CHAPTER 4

RESEARCH METHODOLOGY

Research involves all activities related to an investigation or experimentation aimed at the discovery and interpretation of facts, revision of accepted theories or laws in the light of new facts, or practical application of such new or revised theories or laws. This chapter discusses the research design and the methodology adopted to meet the various objectives of the study mentioned below.

- To Understand the structure of Service quality and to develop a valid scale for its measurement
- Identify the underlying key dimensions of banking service quality as perceived by banking customers
- To examine the linkage among perceived service quality with other variables such as Customer expectations, Customer satisfaction and behavioral intentions in banking context

To meet the first objective, psychometric soundness of alternate structures for perceived service quality construct need to evaluated using statistical tools. A scale development process as explained in sec 3.4 for perceived service quality construct leads to the second objective. The estimation of the theoretical model using appropriate statistical tools will reveal the linkages among various constructs considered in the study. This chapter will outline the development of tools while standardizing them
scientifically establishing validity and reliability for appropriate measurement of the phenomenon under enquiry. Quantitative analysis of data was done using statistical tools wherever applicable. This chapter further elaborates on the research design used in the present study including details of sample, development of research tools, and validation of instruments, data collection procedure and the statistical techniques employed for data analysis. In succeeding chapters, data analysis and results of the study are presented.

Table 4.1 various definitions of Research

<table>
<thead>
<tr>
<th>Author</th>
<th>Definitions</th>
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<tr>
<td>Fellows and Lui, 2003</td>
<td>A voyage of discovery</td>
</tr>
<tr>
<td>Naoum, 1998</td>
<td>An enquiry or investigation conducted in a careful, scientific and/or critical manner</td>
</tr>
<tr>
<td>Williams, et. al., 1996</td>
<td>A quest for answers that involves answers and understanding, adding that it involves “methodical investigations into a subject or problem.”</td>
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The term research generally implies an appropriate process and technique, which are employed in the quest for solutions to problems or answers to questions posed in the inquiry. The investigative process often involves defining a research question and selection of the techniques that will help to resolve the question. The credibility of the findings of any research is generally dependant on the conduct of the investigation (Williams et al 1996). A Research is strategy of enquiry that moves from underlying assumptions to research design and data collection (Myers 2009). Although there are other distinctions in the research modes, the most common classification of research methods is into qualitative and quantitative. At one level, qualitative and quantitative refer to distinctions about the nature of knowledge: how one
understands the world and the ultimate purpose of the research. On another level of discourse, the terms refer to research methods, that is, the way in which data are collected and analysed. Researchers prefer to use both quantitative and qualitative methods, depending on the kind of study and its methodological foundation (Brysman and Burgess 1999). The qualitative research adopted in this study was in the preliminary stage and basically of exploratory nature.

4.1 QUALITATIVE VS QUANTITATIVE RESEARCH

Qualitative research involves analysis of data such as words (e.g., from interviews), pictures (e.g., video), or objects (e.g., an artifact). It attempts to get an in-depth opinion from participants. Qualitative Research is collecting, analyzing, and interpreting data by observing what people do and say. According to Domegan and Fleming (2007), “Qualitative research aims to explore and to discover issues about the problem on hand, because very little is known about the problem. Qualitative research is much more subjective than quantitative research and uses very different methods of collecting information, mainly individual, in-depth interviews and focus groups (Myers, 2009). Maxwell, (1996) enumerates five research purposes for which qualitative studies are particularly useful:

- Understanding the meaning that participants in a study give to the events, situations and actions that they are involved with; and of the accounts they give of their lives and experiences;

- Understanding the particular context within which the participants act, and the influence this context has on their actions;

- Identifying unanticipated phenomena and influences, and generating new, grounded theories about them;
- Understanding the process by which events and actions take place; and
- Developing causal explanations.

Quantitative research generates statistics through the use of large-scale survey research, using methods such as questionnaires or structured interviews (Hittleman and Simon 1997). This type of research reaches many more people, but the contact with those people is much quicker than in qualitative research. Quantitative Research options have been predetermined and a large number of respondents are involved. By definition, measurement must be objective, quantitative and statistically valid. Simply put, it’s about numbers, objective hard data. The sample size for a survey is calculated by statisticians using formulas to determine how large a sample size will be needed from a given population in order to achieve findings with an acceptable degree of accuracy. Generally, researchers seek sample sizes which yield findings with at least a 95% confidence interval. The distinction between both approaches are more apparent than real (Robson (2002), and that research stands to benefit from the use of mixed method approach Creswell (2003). In fact, Robson (2002), points out that the use of “qualitative/quantitative” terminology in labeling research designs invites risk of miscommunication. In this study both qualitative and quantitative approaches were adopted at different stages of research process.

The rationale for adopting both methods was justifiable on following observations. The objective of the research was to identify certain dimensions capable of capturing the domain of service quality in a localized setting that was not explored in detail in prior studies. The first stage in the study was therefore conducted in an elaborative manner to identify and shortlist proper dimensions that are suitable and necessary in the endeavor. Researcher found a qualitative analysis of views expressed by participants in
the preliminary study followed by inductive analysis as most appropriate for the purpose of this research because all these procedures enhanced the possibility of exploring the topics in detail to develop clear directions for next stage.

The quantitative phase cannot be eliminated in this study for the simple reason validation of the scale and estimation of the theoretical model demands statistical procedures. Also generalisability of finding emerged from the study can be analyzed only through checking the significant levels, that presupposes sufficient sample size, randomness and related statistical considerations.

There are three general research design strategies discussed by theorists (Domegan and Fleming 2003; Malhotra and Birks 1999; Kotler et al 2001). They are Descriptive research, exploratory research and casual research. The goal Descriptive research is usually concerned with describing a population with respect to important variables and exploratory research is to discover ideas and insights about variables. Causal research is used to establish cause-and-effect relationships between variables Descriptive research is always used when statistical data and numbers are needed: for example research on customer demographics or purchase frequency. The tool used to conduct descriptive research is almost always survey. If the number of people asked to complete the survey is large enough compared to the total of population, the answer can be even be said to have been proved. Malhotra and Birks (1999) defined exploratory research as “research design characterized by a flexible and evolving approach to understanding phenomena that are inherently difficult to measure.” Malhotra and Birks (1999) define causal research as “conclusive research where the major objective is to obtain evidence regarding cause and effect relationships.” Causal research is very specific and conducted to discover whether the
change a company is planning to make will have a positive or negative effect on customers.

4.3 RESEARCH PROCESS

The research process involved two phases in this study as illustrated in Figure 4.1. Phase one included steps such as literature review, finalization of objectives, and identification of variables and development of Theory. Defining the goals and objectives of a research was one of the most important steps in the research process. Clearly stated objectives provided correct direction to the research process. The process of finalizing objectives was done by an exploratory research (e.g., literature reviews, talking to people, and focus groups) being the mostly adopted procedure. The literature review provided an opportunity to build on other’s work and impart clarity to the problem to be addressed in the study.

![Figure 4.1 Research Process adopted for the study](image)

Figure 4.1 Research Process adopted for the study
Research process adopted for this study included a set of advanced decisions that made the master plan specifying the methods and procedures for collecting and analyzing the needed information. The Research process for this study included stages such as exploratory, descriptive and causal researches. Firstly an exploratory research was conducted where the researcher attempted to find the nature of data required for the research and tried to define the problem more precisely. The researcher also attempted to identify relationships or associations between variables under study to develop the theory to be tested in the study in this stage. In the descriptive stage the details regarding research design was finalized. Causal research was conducted to examine the cause–effect relationship between variables under study in the analysis stage. The research design adopted for this study is explained in Figure 4.2.

Figure 4.2 Stages in Research process
4.2.1 Exploratory Research

Exploratory research forms the foundation of a good study (Churchill and Iacobuci 2004) and it has to be normally flexible, unstructured and qualitative (Aaker et al 2000, Burns and Bush 2002) and serves as an input to further research (Malhotra et al 1999). Exploratory research provided insights into and comprehension of an issue or situation. Exploratory research helped to determine the best research design, data collection method and selection of subjects. Exploratory research in this study was mostly by way of reviewing available literature, qualitative approaches such as informal discussions with consumers, employees, followed by more formal approaches through in-depth interviews with experts followed by pilot studies for testing the survey instrument.

4.2.1.1 The Preliminary Study

A preliminary study also known as key informant technique which taps the knowledge of those familiar with the topic of research was conducted by way of interviews with focus groups to identify the relevant dimensions to be considered for measuring variables considered for the study. In this study, Individual interviews with 20 banking professionals and 20 banking customers with more than 20 years of banking experience was conducted by the researcher to identify the exact nature of problem and dimensions to be considered while developing an instrument to measure customer expectation, service quality, customer satisfaction and behavior intentions in the banking context in Kerala. The 20 banking professionals were senior managers in different branches of various banks at Ernakulam, Kerala. Similarly 20 banking customers were selected across different professions including businessman, professional, retired service personnel, small scale merchants and house wives who have got more than 20yrs of banking experience. The
literature review produced an elaborative list of appropriate indicators from bank customer’s points of view (Appendix 4). The list was given to the experts and was requested to mark the indicators that they feel important in contemporary banking context. The experts were also requested to note down important dimensions they feel more sensible to capture the service quality perceptions. The analysis of the results of exploratory stage gave insights into the dimensions that should be highlighted in the study.

The expectation component of the study was divided into two parts. The first part dealt with dimensions which form the reasons for customer expectation about service quality. The various dimensions identified to measure reasons for customer expectation were past experience of the customer; word-of-mouth from other customers; personal needs of the customer and various communications received by the customer from the service provider such as service promises. The second part of expectation component dealt with measuring the desired expectations of the customer. The experts consisting of 20 banking customers marked their preferred attributes among various attributes shown to them.

The variable “expectation” was assumed to have critical influence in deciding perceived service quality and customer satisfaction. The following two questions were asked to the individual respondents in the focus group consisting of 20 experienced banking customers to streamline the dimensions for measuring expectation.

1. Why do you have expectations about services offered by banks?

2. What are your desired expectations about services offered by banks?
The results of the preliminary study (Appendix 4) helped to finalize relevant constructs and their measurements specific to contextual setting used in the study.

4.2.2 Descriptive Research

Having obtained some primary knowledge of the subject matter from the exploratory study, descriptive research was conducted. Contrary to an exploratory research, a descriptive study is more rigid, preplanned and structured, and is typically based on a large sample (Churchill and Iacobucci 2004; Hair et al 2003; Malhotra et al 1999). Descriptive research designs are basically quantitative in nature (Burns and Bush 2002; Churchill and Iacobucci 2004; Hair et al 2003). There are two basic techniques of descriptive research namely cross-sectional and longitudinal. Cross-sectional studies collect information from a given sample of the population at only one point in time, while the latter deals with the same sample units of population over a period of time (Burns and Bush 2002; Malhotra et al 1999). The cross-sectional study is also referred to as a sample survey in which selected individuals are asked to respond to a set of standardized and structured questions about what they think, feel and do (Hair et al 2003). For the purpose of this study, a cross-sectional study was the appropriate technique as opposed to a longitudinal study for the reason the data from different sample unit were needed to verify the relations between variables of interest in the study.

This study also opted for survey method rather than case study method or action research. The case study approach refers to a group of methods which emphasize qualitative analysis (Yin 2009), whereas an action research aims at finding a solution for an immediate problem facing a society or an industrial/business organization. A case study research is useful when a
‘how’ or ‘why’ question is being asked about a contemporary set of events over which the investigator has little or no control (Yin 2009). Data are collected from a small number of respondents through methods such as participant-observation, in-depth interviews, and longitudinal studies. The case study approach seeks to understand the problem being investigated. It provides the opportunity to ask penetrating questions and to capture the richness of concept, but the conclusions drawn may be specific and may not be generalizable. Lee (1989) identifies four corresponding problems with case study research - a lack of: Controllability, Deductibility, Repeatability and Generalizability. Jick (1983) suggests that survey research may also contribute to greater confidence in the generalizability of the results an essential purpose of this study.

The next stage in the research process was finalization of questionnaire, scale for marking responses, sampling design and data collection strategy. The procedures adopted are narrated in the following sections.

4.2.2.1 Questionnaire Design

This step involved selecting appropriate measurement scales, question wording and content, response format and finally the sequence of questions. The literature review and preliminary study in the form of in-depth interviews with the focus group have given a clear idea of the contents to be included in the questionnaire. The stages involved in questionnaire design process are shown in Figure 4.3.

The questionnaire in this study was designed as closed – end questions where the respondents have to make their response in a 5 point Likert scale varying from “Strongly disagree” to “Strongly agree”. This scale was adopted based on the following reasons (Kassim 2001):
- It yields higher reliability coefficients with fewer items than the scales developed using other methods (Hayes 1998)
- This scale is widely used in market research and has been extensively tested in both marketing and social science (Garland 1991).
- It offers a high likelihood of responses that accurately reflect respondent opinion under study (Burns and Bush (2002), Wong (1999); Zikmund (2000)).
- It helps to increase the spread of variance of responses, which in turn provide stronger measures of association (Aaker et al 2000; Wong 1999).

**Figure 4.3 Questionnaire design stages**

To understand the demographic profile of the respondents, questions related to Age, Sex, Qualification and Income etc were included. One of the minor objectives of the study was to identify the comparative
perception of service quality among customers of private Sector, Public Sector and new Generation banks. Hence a question to mention the name of the bank was included in the questionnaire. The respondents were asked to name only one bank with which they are having more interactions. A question to understand the respondent’s length of association with the bank was also included.

In relation to question content and wording, the questions were designed to be short, simple and comprehensible, avoiding ambiguous, vague, estimation, generalization, leading, double barreled and presumptuous questions (Kassim 2001). Use of negative worded questions are avoided to prevent confusion to respondents in answering the questions. The questionnaire contained questions related to all the indicator variables related to the constructs used for the study (Appendix 1).

The layout of the questionnaire was designed into five sections namely A, B, C, D and E. Part-A consists of general information and demographic profile of the respondent. Part-B contained 13 scale items for measurement of “Expectation” constructs. Part-C consisted of 28 scale items to measure Service Quality. The items related to each of the identified dimensions of the service quality construct were arranged together without mentioning the name of the assumed latent dimension. Part-D contained 12 scale items to measure constructs related to Satisfaction, Part-E contained 4 scale items to measure various Behavioral Intentions of the customer.

A pilot study was conducted by collecting responses from 50 respondents, who were banking customers in Ernakulam, Kerala. The 50 respondents were randomly selected from public sector, private sector and new generation banks in the area. The pilot study provided an opportunity to
detect and rectify a wide range of potential problems with an instrument. These problems may include:

- Questions that respondents don’t understand
- Ambiguous questions
- Questions that combine two or more issues in a single question (double-barreled questions)
- Questions that make respondents uncomfortable

In this study 4 questions were deleted from total of 61 scale items short listed by the expert panel after the pilot study as these questions were found confusing by respondents. One question from part B, three questions from part- C were removed to finalize the questionnaire (Appendix 1) ultimately used in the study.

4.2.2.2 Sampling Design

The sampling design explains the definite plan for obtaining a sample from the population i.e the entire group of people whom the researcher is interested to know about. In this study all the customers who utilize the service offered by the various types of banks in Cochin, kerala was considered as population for the study. The geographical territory considered for the study covered the entire district of Cochin in kerala state that has a population of approximately six lakh as per 2011 census. Even though the bank customers in the area considered as finite, due to lack of exact statistics on the actual number population size and considering the extant of banking penetration in the area, it was assumed that population for the study matches with population of the area. The major steps involved in sampling design was
Deciding the sample unit

Determining Sample size

Deciding the sampling Technique

The sampling unit is an element in the sample and in this study bank customer in Cochin is considered as the sampling unit. A sample represents any number of persons, units or objects selected to represent the population according to some rule or plan. The key to research lies in generating sufficient data so that the illuminate patterns, concepts, categories, properties, and dimensions of the given phenomena can emerge (Strauss and Corbin 1998). Therefore, it is essential to obtain an appropriate sample size that will generate sufficient data (Auerbach and Silverstein 2003). There has been considerable debate over what constitutes an acceptable sample size for the results to be statistically valid (Hinkin et al 1997), with there being no accepted rule to define an appropriate sample size (Flynn and Pearcy 2001). Different authors have suggested different sample sizes as appropriate, including an absolute sample from one hundred to two hundred (Flynn and Pearcy 2001), one hundred or larger (Hair et al 1998), and ratios of items to respondents from 1:4 to 1:10 (Hinkin 1995; Flynn and Pearcy 2001). To determine the sample size, Sample Size Calculator developed by M/S Creative Research Systems, available at www.surveystem.com was used. At the confidence level of 95% and confidence interval of 5 being generally accepted for social sciences (Cohen 1988), the sample size was calculated as 384. Hence a sample size of 500 was selected considering after rejection of invalid responses the final sample size should be more than 384.

Among sampling methods, probability sample are of much importance since most statistical tests fit on to this type of sampling method and also representativeness and generalizability will be achieved well with
probable samples from a population (Thompson 1997). Simple random sampling method was adopted to collect primary data using the structured questionnaire. The samples are selected on a random basis after visiting different branches of various banks in the city without any prejudice on considering or rejecting a particular respondent. The randomness was achieved as selection from all the customers present in the banks at the time of visit was purely by chance and not by prior decision.

4.2.2.3 Data Collection

The data collection was done personally by meeting the respondents individually. The structured questionnaire was distributed to respondents after meeting them and explaining them the purpose of the study. The respondents were met in the premises of banks and only those who offered willingness to participate in the survey are considered. The survey was conducted during the period January 2011 to March 2011. Completed responses from 500 respondents were scrutinized and incomplete responses were eliminated to get 385 full responses.

4.3 DATA ANALYSIS STRATEGY

Subsequent to the descriptive study, causal research was conducted. Descriptive studies may show that two variables are related but are insufficient for examining cause and effect relationships (Malhotra et al 1999). Causal research is most appropriate when the functional relationship between the causal factors and the effect predicted on the performance variable is under investigation (Hair et al 2003). This study was concerned the causal relationships between customer expectation, perceived service quality, customer satisfaction and behavior intentions. Hence, a causal experiment was appropriate to generate the type of evidences necessary to make causal
inferences about relationships between research variables (Parasuraman 1991).

A three level approach was adopted to analyze the data after screening the data for missing values, outliers, normality etc. The first attempt was to identify the existence of five distinct factors with regard to service quality construct by performing an exploratory factor analysis of 28 indicators used for measurement. The analysis confirmed existence of five factors and in the process one indicator variable was eliminated for poor loading.

The second attempt was to develop measurement models for all latent constructs considered for the study. Using Confirmatory factor analysis and by testing the goodness of fit measurement models were developed and final indicators capable of measuring the constructs were finalized. The structural model for Service quality construct was found to represent the data with 21 indicators belonging to five distinct dimensions based on goodness of fit criteria as shown in Figure 4.4.

**Figure 4.4 Model Evaluation stages**
Scale so confirmed was then tested for common methods Variance, Convergent validity, Discriminant validity and multiple group comparison for checking applicability to all group of assumed population. Also based on goodness of fit it was confirmed that service quality construct is a multidimensional second order formative construct with five first order reflective constructs.

Thirdly, the structural model with all the constructs which are measured either as reflective or formative were tested for its ability to represent the data as per guidelines for testing using Warp PLS 2.0. To assess the model fit with the data, it is recommended that the p-values for both the average path coefficient (APC) and the average r-squared (ARS) be both lower than .05. In addition, it is recommended that the average variance inflation factor (AVIF) be lower than 5 (Ned Kock 2009). The significant paths in the model are utilized for drawing various conclusions in the study.

4.4 STRUCTURAL EQUATION MODELLING

The purpose of many research projects is to analyze causal relationships between variables. SEM is a statistical technique for testing and estimating those causal relationships based on statistical data and qualitative causal assumptions. SEM is a confirmatory technique used to determine whether the model developed for the research is valid for data. SEM is a combination of factor analysis and multiple regression. The variables in SEM are measured (observed, manifest) variables (indicators) and factors (latent variables). The SEM can be divided into two parts. The measurement model is the part which relates measured variables to latent variables. The structural model is the part that relates latent variables to one another. Since this study required the hypothesized model to be tested for the best-fit of the data, SEM
seemed to be the appropriate analysis method as it produces more comprehensive overall goodness-of-fit.

Two complementary schools have come to the fore in the field of Structural Equation Modelling namely covariance-based SEM and component-based SEM.

- The first school developed around Karl Jöreskog which is considered as Covariance-based and is usually used with an objective of model validation and needs a large sample (what is large varies from one author to another: more than 100 subjects and preferably more than 200 subjects are often mentioned). The various methods of estimation used for covariance-based SEM, like Maximum Likelihood (ML) or Unweighted Least Squares (ULS), are full information methods. There are various software developed for performing this type of SEM like AMOS, LISREL, EQS etc.

- The second school developed around Herman Wold under the name "PLS" (Partial Least Squares). It is a partial information method. It is a two-step method: (1) latent variables scores are computed using the PLS algorithm and (2) OLS regressions are carried out on the LV scores for estimating the structural equations. There are various software developed for performing this type of SEM like PLS-Graph, SmartPLS, WarpPLS etc.

Recently Hwang and Takane (2004), have proposed a new full information method optimizing a global criterion and named Generalized Structured Component Analysis (GSCA). This new school can be considered as a generalisation of principal component analysis to the case of several data
tables connected by causal links. The method was implemented into a software program. Visual GSCA 1.0

PLS was considered ideal, if the conditions relating to sample size, independence, or normal distribution are not met, and if prediction is more important than parameter estimation. In this study both approaches are used in different stages of analysis.

In this study, for confirmatory factor analysis of the service quality construct, CBSEM based software Amos.16 was used and for the analysis related to conceptual model representing all the constructs, PLS based software WarpPLS2.0 was used. The choice of PLS was justified from two aspects. The first aspect was that PLS can accommodate both reflective and formative scales easily compared to covariance structure analysis. Although the inclusion of formative measures in CBSEM has been well documented (Joreskog and Sorbom 1996), analysts usually encounter identification problems. The second aspect was that PLS does not require any priori distributional assumptions and relatively small sample size is acceptable (Chin et al 2003).

4.4.1 Covariance Based Structural Equation Modeling

There are five distinct steps involved in analyzing a dataset using Covariance based SEM. They are:

- Model specification;
- Model identification;
- Measure selection, data cleaning and preparation;
- Model analysis and evaluation; and
- Model re-specification (Kline 2005).
Model specification involves mathematically or diagrammatically expressing hypothesized relationships amongst a set of variables (Kline 2005). A model is theoretically identifiable if there is a unique solution possible for it and each of its parameters. If a model is not identifiable, then it has no unique solution and SEM software will fail to converge. Such models need to be re-specified to be identifiable (Kline 2005)

The third step involves sub steps such as measure selection, data cleaning and data preparation. To measure each latent construct at least two observed variables (Joreskog 1977) are needed. In this stage it is examined whether sufficient observed variables are there to measure all the latent variables under study. Maximum Likelihood (ML) estimation is the preferred estimation procedure for SEM. The outliers, normality, missing variables etc should be identified and properly treated in this stage.

In Model evaluation using AMOS software involves the use of significance tests to assess the adequacy of model fit. Fit refers to the ability of a model to reproduce the data (i.e., usually the variance-covariance matrix). The fit measures generated by Amos output can be classified as shown in the following Table 4.2. There is wide disagreement among researches as to which fit indexes to report. Jaccard and Wan (1996), recommend use of at least three fit tests, one from each of the first three categories above, so as to reflect diverse criteria. Kline (2005) recommended the use of least four tests, such as chi-square; GFI, NFI, or CFI; NNFI; and SRMR

Many indices are affected by sample size and for this reason CMIN, GFI and AGFI is no longer a preferred measure of goodness of fit. The Parsimonious Fit Measures are used primarily to compare models on the basis of some criteria that take parsimony (in the sense of number of
parameters to be estimated). It is suggested that other goodness of fit measures are used to assess acceptable models and parsimony measures are used to select among the set of acceptable models. Hence are not used in this study where the primary aim is to develop a model which fit the data well. As the indices placed in the same group in above table measure about the same aspect of the model fit, it is decided to adopt most accepted fit indices from each of the above sets. Thus the following fit indices are considered ideal for the study.

### Table 4.2 Model Fit Measures

<table>
<thead>
<tr>
<th>Consideration</th>
<th>Fit indices</th>
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<tbody>
<tr>
<td>Absolute fit measure (reference to other models relevant in the situation)</td>
<td>CMIN, CMIN/df, RMR, SRMR, GFI, AGFI, PGFI</td>
</tr>
<tr>
<td>Relative fit measures (reference to an explicit basis model though unrealistic)</td>
<td>NFI, RFI, IFI, CFI, TLI</td>
</tr>
<tr>
<td>Parsimony measures (introduced by penalizing for lack of parsimony)</td>
<td>PRATIO, PNFI, PCFI</td>
</tr>
<tr>
<td>Fit measures based on non-central chi-square distribution</td>
<td>NCP, FMIN, FO, RMSEA</td>
</tr>
<tr>
<td>Information theoretic fit measures (to choose among several realistic but different models)</td>
<td>AIC, BIC, BCC, ECVI, MECVI</td>
</tr>
<tr>
<td>Fit measures based on sample size</td>
<td>HOELTER</td>
</tr>
</tbody>
</table>

David Garson (1998) recommends reporting chi-square (CMIN), RMSEA, and one of the baseline fit measures (NFI, RFI, IFI, TLI, CFI); and if there is model comparison, also report one of the parsimony measures (PNFI, PCFI) and one of the information theory measures (AIC, BIC, CAIC, BCC, ECVI, MECVI).

Relative chi-square, also called normal or normed chi-square, is the chi-square fit index divided by degrees of freedom, in an attempt to make it less dependent on sample size. Kline (2005) says 3 or less is acceptable.
Some researchers allow values as high as 5 to consider a model adequate fit (Schumacker and Lomax 2004), while others insist relative chi-square be 2 or less. Less than 1.0 is poor model fit. AMOS lists relative chi-square as CMIN/DF.

Standardized root mean square residual, Standardized RMR (SRMR): SRMR is the average difference between the predicted and observed variances and covariance in the model, based on standardized residuals. Standardized residuals are fitted residuals (see above) divided by the standard error of the residual (this assumes a large enough sample to assume stability of the standard error). The smaller the SRMR, the better the model fit. SRMR = 0 indicates perfect fit. A value less than .05 is widely considered good fit and below .08 adequate fit.

The comparative fit index, CFI: Also known as the Bentler Comparative Fit Index. CFI compares the existing model fit with a null model which assumes the indicator variables (and hence also the latent variables) in the model are uncorrelated (the "independence model"). CFI and RMSEA are among the measures least affected by sample size (Fan et al. 1999). CFI varies from 0 to 1 (if outside this range it is reset to 0 or 1). CFI close to 1 indicates a very good fit. By convention, CFI should be equal to or greater than .90 to accept the model.

Root mean square error of approximation, RMSEA, is also called RMS or RMSE or discrepancy per degree of freedom. By convention (Schumacker and Lomax 2004) there is good model fit if RMSEA less than or equal to .05. There is adequate fit if RMSEA is less than or equal to .08. More recently, Hu and Bentler (1999) have suggested RMSEA ≤ .06 as the cutoff for a good model fit. RMSEA is a popular measure of fit, partly because it does not require comparison with a null model and thus does not require the
author posit as plausible a model in which there is complete independence of the latent variables as does, for instance, CFI. In a well-fitting model, the lower 90% confidence limit is very close to 0, while the upper limit is less than .08.

PCLOSE tests the null hypothesis that RMSEA is not greater than .05. If PCLOSE is less than .05, we reject the null hypothesis and conclude that the computed RMSEA is greater than .05, indicating lack of a close fit.

Hoelter's critical N issued to judge if sample size is adequate. By convention, sample size is adequate if Hoelter's N > 200.

The following Table 4.3 gives the accepted values for each of the above indices as considered for the study.

**Table 4.3 Accepted values for each of indices considered in the study**

<table>
<thead>
<tr>
<th>Sl.No</th>
<th>Fit Index</th>
<th>Acceptable Value</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>Normed chi-square (CMIN/df)</td>
<td>&lt; 3</td>
</tr>
<tr>
<td>2</td>
<td>Standardized RMR (SRMR)</td>
<td>&lt;0.08</td>
</tr>
<tr>
<td>4</td>
<td>Comparative fit index (CFI)</td>
<td>&gt;0.9</td>
</tr>
<tr>
<td>5</td>
<td>Root mean square error of approximation</td>
<td>&lt;0.08</td>
</tr>
<tr>
<td>6</td>
<td>PCLOSE</td>
<td>&gt;0.05</td>
</tr>
<tr>
<td>7</td>
<td>Hoelter's critical N</td>
<td>&gt;200</td>
</tr>
</tbody>
</table>

The model re-specification is required when goodness of fit is not achieved in the initial evaluation. Re-specification is done on the basis of modification indices to finalize a good-fitting model. The re-specification of bad-fitting models was done by (Saurina and Carme Germà Coenders 2002):
• Dropping loadings which are not substantively interpretable.

• Adding loadings which are both interpretable and statistically significant.

• Splitting dimensions for which interpretable clusters of positive residual Correlations appear.

• Adding error correlations which are both interpretable and statistically significant.

• Dropping items which would load on nearly all dimensions.

• Merging dimensions whose correlation is close to unity.

• Dropping non-significant regression coefficients among latent variables.

4.4.2 PLS Based SEM

A structural equation model with all constructs used in the study was analyzed using Warp PLS 2.0 for identifying significant relations between variables of interest in the study. The term structural equation model is used to refer to both the structural and measurement model together. In a structural equation modeling (SEM) analysis, the inner model is the part of the model that describes the relationships between the latent variables considered in the model. The outer model is the part of the model that describes the relationships between the latent variables and their indicators. The inner and outer models are also frequently referred to as the structural and measurement models, respectively. Therefore the path coefficients are inner model parameter estimates whereas weights and loading are measurement model parameter estimates depending on whether the measurement model is formative or reflective. Warp PLS 2.0 estimates enables evaluation of measurement model as well as structural model
simultaneously. However when second order constructs is used, measurement model for first order constructs are to be evaluated separately

In this study two constructs namely perceived service quality and satisfaction are conceptualized as second order constructs. For analysis of second order constructs using Warp PLS 2.0, it is required to calculate the LV scores (factor scores) at first by creating models with latent variables and indicators without linking. These LV scores are used to define the second order construct in the final model.

The most important feature of Warp PLS 2.0 as found different from other PLS based software is the inclusion of model fit indices. For assessing the model fit with the data, it is recommended that the P values for both the APC and ARS be both lower than .05; that is, significant at the .05 level. Also it is recommended that the AVIF < 5. Validity Criterion for various constructs in Warp PLS are explained in Table 4.4.

**Table 4.4 Validity / Reliability guidelines in WarpPLS2.0**

<table>
<thead>
<tr>
<th>Sl. no</th>
<th>Consideration</th>
<th>Guideline (WarpPLS2.0)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Reflective constructs</td>
</tr>
<tr>
<td>1</td>
<td>Cronbach alpha coefficient</td>
<td>&gt;0.7</td>
</tr>
<tr>
<td>2</td>
<td>Composite reliability</td>
<td>&gt;0.7</td>
</tr>
<tr>
<td>3</td>
<td>Average variance extracted</td>
<td>&gt;0.5</td>
</tr>
<tr>
<td>4</td>
<td>Convergent validity</td>
<td>( p ) values associated with the loadings be lower than .05; and that the loadings be equal to or greater than 0.5</td>
</tr>
<tr>
<td>5</td>
<td>Discriminant validity</td>
<td>The square root of the average variance extracted should be higher than any of the correlations involving that latent variable</td>
</tr>
</tbody>
</table>
As the correlations between formative indicators may be positive, negative or zero (Bollen 1984; Diamantopoulos and Winklhofer 2001), reliability as a measure of internal consistency sense is not meaningful for formative indicators (Bagozzi 1994; Hulland 1996).

4.5 VALIDITY AND RELIABILITY

The two most important and fundamental characteristics of any measurement procedure are reliability and validity. Patton (2001) opined that validity and reliability are two factors which any qualitative researcher should be concerned about while designing, analysing results and judging the quality of the study.

4.5.1 Validity

According to Davis et al (1993), “A measurement scale is valid if it does what it is supposed to do and measures what it is supposed to measure”. According to Hardy and Byrman (2004), there are different types of validity:

- Face/Content validity – requires a thorough examination of the wording of the items included in the instrument and their connection to the relevant frame of reference used in the particular study. Face validity can also be examined through the use of the opinion and judgment of experts concerning the items and wording used.

- Criterion-related validity – evaluates a scale in terms of a criterion on which people tend to differ. This includes concurrent and predictive validity.

- Construct validity – requires “an examination of the theoretical inferences that might be made about the underlying construct”.
Content validity ensures that the measures include an adequate and representative set of items and the clarity of the definition and concept used. A major threat to content validity is ill-defined terms and concepts. The variable measurements in the study were consistent with prior studies and hence there did not seem to have any threat to content validity. In this study a pilot study of the questionnaire was conducted to determine whether any alterations or rewording of questionnaires was necessary due to any jargon, inconsistencies or leading questions. The pilot test concluded elimination of four indicators whereby avoiding the possible threat to content validity.

Criterion-related validity deals with the instrument’s ability to measure an item accurately and analyze it. Scale used in the study was mainly five-point Likert-type scale. This is a popular scaling technique and is used widely in management research. To ensure criterion validity throughout the questionnaire a common scale is used for measurement. Construct validity explains how well the results obtained from the use of the measure fit in the theories around which the test was designed. This was assessed through convergent and discriminant validity. Convergent validity is established when the scores obtained with two different instruments measuring the same concept are highly correlated. Discriminant validity is established when based on theory two variables are predicted to be uncorrelated and the scores obtained by measuring them are indeed empirically found to be so.

4.5.2 Reliability

Reliability is the extent to which measurements of the particular test are repeatable. In other words, the measuring procedure should yield consistent results on repeated tests. The more consistent the results given by repeated measurements, the higher the reliability of measurement procedures. Kirk and Miller (1986) identify three types of reliability referred to in
quantitative research, which relate to: (1) the degree to which a measurement, given repeatedly, remains the same (2) the stability of a measurement over time; and (3) the similarity of measurements within a given time period. In order to test reliability. There are two aspects of the reliability issue: external and internal reliability. According to Hardy and Bryman (2004), external reliability means that the studied variable does not fluctuate greatly over time which means that it is stable. This kind of reliability can be tested through test-retest reliability, which means measuring the same scale twice in different time frames and see to what extent the two sets of data have yielded the same replies of the respondents. This method of measuring the reliability is time-consuming and tedious and will not be applied in the underlying study. Furthermore, according to Hardy and Bryman (2004), internal reliability means that all the constituent indicators of a variable are measuring the same thing which means that the variable is coherent. One of the most popular methods for estimating internal reliability, also applied in this thesis, is Cronbach’s Alpha (R) Test of Reliability. In this study, Cronbach coefficient alpha value was above 0.7 showing scale reliability for all reflective constructs but for formative constructs reliability may not be a correct criterion as the indicators are not correlated each other.

4.5.3 Various Validity/Reliability Considerations

The various considerations used for testing the soundness of the measures are explained in Table 4.5. This study has adopted Confirmatory factor analysis using AMOS16 for validating the scales developed for measuring perceived service quality construct. Also to evaluate the research model structural equation modeling analysis using Warp PLS 2.0 was adopted. The verification of the results obtained after above procedures with regard to certain parameters indicated various validity and reliability considerations.
### Table 4.5 various validity/Reliability considerations

<table>
<thead>
<tr>
<th>Sl.no</th>
<th>Consideration</th>
<th>Guideline (Checking with AMOS output used for confirmatory Analysis)</th>
<th>Guideline (WarpPLS2.0) Reflective/formative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Unidimensionality</td>
<td>Comparative fit index (CFI) &gt; 0.9 or (Sureshchandar et al. 2001)</td>
<td>na</td>
</tr>
<tr>
<td>2</td>
<td>Common method Variance (CMV)</td>
<td>Exist if first factor on exploratory factor analysis explains for more than 50% the variance in the variables (Podsakoff and Organ 1986)</td>
<td>na</td>
</tr>
<tr>
<td>3</td>
<td>Cronbach alpha coefficient</td>
<td>&gt;0.7</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Composite reliability</td>
<td>&gt;0.7, composite reliability is considered high if “squared multiple correlation” greater than 0.5, moderate if between 0.3 and 0.5 and poor if less than 0.3 (Holmes-Smith 2001, Byrne 2001)</td>
<td>&gt;0.7/nil</td>
</tr>
<tr>
<td>5</td>
<td>Average variance extracted</td>
<td>&gt;0.5 to indicate reliable factors (Hair et al. 1995, Holmes-Smith 200)</td>
<td>&gt;0.5/&gt;0.5</td>
</tr>
<tr>
<td>6</td>
<td>Convergent validity</td>
<td>Critical ratio of measurement items &gt;1.96</td>
<td>P&lt;0.001/VIF&lt;3.3, all indicator weights should be with p&lt;0.05</td>
</tr>
<tr>
<td>7</td>
<td>Discriminant validity</td>
<td>All AVE&gt; squared inter construct correlations</td>
<td>The square root of the average variance extracted should be higher than any of the correlations involving that latent variable/AVE&gt;0.5</td>
</tr>
<tr>
<td>8</td>
<td>Construct validity</td>
<td>Assumed if Sl.nos 3,4,5,6 above are satisfied</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Squared multiple correlation</td>
<td>Shows ability of indicators to measure the latent dimension, &gt;0.5 good, &gt;0.3&lt;0.5 moderate</td>
<td></td>
</tr>
</tbody>
</table>
4.6 SUMMARY

The chapter narrated the various methods adopted to conduct the study. The rationale for each decision regarding data collection strategy, sample size, questionnaire design and analysis methods were explained in detail. This study used qualitative approach in the initial stage to properly define the domain of the study and to develop a sensible theory that can lead fulfillment of the objectives. In the qualitative phase interview were conducted by the researcher with experts in the banking profession as well as experienced customers, who can offer valid suggestions to bring more clarity to the study. This procedure helped in finalizing the theory and items for measurement of the constructs of interest in the study. The second phase concluded on questionnaire design, data collection methods and decisions on sample size. The proposed analysis strategy was finalized and rationale for using each procedure was elaborated. The next chapter presents the report of analysis done with the data collected.