on the characteristic (Malhotra, 2004). Reliability of the scale measures is tested with the Cronbach Alpha value, which best reflects the internal consistency of the indicators that measure each construct (Churchill, 1979). The concept of internal consistency is that the individual items or indicators of the scale should be measuring the same construct and thus be highly correlated. Cronbach Alpha is a measure of squared correlation between true scores and observed scores. According to Nunnally (1978), the suggested value of coefficient alpha should be over 0.7. However a minimum satisfactory value of 0.60 can be considered acceptable as an indication of scale reliability (Hair et al. 2006; Malhotra 2007) for exploratory research.

Validity of the Measurement Scale

The validity of a scale may be defined as the extent to which differences in observed scale scores reflect true differences among objects on the characteristic being measured, rather than systematic or random errors. Most commonly researchers assess content and construct validity. Content validity consists of subjective but systematic evaluation of how well the content of a scale represents the measurement task at hand. To confirm content validity the scale was evaluated by a panel of three academicians.

Construct validity includes convergent and discriminant validity. Convergent validity consists of the extent to which the scale correlates positively with the other measures of the same construct. Confirmatory factor Analysis (CFA) within structural equation modeling (SEM) is a common method for construct analysis. If the measurement items of each construct have individual factor loadings of at least 0.50 and all measurement items are significant with t value greater than 1.96, we can conclude that the scale has convergent validity. Average variance extracted (AVE) and composite reliability are also considered when assessing convergent validity with threshold values (1) AVE at least 0.50 and (2) CR at least 0.70.
Discriminant validity is also a measure of construct validity that assess the extent to which a measure does not correlate with other constructs from which it is supposed to differ. In other words, it reflects the degree to which two conceptually similar concepts are distinct and the correlation here should be low. A SEM-based alternative approach to discriminant validity is to run the model unconstrained and also constraining the correlation between constructs to 1, namely to test, $H_0: \rho = 1$ versus $H_1: \rho \neq 1$ ($\rho$ is the correlation between paired constructs). If the two models differ significantly on a Chi-Square difference test (i.e., $\Delta \chi^2 > \chi^2_{1,0.05}$), we can conclude that the two constructs differ (Anderson & Gerbing, 1988).

4.2.3 Factor Analysis

Factor analysis attempts to bring inter-correlated variables together under more general, underlying variables. More specifically, the goal of factor analysis is to reduce “the dimensionality of the original space and to give an interpretation to the new space, spanned by a reduced number of new dimensions which are supposed to underlie the old ones” (Rietveld & Van Hout 1993). Assumptions regarding exploratory factor analysis are more conceptual than statistical, but it is important to establish the existence of sufficient correlations within the data matrix to justify the application of factor analysis.

Tests for Determining Appropriateness of Factor Analysis

- Examination of the Correlation Matrix: Researchers can visually inspect whether the number of correlations is greater than 0.30 (Tabachnick & Fidell 2007). If most of the number of correlations is not in excess of 0.30 in the matrix, then factor analysis is inappropriate.

- Bartlett’s Test of Sphericity: Bartlett’s test of sphericity is another commonly used, statistical test in determining the appropriateness of factor analysis. The test provides the statistical significance that the correlation matrix has significant correlations among at least some of the variables (Hair et al. 2006). The authors
also suggest that if a statistically significant Bartlett’s test of sphericity (significance value <0.05) exists, then there are sufficient correlations among the variables.

- Kaiser-Meyer-Olkin measure of sampling adequacy, MSA: The last measure in determining the appropriateness of factor analysis is the measure of sampling adequacy (MSA). MSA provides a measure to determine whether the variables belong together, and are therefore appropriate for factor analysis. The KMO index ranges from 0 to 1 with 0.60 suggested as the minimum value for a good factor analysis (Tabachnick & Fidell 2007).

**Factor Extraction**

Fundamental to the use of exploratory factor analysis is selection of the most suitable factoring method: component analysis or factor analysis. Principal Axis Factoring, is used in this research, as it the recommended technique when a researcher wishes to obtain parameter reflecting latent variables or factors (Widaman 1993).

**Factor Rotation**

Factor rotation makes the factor structure more interpretable when the dimensions are rotated. The goal of factor rotation is to manipulate, or to adjust, the factor axes to achieve a simpler and pragmatically more meaningful factor solution (Hair et al. 2006). Two factor rotation methods commonly used in computation are orthogonal and oblique rotations. When the factors are intentionally rotated and result in no correlation between the factors in the final solution, this procedure is called an orthogonal rotation (Hair et al. 2006). There are three major orthogonal approaches: VARIMAX, QUARTIMAX and EQUIMAX. Oblique factor rotations are similar to orthogonal rotations, except that oblique rotations allow correlation between the factors, instead of maintaining independence between the rotated factors (Hair et al. 1998). Oblique rotations are applicable when correlation between the factors is required since the factors are conceptually alike. Therefore, oblique rotations are appropriate for developing
theoretically meaningful factors or constructs (Hair et al. 2006). The two common methods in oblique factor rotation are OBLIMIN and PROMAX. OBLIMIN is a standard method that seeks a non-orthogonal (oblique) solution.

The orthogonal factor rotation method is frequently applied in marketing. However as selection of the best rotational method aids interpretation of factors, and since the underlying dimensions of perceived quality were believed to be correlated, an oblique rotation (Direct Oblimin) was used in this research.

**Interpretation of Factors**

When interpreting the interrelationships represented in factors, researchers need to identify those distinctive variables for each factor, as well as referring back to the conceptual foundation or the managerial expectations to ensure practical significance (Hair et al. 2006). Following criteria were used to assist in interpreting the factors:

- Only factors with Eigen values greater than 1 were retained for further investigation (Guttman-Kaiser rule). The Eigen value of a factor represents the amount of total variance explained by that factor.

- Items with Factor loadings of less than 0.30 were eliminated. As the goal of exploratory factor analysis is to retain only those items that represent the content domain of the dimension, items with factor scores less than .30 were eliminated unless they contributed conceptually to explain their respective dimensions.

- Variables that cross-load (load highly on two or more factors) is usually deleted unless theoretically justified or the objective is strictly data reduction. It was decided to delete any variable which has a loading of 0.32 or higher on two or more factors (Tabachnick & Fidell 2007).
A factor with fewer than three items is generally considered weak and unstable (Anna et al. 2005). So, a factor was retained only when it was defined by at least three variables.

Considering these criterions, items were deleted and iterative process of factor analysis was run again and again to obtain the clearest factor structure possible.

4.2.4 Structural Equation Modeling

Structural Equation Modeling (SEM) is a statistical technique for evaluating causal relationships using a combination of statistical data and qualitative causal assumptions. It is a multivariate technique combining aspects of multiple regression and factor analysis to estimate a series of interrelated dependence relationships simultaneously. Similar to multiple regression equation, the technique examines the structure of the relationships expressed in a series of equations. By using SEM, each variable needs to be linked to its theoretical construct in a reflective manner. SEM is mainly used as a confirmatory rather than an exploratory technique. So in SEM, models are often constructed to test hypothesis derived from theory. The superiority of SEM over other statistical technique is its ability to estimate multiple dependence relationships, represent latent variable in those relationships and estimate measurement errors in the process. The reasons for selecting SEM for data analysis were, firstly; SEM has the ability to test causal relationships between constructs with multiple measurement items (Hair et al. 2006). Secondly, it offers powerful and rigorous statistical procedures to deal with complex models (Tabachnick & Fidell 2001; Hair et al. 2006).

SEM is characterized by two basic models: (1) the measurement model and (2) the structural equation model. The measurement model depicts how the observed variables represent the latent or unobserved variables (construct). It represents the theory that specifies the observed variable for each construct and permits the assessment of construct validity. The observed variables are measured and are also referred to as measured variables, manifest variables, indicators or items of the construct. The measurement
model uses the technique of confirmatory factor analysis (CFA) in which the researcher specifies which variables define each construct (or factor). It seeks to confirm if the number of factors and the loadings of items on them conform to what is expected on the basis of theory. A Structural model shows how the constructs are interrelated to each other, often with multiple dependence relationships. It specifies whether a relationship exists or does not exist.

Sample size consideration
The sample size required for SEM depends upon several considerations including the complexity of model, estimation technique, amount of missing data, and amount of average error variance among the indicators and multivariate distribution of the data. In terms of complexity, models with more constructs or more measured variables require larger samples. Larger samples are also needed if there are less than three measured variables for each construct and communalities (a measure for average error variance of indicators) are smaller. According to Malhotra & Dash (2011) when there are more than five constructs, with several constructs being measures with fewer than three indicators and there are multiple low (less than 0.5) communalities, the sample size should be at least 400.

Assessing model fit
Goodness to fit measures the correspondence of the actual or observed input (covariance or correlation) matrix with that predicted from the proposed model. In other words, goodness of fit test is used to determine whether the proposed model should be or should not be rejected. However, assessing the overall goodness of fit for SEM is not as easy and straightforward as with other multivariate techniques. Instead of a single statistical test, a number of goodness of fit measures have been developed and used to describe the strength of the proposed model. The various measures used to assess fit consist of absolute fit, incremental fit and parsimony fit indices. Table 4.3 describes, various goodness of fit indices, with their corresponding guidelines, that were used to assess the model fit in the current study.
Table 4.3 Key Goodness-of-fit Indices

<table>
<thead>
<tr>
<th>Type of fit</th>
<th>Goodness of fit measure</th>
<th>Level of acceptable fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute Fit Indices</td>
<td>Chi-square (CMIN in AMOS output)</td>
<td>P(CMIN) &gt; 0.05 → Good fit</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CMIN/df &lt; 2 → Over fit</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2 ≤ CMIN/df ≤ 5 → Good fit</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CMIN/df &gt; 5 → Adequate fit</td>
</tr>
<tr>
<td></td>
<td>Root mean squared error of approximation (RMSEA)</td>
<td>RMSEA ≤ 0.05 → Good model fit</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.05 ≤ RMSEA ≤ 0.1 → Reasonable model fit</td>
</tr>
<tr>
<td></td>
<td></td>
<td>RMSEA ≥ 0.1 → Poor model fit</td>
</tr>
<tr>
<td></td>
<td>Goodness-of-fit (GFI)</td>
<td>GFI ≥ 0.9 → Good fit</td>
</tr>
<tr>
<td></td>
<td>Adjusted Goodness-of-fit (AGFI)</td>
<td>AGFI ≥ 0.9 → Good Fit</td>
</tr>
<tr>
<td></td>
<td>Root mean squared residual (RMR)</td>
<td>RMR ≤ 0.05 → Good model fit</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.05 ≤ RMR ≤ 0.1 → Reasonable model fit</td>
</tr>
<tr>
<td></td>
<td></td>
<td>RMR ≥ 0.1 → Poor model fit</td>
</tr>
<tr>
<td>Comparative Fit</td>
<td>Normed fit index (NFI)</td>
<td>NFI ≥ 0.9 → Good fit</td>
</tr>
<tr>
<td></td>
<td>Incremental fit index (IFI)</td>
<td>IFI ≥ 0.9 → Good fit</td>
</tr>
<tr>
<td></td>
<td>Comparative fit index (CFI)</td>
<td>CFI ≥ 0.9 → Good fit</td>
</tr>
<tr>
<td></td>
<td>Tucker-Lewis (TLI)</td>
<td>TLI ≥ 0.9 → Good fit</td>
</tr>
<tr>
<td>Parsimonious fit</td>
<td>Parsimonious goodness-of-fit index (PGFI)</td>
<td>PGFI &gt; 0.5</td>
</tr>
<tr>
<td></td>
<td>Parsimonious normed fit index (PNFI)</td>
<td>PNFI &gt; 0.5</td>
</tr>
<tr>
<td></td>
<td>Parsimonious comparative fit index (PCFI)</td>
<td>PCFI &gt; 0.5</td>
</tr>
</tbody>
</table>

Adapted from (a) Kelloway, 1998; (b) Byrne, 2001; (c) Kline, 2005
Using SEM technique, a confirmatory factor analysis (CFA) is computed and the relationships are tested using with the AMOS 18.0 software for the current study.

**4.2.5 Multiple Regression Analysis**

Regression is a statistical technique that is used to relate a dependent variable to one or more independent variables. Basically, there are two types of regression models: simple linear regression and multiple linear regression. Multiple linear regression is used in this study to test the relationship between customer satisfaction and dimensions of service quality.

The multiple regression analysis equation takes the form of:

\[ y = a + b_1X_1 + b_2X_2 + \ldots + b_nX_n \]

where \( y \) is the dependent variable, \( X \) is the independent variable The \( b_1, b_2, \ldots, b_n \) are the regression coefficients that represent, on average, to a unit of increase in independent variable, how much of an increase or decrease will occur in the dependent variable. Regression coefficients can be used to evaluate the strength of the relationship between the independent variables and the dependent variable. The \( c \) coefficient is the constant term, where the regression line intercepts the \( y \) axis. The \( r^2 \) value in the model provides a measure of the predictive ability of the model. The closer the value \( r^2 \) equals 1, the better the regression equation fits the data.

**4.2.6 Analysis of Variance (ANOVA)**

Analysis of variance (ANOVA) is a univariate procedure that “assesses group differences on a single metric dependent variable” (Hair et al. 2006). ANOVA is used to compare the statistical differences between three or more means (Hair et al. 2006). ANOVA tests the null hypothesis that the means of several independent populations are equal. This research uses ANOVA to examine customers’ perceptual differences of the constructs based on several demographic characteristics. The statistic calculated by ANOVA, which reveals the significance of the hypothesis that \( Y \) depends on \( X \). If the ANOVA test is
significant, it indicates that at least two of the groups have means that are significantly different from each other. To determine if the likelihood of any difference between the groups occurred, a critical value $P=0.05$ is generally taken as marking an acceptable boundary of significance. $P$ value needs to be less than 0.05 for the F ratio to be termed as significant.

4.2.7 Independent Sample t test
An independent sample t test is used when it is required to compare the mean score on some continuous variable for two different groups of subjects. The independent variable should be categorical (e.g. male/female), whereas dependent variable should be continuous. This test will explain whether there is a statistically significant difference in the mean scores for the two groups. The p value needs to be less than 0.05, for the t test to be termed as significant.
4.2.8 Data Analysis Summary

To summarise, the process of data analysis to be used in the current study is as follows:

**Figure 4.2 The Process of Data Analysis- Phase II**

1. **Descriptive statistic**
2. **Confirmatory factor Analysis (CFA)**
3. **Reliability and Validity**
   - Construct reliability
   - Convergent validity
   - Discriminant validity
4. **Structural Equation Model (SEM)**
5. **Analysing association between variables:**
   - Correlation & Regression
6. **Analysing differences between variables**
   - ANOVA & Independent t test
4.3 Chapter Summary

This chapter incorporated an account of the methodology and procedures that were used for the collection and analysis of data. It explores the rationale behind the selection of research design, sampling frame and the analysis techniques. The methodology used for the development of the scale used to measure perceived service quality is explained in detail. This chapter also includes the statistical procedures used to ensure the validity and reliability of the instrument.