Chapter IV
RESEARCH METHODOLOGY

4.1 Overview
This chapter explains the methodology used in this research in detail. This is an empirical research with mixed methods approach using both quantitative and qualitative analysis through which results are interpreted and implications are drawn. The nature of research and the variables involved therein are highlighted in the beginning of this chapter. The methods used in this research are listed. Sample selection and its justification have been given. The research instruments used and the procedure of developing them have been listed. Organizational profile has also been given. The research design and the multivariate analysis have been explained. The systematic procedure for performing reliability, validity and practicality test has been described. The best practices incorporated in developing the questionnaire, data collection strategies, statistical procedures, data analysis and limitations of these methods are discussed. The stepwise research methodology adopted in System Dynamics has been included. The model validation procedure has been discussed. Finally, the methodological limitations have been discussed.

4.2 Type of research and the variables
This is basically an empirical research of correlational type of research, from the study results of which, inferences are drawn and implications are made. The following are the exogenous and the endogenous variables of study.
4.2.1 **Exogenous variable**

**Organizational citizenship behaviour (OCB):** This is a construct which has five dimensions, viz., altruism (ALT), courtesy (COU), sportsmanship (SPT), conscientiousness (CON), and civic virtue (CVI).

Thus,

\[ OCB = f(ALT, COU, SPT, CON, CVI) \] \[ 1 \]

**4.2.2 Endogenous variables**

There are three endogenous variables in this study. They are formulated as follows.

1. **Knowledge Management (KM):** This is a construct which has six dimensions, viz., knowledge diagnosing (KD), knowledge acquisition (KA), knowledge generation (KG), knowledge sharing (KS), knowledge storing (KST), knowledge application (KAP).

Thus,

\[ KM = f(KD, KA, KG, KS, KST, KAP) \] \[ 2 \]

2. **Total quality management (TQM):** TQM has seven dimensions, viz., customer management (CM), process management (PM), continuous improvement (CI), quality information management (QIM), organizational learning (OL), people management (PLM), and top management leadership (TML).

Thus,

\[ TQM = f(CM, PM, CI, QIM, OL, PLM, TML) \] \[ 3 \]

3. **Performance of the organization (PERF):** Performance of the organization has three dimensions, viz., operational performance (OPERF), financial performance (FP), and non-financial performance (NFP).

Thus,

\[ PERF = f(OPERF, FP, NFP) \] \[ 4 \]
4.3 The research methods and the tools

This research makes an attempt to study in detail the influence of OCB on KM, TQM and PERF. Accordingly, the hypothetical research models have been constructed (chapter 3) and an appropriate research methodology has been chosen to test the hypotheses postulated. The research makes use of statistical methods for the hypothesis testing and system dynamics modelling and simulation for studying the influence of various dimensions of OCB on the endogenous variables of interest.

The research aims at *posteriori* (or empirical) knowledge. So, the knowledge available will have to be systematically collected and analysed through the most appropriate data source. In this research the empirical study makes use of statistical techniques to analyse the data collected for this purpose. The statistical methods use both descriptive statistics and inferential statistics. While the former is used to describe the general pattern and nature of the data, the latter is used to draw inferences so as to arrive at specific conclusions of the study. Descriptive statistics include tools such as mean, standard deviation, demographic distribution of respondents, Skewness and Kurtosis, overall perceptions of the respondents, and inter-sector comparisons. The inferential statistics in this research includes the empirical study in the form of non-experimental hypothesis testing research. The non-experimental hypothesis testing research involves experimentation with the independent variables but the experimental hypothesis testing research has no control over the independent variables, and hence, the researcher cannot manipulate the independent variables at his/her will and study the influences, instead the metric in the form of a Likert 5-point scale are used to collect both the qualitative and quantitative data. These data are subjected to the statistical tests such as t-test and the second generation statistical technique – structural equation modelling (SEM) to test the hypotheses which have been formulated to answer the research questions.
The second part of the analysis makes use of System Dynamics (SD) modelling and simulation. Here, the researcher has manipulated the exogenous variables and study their influences on the endogenous variables through the modelling and simulation technique. The regression model developed through the analysis of the data collected through the metric forms the basis for the modelling and simulation.

The above two distinct components of research have been separately explained in the following sections.

4.4 Organization profile

This research is oriented towards the influence of OCB on the performance of the service organizations and the data for this research was collected from the three prominent service sectors in the country, viz., healthcare, information technology and higher education. A brief mention about the three service sectors is as follows.

4.4.1 Healthcare sector

Indian healthcare administration is governed by the Ministry of Health and Family Welfare and is a 22 billion US$ industry. The growth rate of the sector is about 13% annually and employs 4 million people directly or indirectly. The healthcare sector includes: Medical care providers, Diagnostic service centres and pathological labs, Medical equipment manufacturers, Contract research organizations, Pharmaceutical manufacturers, and Third party support service providers. In terms of the human and physical infrastructure, for 1000 population, Indian healthcare providers have 1.5 beds (world average 3.3), 1.2 physicians (world average 1.5), 1 nurse (world average 3.3). Approximately about 5, 92, 215 doctors, 80,000 dentists and 7, 37, 000 nurses in the country in 4,049 public hospitals and 11,344 private hospitals and 170 medical colleges (ASA Report, 2012). So, about 1,409,215 employees are offering service to the patients. This number does not include administrative staff. Major healthcare service providers in
Chapter IV: Research Methodology

the public sector are All India Institute of Medical Sciences, New Delhi, Armed Forces Medical College, Pune, Madras Medical College, Chennai, Maulana Azad Medical College, New Delhi, Stanley Medical College, Chennai, Grant Medical College, Mumbai and in the private sector Appollo Hospitals, Wockhardt hospitals, Fortis Healthcare, Max Healthcare, Aravind Hospitals, Manipal Group and Escorts Group.

About 60 percent of the global clinical trials market is outsourced to developing countries like India. Indian generic pharma companies like Daiichi Sankyo, Dr Reddy’s along with the global players such as Pfizer and Merck are involved in the outsourcing in the Indian market. Hospital chains are venturing into contract research to reduce their operational and clinical costs. Fortis Healthcare has become the latest entrant in contract research with its Fortis Clinical Research Services. Clinical research in many specialities has led to improved disease management and patient care, reduced ALOS, better BTR (Bed Turnover Rates) making healthcare delivery more sustainable. This also significantly improves the DALY (Disease Adjusted Life Years).

The private sector has evolved a multi-pronged approach to increase accessibility and penetration. It has tackled the issue of Lifestyle related diseases with the development of high-end tertiary care facilities. Also new delivery models such as Day-care centres, single specialty hospitals, end-of-life care centres, etc. are on the horizon to service larger sections of the population and address specific needs. The Public Sector is keen to continue to encourage private investment in the healthcare sector and is now developing Public – Private Partnerships i.e. PPP models to improve availability of healthcare services and provide healthcare financing. Both sectors have also undertaken initiatives to improve functional efficiencies in the form of Accreditations, Clinical research, outsourcing of non-core areas, increased penetration of healthcare insurance and third party payers (KPMG, 2011). Thus, the healthcare industry of India is ultramodern and has
initiated programmes which are very well supported by ICT and have systems such as Knowledge Management Systems in place.

4.4.2 Information Technology (IT) Sector

India is referred to as the back office of the world owing mainly to IT Sector. The revenue of the information technology sector has grown from 1.2 per cent of the gross domestic product (GDP) in 1997-98 to an estimated 5.8 per cent in 2008-09. Today, Indian IT companies have carved a great niche for themselves in the global market and are known for their IT prowess. Global giants are using the successful outsourcing strategy and keeping ahead of their rivals - thanks to the competitive advantage gained by investing in India. India’s IT sector has driven the growth of economy in terms of employment, revenue generation, standards of living, etc., and has projected India into the global market. IT services include a wide spectrum of services including: system management and maintenance, consultancy services, system integration, chip design, E-governance, E-commerce, IT enables services covering banking/financial/insurance sector. Indian IT sector is about 100 Billion US$ business and contributes to about 7.5% to the national GDP (ASA Report 2012). The IT sector has provided employment to about 25, 00,000 in India. Major players in the IT business are TCS, Wipro, and Infosys.

The value proposition has shifted from labour arbitrage to skill availability, transformational objectives, innovation and non-linear models for growth. The recent downturn notwithstanding, India’s success has given rise to competition from low cost economies which has encouraged bigger players to add offerings, move towards full service offerings with wider geo-diversity in their delivery models. The centre of gravity of consumption geographies are shifting from US and UK to emerging markets of India, China and Latin America. With exports accounting for the predominant share in overall IT revenues, the performance of technology sector is closely linked to the overall health
of the global economy. Over the past decade, the IT sector in India has been a story of unparalleled growth. The compounded annual growth rate (CAGR) of the industry has been over 25% in the last 5 years. Over these years four main components have formed the industry – IT Services, BPO, Engineering Services and Hardware. The Indian IT sector has largely been India centric – both in terms of delivery centres and human capital. Within India, the activity is currently concentrated around Bangalore, Chennai, NCR-New Delhi, Hyderabad, Pune, Mumbai and Kolkata. In addition to central government intervention, we also see the IT sector including more and more state governments vying with each other to offer a favourable business environment in order to attract IT companies to set up development units in their states.

The Indian IT sector is dominated by large players; however the Small and Medium Providers (SMPs) form a significant portion of the industry, contributing over 30% of the exports. The classical “scale” vs. “scope” debate is now playing out in the strategies of companies in the Indian IT sector. While most of the large players have established their brand positions in the global market place and are ready to take on the largest global service providers in a “full-service” mode, the SMPs still face the challenge of having to evolve their own focused, niche and differentiated value propositions. Both segments will have to focus on high growth rates, retain their sharp focus on profitability where they have set an enviable global and local “gold standard” benchmark and minimize risk which can broadly be defined as “predictability of cash flows” (CII Report, 2013).

4.4.3 Higher Education Sector

India’s demographic trend means it will soon overtake China as the world’s largest population, and with an average GDP annual growth of 8% over the last decade, its middle classes that demand higher education will swell to over 500 million people in the next ten years. India’s higher education system, originally designed to serve the elite, will
now have to serve the people. Innovation and change are required and understanding that change will be essential (BC Report, 2013).

Government plans are in place to transform the sector over the next five years. Every aspect of higher education is being reorganised and remodelled: funding, leadership and management, quality assurance, accountability, relationships with industry, international collaboration, and the way research and teaching are conducted. If these reforms succeed, the breadth and depth of the change will be transformational (BC Report, 2013).

Higher education in India is undergoing considerable change. With over 600 million people in India under 25 years of age, the system is under tremendous pressure to expand. India’s young population has a huge appetite for education and, as the growth in the size of the middle classes escalates, millions are increasingly able to pay for it. By 2020, India will have the largest tertiary-age population in the world and will have the second largest graduate talent pipeline globally, following China and ahead of the USA. The opportunities for the UK to engage with India through education are considerable.

India has 33,023 colleges of higher education run under State universities (47%), Deemed universities (20%), private universities (16%), National Institutes (10%) and Central universities (7%) (UGC, 2012). Higher education contributes about 4% to the national GDP. The total students in the higher education sector is 16,974,883 in the faulty of Science, Commerce, Management, Education, Engineering/Technology, Medicine, Agriculture, Veterinary Science, Law, Arts and other disciplines. Considering at a faculty to student ratio of 1:15 about 1,131,659 faculty are employed in these institutes. The UGC provides several schemes for the quality enhancement of the faculty in the form of Research fellowship in Science for meritorious students, Junior research fellowship in Engineering and Technology, fellowship to M.Phil./Ph.D. scholars in central universities, Dr. Radhakrishna Post-Doctoral Fellowship in Humanities & Sciences, Dr. D.S. Kothari
Post-Doctoral Fellowship in Science, Medical Sciences and Engineering Sciences etc.
These higher educational institutes are governed by regulatory bodies such as: All India Council for Technical Education (AICTE), Bar Council of India (BCI), Central Council of Homeopathy (CCH), Central Council of Indian Medicine (CCIM), Council of Architecture (CoA), Dental Council of India (DCI) etc. These regulatory bodies are responsible for the quality assurance in these higher educational institutes.

4.5 The Research Framework

This research is carried out in eight distinct phases (Figure 4.1) in this research. Each phase has been explained in the following paragraphs.

**Phase I – Problem Statement**

The problem identified in this research is the study of the influence of OCB on the PERF with the direct and moderating influences of KM and TQM in the service organizations based in India. These terms have been in wide use since the past several decades and a multitude of theoretical models were developed to link these constructs; nevertheless, the empirical relationships between these constructs have not been established fully. So, the research under consideration has attempted a solution to this problem.

**Phase II – Purpose of Research**

The main purpose of this research is to provide empirical evidence for the relationships among the research variables of interest. The reason is that, a huge amount of both physical and human resources have been invested on the enablers such as OCB, KM and TQM as they are supposed to have an influence on the PERF of the organization. While many researchers have even attempted for the empirical evidence for the relationships between these constructs individually, no single research has related all these variables
collectively in a holistic manner. So the purpose of this research is to provide a holistic solution to the addressing of the interrelationships between these variables.

**Phase III – Research Background**

The research topic has its roots in organizational performance based literature. The three most commonly identified enablers of performance as identified in the research literature are OCB, KM and TQM. The literature review has provided a strong base not only for the influence of these constructs on the PERF, but also, an evidence for their interrelationships. While the observations are based on both production and service organizations in general, not many studies have focussed on knowledge intensive service organizations despite the fact that it is one of the fastest growing sectors in the country. The observation through the literature review is that there are adequate number of theoretical models to relate these variables, but not many of them have empirically tested these relationships. So, this research investigates the dimensions of each of the constructs individually and then also attempts to find the interrelationships between them in the context of the knowledge intensive service organizations in India. These service organizations are based in India, however the working environment is multicultural as most of them are multinationals operating in several countries including India. The background study undertaken in this research has provided a strong base for building of the constructs in terms of their dimensions and variables.

**Phase IV – Research Premise**

The four constructs of this research are very widely used in both production and service organizations. So, the very definitions of these constructs vary from organization to organization as it is context specific. However, in the context of this research a need has been identified to provide a general premise for the undertaking of the research. The definitions chosen fix the premises of aspects covered by these constructs and limit the
boundary of the study. These definitions govern the entire research from the formulation of the hypothetical models to the empirical tests to be conducted on these models. A total of 39 hypotheses have been formulated and tested to seek answers to the research questions and that provides a clear research premise for this research.

**Phase V – Research Design**

The research design is chosen in accordance to the nature of this research. As this is basically an empirical study that involves hypothesis testing, the research methodology adopted is mixed method study with qualitative and quantitative components. Both primary and secondary data are collected. While the former is used for both qualitative and quantitative analysis, the latter is used for qualitative analysis. The quantitative methods use statistical techniques to using SPSS to find the Kurtosis, Skewness, mean, and standard deviation for the descriptive statistics. Second generation statistical technique of structural equation modelling (SEM) with partial least square method (PLSM) will be adopted for testing the hypothetical research model. The SEM approach will comprise both measurement model and the analysis model for the quantitative analysis. The Design of Experiments (DOE) has been adopted to study the main effect and interaction effect of the variables of interest. Finally, Modelling and Simulation Technique using System Dynamics (SD) has been used for scenario planning to study the variation in the performance levels of the endogenous variables of interest for a given change in the exogenous variables.

**Phase VI – Execution**

As mentioned before, two types of data have been collected in this research. First, the primary data will be collected through the questionnaire served to the managers of the knowledge intensive service organizations. The primary data will be both qualitative and quantitative in nature. Second, the secondary data will be collected through literature
review. This will be qualitative in nature. While the primary data will be used to test the hypotheses, secondary data will be used for qualitative analysis. Standard formulae will be used to fix the sample size, however, for SEM analysis according to the principles a sample size of 200 is adequate as long as randomization and bias is taken care of.

**Phase VII – Analysis**

The analysis undertaken in this research are both qualitative and quantitative in nature. Qualitative analysis is basically through rationalization of the results and the evidence collected through the Meta analysis of the literature. The quantitative analysis is basically for the empirical study in the form of hypothesis testing. Quantitative analysis includes two distinct components viz., descriptive statistics and inferential statistics. The descriptive statistics deal with the mean, standard deviation, Skewness and Kurtosis measurement, percentage calculations and the perception study of the respondents on the dimensions of the various constructs. The inferential study is mainly through the SEM using PLSM. The SEM has two separate models: the measurement model and the structural model. While the former deals mainly with the descriptive statistics the latter deals with the hypothesis testing. The DOE is used to study the main and interaction effect of the various dimensions within a construct. Both the first and second order interaction has been studied. In the scenario planning exercise using SD approach, the exogenous variable of interest is varied from 20% to 80% in the steps of 20%. The qualitative and quantitative analysis provide the means to interpret and draw implications of the study.

**Phase VIII – Interpretation, Implications and Contribution**

The reliability and validity are undertaken to ensure that the data collected serves the purpose and the metric has measured what it was intended to measure. The path coefficients and t-statistic are be the indicators for the conclusions to be arrived about
hypotheses testing. Based on the hypotheses testing results and the regression analysis the causal relationships between the research variables of interest are tested. Thus, the empirical relationships are also tested. This has led to the drawing of the suggestions for the managers to consider in order for enhancing the performance of the organizations for gaining competitive advantage in business.

**Figure 4.1: The Research Framework**
4.6 The Metric

The metric (measurement instrument) used in this research is a self-administered questionnaires. The reason for choosing this instrument is that it is a relatively systematic and standardized method of collecting data, which lays emphasis on measurement and conversion of data from qualitative to quantitative form. Further, it is evolved from studying sampling population to probability sampling and provides means for simple counting to statistical description and inferential analysis. Finally, this method is considered to be economical and convenient for this kind of research.

The questionnaires have been designed to study the perceptions of the respondents on the research issues. They obtain the answers to the research questions and provide the necessary data to test various hypotheses.

Although the literature review, meta-analysis, and interviews with the knowledge workers in the service sectors identified several specific problem areas under the topics of study, only those areas specific to the research questions of this study were selectively chosen. The problem areas were categorized, simplified and redundancy was eliminated to develop a set of questions for the research questionnaire. Further, while developing the questionnaire the following points were taken into consideration:

- Are the categories of respondents competent enough to provide the necessary information?
- Do the chosen items of each questionnaire truly measure the dimension to which they correspond?

Questions were framed to be uniformly understood by all respondents belonging to different service sectors. During the trial run, it was confirmed whether the respondents are familiar with the terms used in the instrument. Also during the initial trial run, the questionnaires were reviewed for problems with bias and it was confirmed that no
particular question caused any problem of understanding. Simple language was used throughout the questionnaire and all possible ambiguity was eliminated. Moreover, it was ensured that all the questions were effective in obtaining information relevant to hypothesis testing in all the cases and eliciting the qualitative information that was required.

The questionnaire had three distinct parts. The first part was designed to collect the demographic details of the respondents, the second part had questions related to the constructs - OCB, KM, TQM and PERF, and the third part had qualitative component in which their opinions, suggestions and general perceptions were solicited in qualitative form. The quantitative part of the questionnaire used a five-point Likert-type scale, measuring the degree to which the respondents believed the statements in the questionnaire to be true, the highest being ‘strongly agree’ and the least being ‘strongly disagree’. The delivery was both on personal mode and electronic mode in the three sectors.

4.6.1 Development of the questionnaire

The development of the questionnaire was through the standard method of meta-analysis of the literature on the construct. There are four different components in the questionnaire and each one of them is dealt separately in the following sections.

4.6.1.1 Organizational Citizenship Behaviour (OCB)

OCB is all about the right kind of performance of the individual and the ‘extra-role’ the individual may play so that the organization would function efficiently and effectively. The meta-analysis of the literature has resulted in the identification of the various dimensions of OCB and the dimensions, meaning, researchers and the sample item for each dimension has been given in Table 4.1.
<table>
<thead>
<tr>
<th>Dimension</th>
<th>Meaning</th>
<th>Literature</th>
<th>Sample item</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1. Altruism</strong></td>
<td>Taking the initiative to help members of an organization resolve problems and helping each other. It need not be confined only to fellow workmen; it can be extended to the customers, vendors, suppliers and any stake holder.</td>
<td>Organ (1988), MacKenzie et al. (1991), Van Scotter &amp; Motowidlo (1996), Van Scotter and Motowidlo (1996), Podsakoff et al. (1997), Van Dyne and LePine (1998), Podsakoff and et al. (2000), Rhoades and Eisenberger (2002), Aselage and Eisenberger (2003), Turnipseed &amp; Rassuli (2005), Lähdesmäki &amp; Takala (2012), and Chiang &amp; Hsieh (2012).</td>
<td>I will help doing tasks for others when they are sick or absent.</td>
</tr>
</tbody>
</table>

**Table 4.1: The Dimensions of OCB**
4. Conscientiousness


I keep up to date with organizational procedures and standards.

5. Civic virtue


I help others who have heavy workloads.

### 4.6.1.2 Knowledge Management (KM)

In today’s knowledge based economy, KM has been a strategic tool in knowledge intensive service sectors. The key component of KM has been the practices which facilitate the KM system. The meta-analysis of literature has resulted in the selection of the following dimensions based on the earlier contribution of various researchers in this area and considering their relevance to service industry.
Table 4.2: Dimensions of KM

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Meaning</th>
<th>Literature</th>
<th>Sample Item</th>
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<tbody>
<tr>
<td>6. Knowledge</td>
<td>Having the flexibility</td>
<td>Scarbrough (2003),</td>
<td>Company's systems</td>
</tr>
</tbody>
</table>
Application to convert available knowledge into useful applications and continuously evaluating the results obtained.

Politis (2005), Hedgebeth (2007), Kamasak & Bulutlar (2010), Wu et al. (2010), Arthur et al. (2011) and Cristiana et al. (2013).

and procedures have enough flexibility to make immediate modifications and improvements to apply new knowledge.

### 4.6.1.3 Total Quality Management

TQM practices have been in practice since the past several decades and there are several dimensions which describe this construct as a whole. The choice of the most appropriate dimensions among the available dimensions has been a matter of choice of the researchers, but to a great extent it is found to be context specific. In the context of knowledge intensive service sectors through the meta-analysis following dimensions have been chosen in the context of service sectors (Table 4.3).

**Table 4.3: Dimensions of TQM**

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Meaning</th>
<th>Literature</th>
<th>Sample Item</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.Process Management</td>
<td>Applying the principles of management so that the processes in the organization are under control through clear instructions, constant monitoring, inspection, and standardization.</td>
<td>Yong &amp; Wilkinson (1992), Gonzalez &amp; Guillen (2002), Brah &amp; Lim (2006), Demirbag et al. (2006), Sharma &amp; Kodali (2008), Khanna et al. (2011), and Yunis et al. (2013).</td>
<td>Processes have been identified, defined and documented.</td>
</tr>
<tr>
<td>3.Continuous Improvement</td>
<td>Striving to improve the level of service at all levels in the form of small improvements on a continuous basis.</td>
<td>Pheng and Wei (1996), Spires, (1996), Coyle-Shapiro (1997), Yang (2005), Fassoula (2006), Rampersad (2001), Fryer</td>
<td>The company provides relatively a sophisticated infrastructure that would increase the level of service quality.</td>
</tr>
<tr>
<td>6. People Management</td>
<td>Managing the human resources through efficient training, quality consciousness, team building etc., and having all the processes such as appraisal, training need analysis etc. so that the employees may contribute to the growth of the organization.</td>
<td>Kols &amp; Sherman (1998), Tata &amp; Prasad (1998), Yusof &amp; Aspinwall (2000), Rahman (2001), Dayton (2003), Karia &amp; Asaari (2006), Toor (2009), Harrington et al. (2012) and Singh &amp; Sushil (2013).</td>
<td>Provides feedback to employees on performance.</td>
</tr>
</tbody>
</table>
4.6.1.4 Overall Performance

There are several measures of performance of an organization and it varies from tangibles to intangibles and from financial to non-financial measures. However, the meta-analysis of the literature yielded some key measures of performance of an organization which are given in the Table 4.4.

Table: 4.4: Dimensions of PERF

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Meaning</th>
<th>Literature</th>
<th>Sample Item</th>
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Finally, the result of the meta-analysis of the literature, the in-depth study of the existing standard questionnaires, and the discussions with the knowledge workers in the service sectors resulted in the development of a 127 item scale, which was to measure the four constructs discussed above.
4.6.2 The Research Process

The research processes (Figure 4.2) are aligned to the eight phases explained in the research framework. This part mainly focusses on the data collection and the analysis of it leading to the accomplishment of the objectives of the research. There are four distinct constructs: OCB, KM, TQM, and PERF which need to be analysed both qualitatively and quantitatively in the context of knowledge intensive service organizations. A metric in the form of questionnaire is designed, developed, and validated to measure the qualitative and quantitative information. Initially a pilot run is undertaken for a sample size of 33 which has led to the refinement of questions and the factor reduction. This resulted in a 63 item
questionnaire using 5-point Likert type questionnaire from the original 127 item scale which was developed based on the existing scales and the theoretical models available. The reduced scale was distributed to a sample size of 742 respondents who were the knowledge workers in the knowledge intensive service organizations. The data thus collected is subjected to qualitative and quantitative analysis. While qualitative analysis was through rationalization of the inputs and the relevance finding to the theoretical models, the quantitative analysis involved descriptive statistics and inferential statistics. While the descriptive statistics in the form of mean, standard deviation, Skewness, and Kurtosis was used to describe the data, as the name itself suggests, the inferential statistics was mainly used for the hypothesis testing. The research process was basically designed to follow the cycle of theory-hypothesis-observation-empirical generalization relationship (Creswell, 2008). So, the research process ends with the analysis of the data, drawing of the inferences, and generalization of results for the building of the model.

4.7 Statistical Methods and the Instruments

4.7.1 Identification of the sample and rationale for its selection

The purpose of this research was to establish an empirical evidence for the link between the OCB and the endogenous variables of research interest (KM, TQM and PERF) as applicable to the service organizations. It was necessary to consider a cross section of service organizations so three main service sectors, which mainly contribute to the GDP of the country, viz., IT sector, higher education sector, and healthcare sector were considered to be the sources of data. The respondents chosen were the knowledge workers in these three service sectors. The first rationale for the selection of these three service sectors is their collective representation ability of the service sectors of the country. The second rationale is the diversification of these three sectors in terms of their geographical locations and multi-cultural environment. The third rationale is the
organization types of these sectors, which include national and multi-national context. The rationale for choosing the knowledge workers of these three sectors lies in their ability to provide the data and information with references to the constructs of the study. Thus sampling frame and the unit of analysis truly meets the requirements of the study.

**Sample design:** Simple random sampling has been used as the basic design of sampling in this research. Even though there are strata in each of the service sector chosen their stratification has no relevance to this study which is at macro level of analysis seeking relationships between variables stratification is not used.

**Sample size (n):** The universe is finite with a total population of 5,040,874 knowledge workers in the three service sectors under consideration. As SEM analysis has been used in this research for the testing of the integrated hypothetical model of this research, sample size is not an issue as long as the minimum sample size criterion is satisfied, which is 200. The software has the technique of bootstrapping through which extrapolation into any number is possible. However, to be sure of the minimum sample size the approach of specifying the precision of estimation desired first, and then determining the sample size necessary to ensure it (Kothari, 2000) was adopted, according to which, the sample size necessary is about 188, however, to get a better sample distribution the sample size chosen in 742 (38 - healthcare sector, 498 - higher education sector, and 206 – IT sector). Proportionate representative sampling basis has been used to choose the sample from the individual sectors. This is based on the 2% defect in sample (based on pilot study) and an acceptable error of 2%. Again, the optimum size of the sample in a social research is based on the nature of the empirical study, time and resources available, and various other considerations such as size of questionnaire, size of universe, nature of classes proposed etc. In practice, the complexity of the competing factors of resources and accuracy means that the decision regarding a
sample size tends to be based on experience and good judgment, rather than relying on a strict mathematical formula (Hoinville & Jowell, 1978). Also the use of surveys in social research does not necessarily have to involve samples of 1000 or 2000 people or events. Instead, research involving a number between 30 and 250 cases is adequate (Denscombe, 1999).

\[ N = \frac{(z^2 \cdot p \cdot q \cdot N_U)}{e^2 (N_U - 1) + z^2 \cdot p \cdot q}. \]

where,

\[ p = \text{Proportion of defectives in the universe} \]

(Based on the pilot study, a 2% defect is assumed).

\[ q = (1 - p). \]

\[ z = 1.96 \] (as per table of scores in a normal distribution within a selected range of \( z \) for a confidence level of 95%).

\[ e = \text{Acceptable Error} \] (an error of 2% of the true value is assumed).

\[ N_U = \text{Size of Universe}. \]

4.7.2 Reliability, Validity and Practicality of the Metric

Sound measurement must meet the tests of Reliability, Validity and Practicality. These are the three major considerations used in a research, which involves data collection through instruments such as questionnaires (Kothari, 2000). ‘Reliability’ has to do with the accuracy and precision of measurement procedure (Litwin, 1995). A reliable instrument should give identical responses if the questionnaire is served two or more times. ‘Validity’ refers to the extent to which a test measures what we wish to measure. Even though validity to a great extent depends upon the judgment of the researcher three types of validity: content, criterion and construct validity are strongly recommended. ‘Practicality’ of a measuring instrument is judged in terms of economy, convenience and interpretability. Economy consideration of practicality suggests that some trade-off is
needed between the ideal research project and that which the budget can afford. The length of the questionnaire is an important area where economic pressure is felt. More items in a questionnaire will give greater reliability (Kothari, 2000) but this is time consuming and tedious.

A pilot study was conducted for a sample size of 33 across the three sectors with an intention to check the instrument for the reliability, validity, and practicality of the metric. The Alpha Cronbach’s reliability, Composite reliability, average variance extracted, communality, redundancy, inter-item correlation and factor loadings were tested. The results are given in Appendix I.

4.7.2.1 Reliability

The ‘stability’ aspect of reliability is concerned with securing consistent results with repeated measurements of the same person with the same questionnaire. But for a sample size of 742, as in the present case, with four different constructs it is not very practicable, and hence, the method of determination of the degree of stability by comparing the results of repeated measurements has been adopted. The most common approach of estimating the reliability of an instrument that is presented to respondents only once is ‘split-half reliability’. In this approach the test is split into two equivalent halves and the scores for respondents on one half are correlated with those scores on the second half of the test. The difficulty in this approach is determining whether the two halves are equivalent. Cronbach proposed the coefficient ‘alpha’ (called Cronbach’s Alpha), which may be thought of as the mean of all possible split-half coefficients. A test with ‘robust’ reliability would be expected to display a Cronbach’s Alpha in excess of 0.9. However, values above 0.7 are usually acceptable indicators of internal consistency as suggested in the literature (Santos, 1999; SPSS, 2000; and Gefen et al., 2000). The reliabilities of all the three instruments have been tested on this basis.
4.7.2.2 Validity

The instrument used in this research has been subjected to content and criterion related validity, as they are derivatives of standard instruments used before in different organizations. However, in this research they have been used in a service-sector setting, so the content validity was checked again for suitability in this sector. The language of the questionnaire was revised wherever necessary to make the questionnaire more precise and understandable.

Content Validity: Having successfully conducted these validation steps as explained in the previous section, it can be assumed that the content validity of the measurement models analysed has been established. In this context, content validity refers to the degree to which items in an instrument reflect the content universe to which the instrument will be generalized (Straub et al., 2004). Generally, content validity is not easy to assess, since the commonly employed evaluation of this validity is judgmental and highly subjective (Straub et al., 2004). The content validity is further established through adoption of the instruments validated by other researchers.

Construct Validity: Construct validity assesses whether the scales were measuring what they were designed to measure. The questionnaire was mailed to a group of six knowledge workers in the service sector and their opinion on its ability to measure what it intends to measure was collected. They were asked to assess the understandability, readability and suitability of the instrument. As the response was positive except some minor modifications the construct validity was ascertained. Further, a group of researchers including Wiig (1993), Stebbins, Abraham & Shani (1995), Organ (1988), MacKenzie et al. (1991), Van Scotter & Motowidlo (1996), Van Scotter & Motowidlo (1996), Karsten & Langen (2002), Turnipseed & Rassuli (2005), Lähdesmäki & Takala (2012), and Chiang & Hsieh (2012), Wu et al. (2010) and Ramachandran et al (2013),
Singh (2011), Harrington et al. (2012), and Yunis et al. (2013) had repeatedly measured the construct validity of the factors under consideration and hence, the construct validity was proved.

**Convergent and Discriminant Validity:** The AVE values for all reflective constructs were tested to be greater than the minimum recommended value of 0.40. Further the square root of AVE for each construct in the model, as reported in the diagonal of the correlation of constructs matrix was larger than the corresponding off-diagonal correlations of the construct to their latent variables. These two measures ensured the convergent and discriminant validity of the questionnaire.

### 4.7.2.3 Practicality

“Practicality” of a measuring instrument is judged in terms of economy, convenience and interpretability, as mentioned before. This is one of the reasons for retaining a maximum of 63 questions in the questionnaire taking care to give a maximum coverage of the study topic. “Convenience” forms another key factor of practicality. The questionnaire was designed to be self-administrative in nature and clear guidelines were given in the instrument itself, so that there would be minimum number of queries regarding how it has to be filled. The Likert scale scoring keys were stated in the beginning and separate columns were provided for clicking on the responses, under each category. Interpretability of the items was given enough importance to see that each question gives only one meaning, free from ambiguity.

Thus with a fair degree of certainty the instrument was tested for the reliability and validity so as to ensure that it measured what it was expected to measure and the data collected through the metric was reliable to the given degree of requirement.
4.7.3 Statistical Analysis

The analysis carried out in this research includes both the descriptive statistics and inferential statistics. Descriptive statistics have been used in this research to consolidate on the results in the form of demographics, Skewness and Kurtosis, percentages, ranking, overall perceptions, inter-sector comparisons, etc., whereas, the inferential statistics have been used for providing the basis for drawing inferences and conclusions mainly through hypotheses testing.

4.7.3.1 Descriptive Statistics

Skewness and Kurtosis: Skewness is an indicator used in distribution analysis as a sign of asymmetry and deviation from a normal distribution, whereas, Kurtosis is the indicator used in distribution analysis as a sign of flattening or "peakedness" of a distribution. If Skewness is greater than zero it is a Right skewed distribution, with most values are concentrated on left of the mean, with extreme values to the right. If the Skewness is less than zero it is a left skewed distribution and most values are concentrated on the right of the mean, with extreme values to the left. If Skewness is equal to zero the mean equals median and the distribution is symmetrical around the mean and this refers to the ideal situation. In case of the Kurtosis, if the value is above 3, it is called Leptokurtic distribution, sharper than a normal distribution, with values concentrated around the mean and thicker tails. This means high probability for extreme values. If the Kurtosis is less than 3, it is called Platykurtic distribution, flatter than a normal distribution with a wider peak. The probability for extreme values is less than for a normal distribution, and the values are wider spread around the mean. If the Kurtosis equals 3, it is called Mesokurtic distribution and represents normal distribution. This analysis has been performed in this research as it is important to confirm the normality of distribution for applying the statistical techniques.
Overall Perceptions: To study the overall perception of the respondents about the four constructs, the response on the Likert 5-point scale was rated under five distinct categories. If the response was 1 it was rated as ‘Bad’, 2 was rated ‘Poor’, 3 was rated ‘Average’, 4 was rated as ‘Good’ and 5 was rated as ‘Very good’, based on the total responses received on the questionnaire on these categories for the individual constructs. Based on the total number of responses in each category, the percentage response was calculated in each category so as to obtain the overall perception on each of the constructs.

4.7.3.2 Inferential Statistics

The inferential statistical techniques used in this research include both the conventional statistical analysis in the form of t-tests, the second generation statistical technique of Structural Equation Modelling (SEM) using partial least square technique, Design of Experiments (DOE), and Multiple Regression Analysis (MRA). These methods have been explained below.

4.7.3.2.1 The t-test

The t-test is the obvious choice to test the significance of relationship between the variables when a group of variables have influence on the dependent variable. It is based on the t-distribution. The t-tests are tests for statistical significance that are used with interval and ratio level data. T-tests can be used in several different types of statistical tests:

- to test whether there are differences between two groups on the same variable, based on the mean (average) value of that variable for each group;
- to test whether a group's mean (average) value is greater or less than some standard;
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- to test whether the same group has different mean (average) scores on different variables;

To calculate a value of t, the standard procedure adopted is:

a) state the research hypothesis;
b) state the null hypothesis;
c) stipulate whether the t-test will be a one-tailed test or a two-tailed test for significance
d) select the level of alpha; and
e) Calculate t, compare with the tabulated value of t and decide if it lies on the acceptance or rejection region, and accordingly, accept or reject the null hypothesis.

4.7.3.2.2 Design of Experiments (DOE)

Even though DOE was invented through agricultural experiments, it was widely in use in many industrial sectors, for instance, in the development and optimization of manufacturing processes. Typical examples of DOE application are the production of wafers in the electronics industry, the manufacturing of engines in the car industry, and the synthesis of compounds in the pharmaceutical industry. Another main type of DOE-application is the optimization of analytical instruments. Many applications are found in the scientific literature describing the optimization of spectrophotometers and chromatographic equipment. Design of Experiments (DOE) has been used extensively by DuPont, Dow, Goodrich and others for over 30 years.

The DOE was introduced by Genichi Taguchi in Japan in early sixties. Taguchi’s methods became known in the USA in the early 80s when Toyota, Honda, Canon, and many others overtook their American counterparts with high quality products.
In any experimentation process which involves several independent variables influencing one dependent variable, an experimenter would keep all the rest of the variables constant and vary one variable and study the influence of this variable on the dependent variable. But this method has a disadvantage that it is tedious process, and moreover, this method may miss the ‘interaction effect’. This means the dependent variable may have a particular response for the combined effect of two independent variables which could be completely missed during the one factor at a time kind of experimentation. So, the alternative is to go for multifactor testing. During this method several independent variables can be varied simultaneously and their influence on the dependent variable can be studied. This is of particular interest in the present thesis. For instance, while studying the influence of the dimensions of organizational citizenship behaviour on performance of the organization, the main effect of Altruism may not be dominant. But, the interaction effect of Altruism, Conscientiousness, and Civic Virtue on the performance of the organization could be statistically significant. So, if such effect has to be studied, then DOE is the most obvious choice. However, the analysis will have to be done through the conventional ANOVA.

Design of Experiments (DOE) or Multifactor Testing is fundamental and crucial to increase the understanding of a product, process or service behaviour. It provides a powerful means to achieve breakthrough improvements in product quality and process efficiency. DOE is a direct replacement of the traditional one-factor-at-a-time or “hit or miss” approach to experimentation. Although it has been around for several decades, few business leaders in service organisations have a good grasp of its power in tackling problems associated with service process efficiency and effectiveness. Customers are getting more critical of the service they receive today and therefore most modern organisations are paying more attention to their transactional service processes.
This research is undertaken in the service sectors and application of DOE in this setting is relatively new. There are a number of reasons as to why DOE has not been commonly employed in service settings. The most fundamental barriers and challenges in the application of DOE in a service environment obtained from a thorough review of existing literature are (Antony and Sivanathan, 2014):

- As service is often simultaneously created and consumed and intangible dimensions are important indicators of quality on service context, experimental control of inputs and measurement of output requires careful consideration.
- Service process performance depends a great deal on the behaviour of the human beings involved in delivering it.
- Lack of awareness, ignorance and misconceptions discourage experimentation in many service organisations.
- In any service process, a clear description and distinction of service processes is needed for quality control and improvement. A good understanding of front office, back office and customer processes is required for quality and process improvements.

DOE is being attempted in a service context and the potential applications of DoE in the service environment include:

- Identifying the key service process or system variables which influence the process or system performance.
- Identifying the service design parameters which influence the service quality characteristics or Critical-to-Quality characteristics in the eyes of customers.
- Minimizing the time to respond to customer complaints.
- Minimizing errors on service orders.
• Reducing the service delivery time to customers (e.g. banks, restaurants, etc.); and reducing the turn-around time in producing reports to patients in a healthcare environment, educational institutes etc.

In DOE, inputs to a process are called factors and the one or more process outputs are called response variables. An experiment may start with several factors, each of which may have two or more levels. DOE is at its best (Aughton, 1993) when the number of levels for each factor is initially small (preferably two). This is not a limitation as an iterative set of experiments can be conducted once a factor is known to be significant by bisecting the range of values for that factor, then bisecting the significant range and so forth. Once factors have been identified as having no effect on the response variables they can be discarded.

In this research DOE is mainly used to study the main effects and interaction effects between the variables of research interest. Following are the factors and the variables:

**Factors (Independent Variable)** – Altruism, Courtesy, Sportsmanship, Conscientiousness, Civic virtue.

**Dependent Variable** – Performance.

The DOE technique has been adopted to determine the ‘main effects’ and the ‘interaction effects’ of the variables of OCB on the performance of the organization. The main effect refers to the overall effect of one independent variable on the dependent variable. Interaction effect exists if the effect of one independent variable depends upon the level of another independent variable. In such situations the independent variables are considered to interact with each other to produce an effect on the dependent variable which is called the “interaction effect”. In the present research considering OCB as a multi-dimensional construct if we consider Altruism as one dimension and Courtesy as the second, then the influence of both these dimensions on the Performance of the
organization could be the main effects of these two independent variables. But, if the influence of Altruism is influenced by the different levels of Courtesy then the resulting influence on the Performance of the organization becomes the interaction effect. The interaction between two independent variables will be the ‘first order interaction effect’ and that between three variables is considered to be the ‘second order interaction effect’.

When there are 2 variables interacting with each other it is a 2x2 factorial design and when more than 2 variables interact with each other it will be multi-factorial design. Analysis of variance (ANOVA) will be used to find the relationship between the variables. This research makes of IBM SPSS Statistics 19® software for the DOE application.

4.7.3.2.3 **Multiple Regression Analysis (MRA)**

Multiple Regression Analysis (MRA) has been used to associate the research variables in this research. The general regression model is given by,

\[ y_i = \beta_0 + \beta_1 x_{i1} + \ldots + \beta_p x_{ip} + e \]  

Where,

\[ y_i = \text{the value of the } i^{\text{th}} \text{ case of the dependent variable} \]

\[ p = \text{the number of predictors (independent variables)} \]

\[ \beta_j = \text{the value of the } j^{\text{th}} \text{ coefficient, } j=0,\ldots,p \]

\[ x_{ij} = \text{the value of the } i^{\text{th}} \text{ case of the } j^{\text{th}} \text{ predictor} \]

\[ e_i = \text{the error in the observed value for the } i^{\text{th}} \text{ case, or the difference between the predicted value of the dependent variable and its true value.} \]
4.7.4 Structural Equation Modelling (SEM)

“Structural Equation Modelling” (SEM) is a second generation statistical technique for simultaneously testing and estimating causal relationships among multiple independent and dependent constructs. The primary assumptions of research applying SEM and the basic properties of a structural equation model along with different types of indicator sets for latent variables is presented in the next section.

Generally, research that applies structural equation modelling follows a positivist epistemological belief. According to the work of Orlikowski and Baroudi as well as Dubé and Paré (cited in Urbach and Ahlemann, 2010), a set of characteristics classifies research as positivist. Ontologically, positivist research assumes an objective, physical, and social world that exists independently of humans. Furthermore, the nature of this world can be relatively easily apprehended, characterized, and measured. The researcher plays a passive, neutral role and does not intervene in the phenomenon of interest.

Urbach and Ahlemann (2010) explained that epistemologically, the positivist perspective is concerned with the empirical testability of theories. In other words, these theories are either confirmed or rejected. They are premised on the existence of ‘a priori’ fixed relationships within phenomena that can be identified and tested through hypothetico-deductive logic and analysis. The relationship between theory and practice is considered as primarily technical. In contrast with the position adopted by the interpretive and critical philosophies, researchers can objectively evaluate or predict actions or processes, but cannot become involved in moral judgments or subjective opinions.

SEM techniques can be considered the second generation of multivariate analysis. In contrast to first-generation techniques, such as factor analysis, discriminant analysis, or multiple regression, structural equation modelling allows the researcher to simultaneously
consider relationships among multiple independent and dependent constructs. Thus, SEM answers a set of interrelated research questions in a single, systematic, and comprehensive analysis.

The structural equation model also supports latent variables (LVs) and this is an important aspect of SEM. LVs can be considered hypothetical constructs invented by a scientist for the purpose of understanding a research area. Since LVs are unobservable and cannot be directly measured, researchers use observable and empirically measurable indicator variables (also referred to as manifest variables (MVs)) to estimate LVs in the model. Thus, the relationships can be analyzed between theoretical constructs, such as intentions, perceptions, satisfaction, or benefits, which are important to almost every discipline. Consequently, the use of LVs has the potential to model theoretical constructs that are hard or impossible to measure directly.

A structural equation model consists of different sub-models which are the structural model and the measurement model. In the structural model, also called inner model, the LVs are related with each other according to substantive theory. LVs are divided into two classes, ‘exogenous and endogenous’. Exogenous LVs do not have any predecessor in the structural model, all others are endogenous LVs.

The ‘measurement model or outer model’ relates observed variables (MVs) to their latent variables (LVs). Often observed variables are referred to as manifest variables or indicators, latent variables as factors. Within the PLS framework one manifest variable can only be related to one LV. All manifest variables related to one LV are called a block. So each LV has its own block of observed variables. A block must contain at least one MV. The way a block can be related to an LV can be either reflective or formative. The
combination of structural model and measurement models leads to a complete structural equation model.

SEM adopts the Partial least Square Method (PLSM) as a replacement for Principal Component Analysis (PCA) of factor analysis. The method emerged in order to remove the problem of multicollinearity in a regression model. When the coefficients of a regression model are to be estimated and there is a relatively large number of explanatory variables X with an extreme dependence relationship between them, multicollinearity exists. The problem of multicollinearity means the regression coefficients can be insignificant to the explained variable and this may cause difficulties in interpreting the regression equation due to erratic coefficient signs.

When this problem appears, the most direct solution is to reduce the dimensionality of X, the set of explanatory variables. The immediate question is then how to carry out this reduction. The answer usually involves finding a set of new variables which are created as a linear combination of the originals in such a way that the problem of multicollinearity is eliminated. The principal components method has been widely used for many years and until recently it was a reference point among dimensionality reduction techniques. The application of the principal components method to regression was usually referred to as Principal Components Regression (PCR).

The PCR performs a principal components analysis on X and these principal components are used as explanatory variables for Y. But the problem of choosing an optimum subset of independent variables, principal components, still exists, since they have been chosen to explain X, but there is no guarantee that the principal components that explain X will be pertinent for explaining Y. PLS Regression finds principal components that explain X and are also the best for explaining Y. This means that it extends principal components
analysis with a regression phase so that X’s principal components will explain the covariance between X and Y as far as possible. In other words, PLS Regression attempts to extract latent (non-observable) variables so that they collect most of the variation of the real X (observable) variables in such a way that they may also be used to model the Y response (dependent) variables.

As a result, the PLS-R (Partial Least Squares Regression) technique was developed to avoid the effect of multicolinearity (among other factors) in the estimation of regression parameters. In turn, the PLS-R model seeks to predict dependent variables. In practice, this objective represents an attempt to maximize the explained variance of the said variables (variance of Y explained by the correlation existing between X and Y). Therefore, PLS Regression may be more appropriate for predictive purposes (Chin et al., 2003). Indeed, PLS Regression is mainly suited to predictive causal analyses in highly complex situations with poorly developed theoretical understanding. PLS-R is generally recommended for predictive research models. In other words, PLS-R is a more prediction-oriented method than PCR, since the latter focuses on reducing the dimensionality of X without taking into account the relationship that exists between X and Y.

The two techniques - one based on Principal Components Regression and one on PLS Regression- are compared in solving the problem of multicolinearity in the estimation of regression parameters. Both PLS-R and PCR aim to reduce dimensionality and to thereby tackle the problems that often occur in sets of explanatory variables which have high multicolinearity. However, the two techniques take different approaches and therefore obtain different results. PCR is to establish the maximum variability or variance of the explanatory variables and PLS-R aims to do the same whilst also taking into account the relationship between X and Y. That is, PLS Regression estimates regression parameters
so that the variance of Y explained by the correlation existing between X and Y is maximal, or, equivalently, so that the residual variance of the predictive relationships is minimal. This has been effectively used by structural equation modelling.

Structural equation modelling (SEM) has gained popularity across many disciplines in the past two decades for its generality and flexibility. As a second generation statistical modelling tool, its development has been by leaps and bounds since the past decade. With advances in estimation techniques, basic models, such as measurement models, path models, and their integration into a general covariance structure SEM analysis framework have been expanded to include, but are by no means limited to, the modelling of mean structures, interaction or nonlinear relations, and multilevel problems.

Structural equation modelling is a general term that has been used to describe a large number of statistical models used to evaluate the validity of substantive theories with empirical data. Statistically, it represents an extension of general linear modelling (GLM) procedures, such as the ANOVA and multiple regression analysis. One of the primary reasons why SEM is chosen in this research is that it can be used to study the relationships among latent constructs that are indicated by multiple measures. It is also applicable to both experimental and non-experimental data, as well as cross-sectional and longitudinal data. SEM takes a confirmatory (hypothesis testing) approach to the multivariate analysis of a structural theory and gives empirical evidence to the causal relations among multiple variables. The causal pattern of inter-variable relations within the theory is specified a priori (beforehand). The goal is to determine whether a hypothesized theoretical model is consistent with the data collected to reflect this theory.

In this research there is a need to establish the empirical evidence for the causation between OCB, TQM, KM and PERF. The consistency in SEM is evaluated through
model-data fit, which indicates the extent to which the postulated network of relations among variables is plausible.

The research methodology adopted in SEM involves eight stages (Figure 4.3).

**Figure 4.3:** Stages in SEM Analysis (Vinzi et al., 2010; Hwang et al., 2010; Wong, 2011)
1. Specifying the Structural Model

A sound model must be grounded well in theory. Theory in turn is based on findings in the literature, knowledge in the field, or one’s educated guesses, from which causes and effects among variables within the theory are specified. Models are often easily conceptualized and communicated in graphical forms. In these graphical forms, a directional arrow (→) is universally used to indicate a hypothesized causal direction. The variables to which arrows are pointing are commonly termed endogenous variables (or dependent variables) and the variables having no arrows pointing to them are called exogenous variables (or independent variables). Observed variables are commonly enclosed in rectangular boxes and latent constructs are enclosed in circular or elliptical shapes.

Due to the flexibility in model specification, a variety of models can be conceived. However, not all specified models can be identified and estimated. A basic principle of identification is that a model cannot have a larger number of unknown parameters to be estimated than the number of unique pieces of information provided by the data. Because the scale of a latent variable is arbitrary, another basic principle of identification is that all latent variables must be scaled so that their values can be interpreted. These two principles are necessary for identification but they are not sufficient. The issue of model identification is complex as in the present research, where the four interconnected constructs with each construct having several indicators.

When a model is identified, every model parameter can be uniquely estimated. A model is said to be over-identified if it contains fewer parameters to be estimated than the number of variances and covariance, just-identified when it contains the same number of parameters as the number of variances and covariance, and under-identified if the number of variances and covariance is less than the number of parameters. Parameter estimates of
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an over-identified model are unique given a certain estimation criterion (e.g., maximum likelihood). All just-identified models fit the data perfectly and have a unique set of parameter estimates. However, a perfect model-data fit is not necessarily desirable in SEM.

Model estimates for path coefficients and their standard errors are generated under the implicit assumption that the model fit is very good. If the model fit is very close, then the estimates and standard errors may be taken seriously, and individual significance tests on parameters (path coefficients, variances, and covariances) may be performed. Structural model adopts path analysis which is an extension of multiple regression that involves various multiple regression models or equations that are estimated simultaneously. This provides a more effective and direct way of modelling mediation, indirect effects, and other complex relationship among variables. Path analysis can be considered a special case of SEM in which structural relations among observed vs. latent variables are modelled. Structural relations are hypotheses about directional influences or causal relations of multiple variables e.g., how independent variables affect dependent variables. Hence, the structural model is sometimes referred to as causal modelling. Because analysing interrelations among variables is a major part of SEM and these interrelations are hypothesized to generate specific observed covariance (or correlation) patterns among the variables, SEM is also sometimes called covariance structure analysis. In SEM, a variable can serve both as a source variable (called an exogenous variable, which is analogous to an independent variable) and a result variable (called an endogenous variable, which is analogous to a dependent variable) in a chain of causal hypotheses. This kind of variable is often called a mediator. As an example, suppose that family environment has a direct impact on learning motivation which, in turn, is hypothesized to affect achievement. In this case motivation is a mediator between family environment and
achievement; it is the source variable for achievement and the result variable for family environment. Furthermore, feedback loops among variables (e.g., achievement can in turn affect family environment in the example) are permissible in SEM, as are reciprocal effects (e.g., learning motivation and achievement affect each other).

In the structural model, observed variables are treated as if they are measured without error, which is an assumption that does not likely hold in most social and behavioural sciences. When observed variables contain error, estimates of path coefficients may be biased in unpredictable ways, especially for complex models (Bollen, 1989). Estimates of reliability for the measured variables, if available, can be incorporated into the model to fix their error variances (e.g., squared standard error of measurement via classical test theory). Alternatively, if multiple observed variables that are supposed to measure the same latent constructs are available, then a measurement model can be used to separate the common variances of the observed variables from their error variances thus correcting the coefficients in the model for unreliability.

2. Specifying the Measurement Models
The measurement of latent variables has originated from psychometric theories. Unobserved latent variables cannot be measured directly but are indicated or inferred by responses to a number of observable variables (indicators). Latent constructs such as intelligence or reading ability are often gauged by responses to a battery of items that are designed to tap those constructs. Responses of a study participant to those items are supposed to reflect where the participant stands on the latent variable. Statistical techniques, such as factor analysis, exploratory or confirmatory, have been widely used to examine the number of latent constructs underlying the observed responses and to evaluate the adequacy of individual items or variables as indicators for the latent constructs they are supposed to measure.
The measurement model in SEM is evaluated through confirmatory factor analysis (CFA). CFA differs from exploratory factor analysis (EFA) in that factor structures are hypothesized a priori and verified empirically rather than derived from the data. EFA often allows all indicators to load on all factors and does not permit correlated residuals. Solutions for different number of factors are often examined in EFA and the most sensible solution is interpreted. In contrast, the number of factors in CFA is assumed to be known. In SEM, these factors correspond to the latent constructs represented in the model. CFA allows an indicator to load on multiple factors (if it is believed to measure multiple latent constructs). It also allows residuals or errors to correlate (if these indicators are believed to have common causes other than the latent factors included in the model). Once the measurement model has been specified, structural relations of the latent factors are then modelled essentially the same way as they are in path models. The combination of CFA models with structural path models on the latent constructs represents the general SEM framework in analysing covariance structures. In the present research, all the dimensions: OCB, TQM, KM and PERF have a fixed dimensions and the metrics for each of them have proved validity. So, the approach of CFA is most applicable and hence it is used.

3. Data collection and Validation
SEM is based on covariance and covariance is less stable when estimated from small samples. So generally, large sample sizes are needed for SEM analyses. Parameter estimates and chi-square tests of fit are also very sensitive to sample size; therefore, SEM is a large sample technique. However, if variables are highly reliable it may be possible to estimate small models with fewer participants. MacCallum, Browne, and Sugawara (1996) presented tables of minimum sample size needed for tests of goodness-of-fit based on model degrees of freedom and effect size. In addition, although SEM is a large sample
technique and test statistics are effected by small samples, promising work has been done by Bentler and Yuan (1999) who developed test statistics for small samples sizes. As SEM is a large sample technique (usually N > 200) the sample size required is somewhat dependent on model complexity, the estimation method used, and the distributional characteristics of observed variables (Kline, 2005). SEM has a number of synonyms and special cases in the literature including path analysis, causal modelling, and covariance structure analysis.

Problems of missing data are often magnified in SEM due to the large number of measured variables employed. The researcher who relies on using complete cases only is often left with an inadequate number of complete cases to estimate a model. Therefore, missing data imputation is particularly important in many SEM models. When there is evidence that the data are missing at random (MAR; missing if a variable may depend on other variables in the dataset but the missing of the data does not depend on the variable itself) or missing completely at random (MCAR; missing of data is unrelated to the variable missing data or the variables in the dataset), a preferred method of imputing missing data, the EM (expectation maximization) algorithm to obtain maximum likelihood (ML) estimates, is appropriate (Little & Rubin, 1987). SmartPLS® include procedures for estimating missing data which has been used in the present research. Once there is no missing data the data gets validate for the subsequent analysis.

4. PLS-SEM Model Estimation
After the model specification component is completed the population parameters are estimated and evaluated. PLS is a soft modelling approach to SEM with no assumptions about data distribution and particularly suitable under following situations (Vinzi et al., 2010; Hwang et al., 2010; Wong, 2011):
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1. Sample size is small.
2. Applications have little available theory.
3. Predictive accuracy is paramount.
4. Correct model specification cannot be ensured.

It is important to note that PLS-SEM is not appropriate for all kinds of statistical analysis. There are some weaknesses of PLS-SEM, including:

1. High-valued structural path coefficients are needed if the sample size is small.
2. Problem of multicollinearity if not handled well.
3. Since arrows are always single headed, it cannot model undirected correlation.
4. A potential lack of complete consistency in scores on latent variables may result in biased component estimation, loadings and path coefficients.
5. It may create large mean square errors in the estimation of path coefficient loading.

In spite of these limitations, PLS is useful for structural equation modelling in applied research projects especially when there are limited participants and that the data distribution is skewed (Wong, 2011). PLS-SEM has been deployed in many fields, such as business strategy (Hulland, 1999), behavioural sciences (Bass et al, 2003), management information system (Chin et al., 2003), organization (Sosik et al., 2009), marketing (Henseler & Sarstedt, et al., 2013). Considering the nature and context of these studies it is also relevant to the present context of research.

5. Assessing PLS-SEM Results for Reflective Measurement Models
Reflective measurement model is often referred to as outer model in SmartPLS®. The Figure 4.4 shows an endogenous variable Y3 with two exogenous variables Y1 and Y2. Both the exogenous variables have two indicators each (X1, X2, X3 & X4), the
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endogenous variable also has two indicators (X5 & X6). These measurements include the unidirectional predictive relationships between each latent construct and the associated observed indicators. Multiple relations are not permitted here therefore, indicator variables are associated with only a single latent construct. PLS-SEM can handle both formative and reflective measurement models. Reflective indicators are seen as functions of latent constructs, and changes in the latent construct are reflected in the changes in the indicator (manifest) variables. Reflective indicators are indicated as single headed arrows pointing from the latent construct outwards towards the indicators. The associated coefficients are called outer loadings (W1, W2 etc.).

![Diagram](image.png)

**Figure 4.4: Stages in SEM Analysis**

6. **Assessing PLS-SEM Results for Formative Measurement Models**

The formative indicators are assumed to cause the latent constructs, and changes in the indicators determine changes in the value of the latent construct (Figure 4.4). Formative indicators are represented by the single headed arrows pointed towards the latent constructs inwards from the indicator variables and their strengths are indicated by the path coefficients (P1, Pe etc). The associated coefficients for these formative relationships are called outer weights (W4, W5 etc.).
7. Assessing PLS-SEM Results for Structural Model

The PLS-Algorithm follows a two stage approach for obtaining the results. In the first stage the latent variables constructs’ scores are estimated via a four step process (Table 4.5). The second stage calculates the final estimates of the outer weights and loading as well as structural model’s path coefficients. The path modelling procedure is called ‘partial’ because, the interactive PLS-SEM algorithm estimates the coefficients for partial least square regression models in the measurement models and structural model. More specifically, when a formative measurement model is assumed, a multiple regression equation is estimated with the latent construct as the dependent variable and the assigned indicators as independent variables (computation of outer weights). In contrast when a reflective measurement model is assumed, the regression model includes the single regression with each indicator individually being the dependent variable, whereas the latent construct is always the independent variable (computation of outer loadings). When the structural model relationships are calculated each endogenous latent construct represents the dependent variable with its latent construct antecedents as independent variable in a partial regression model. All the partial least square models are estimated by the iterative procedures of the PLS-SEM algorithm.

**Table 4.5: Stages and Steps in Calculating the Basic PLS-SEM Algorithm**

<table>
<thead>
<tr>
<th>Stage 1: Iterative estimation of latent construct scores</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Step 1</strong></td>
</tr>
<tr>
<td><strong>Step 2</strong></td>
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<tr>
<td><strong>Step 3</strong></td>
</tr>
<tr>
<td><strong>Step 4</strong></td>
</tr>
</tbody>
</table>

| Stage Two: Final estimates of coefficients (outer weights and loadings, structural model relationships) are determined using the ordinary least squares method for each partial regression in the PLS-SEM model. |
The four steps in stage one are repeated until the sum of the outer weights’ changes between two iterations are sufficiently low. That is, the sum of the changes drops below a predetermined limit (usually $10^{-5}$). If the algorithm converges in step four of stage one, then the final outer weights are used to compute the final latent construct scores in stage two. The final latent constructs scores are used to run the ordinary least square regressions for each construct to determine the structural model relationships’ estimates (path coefficients)

8. Interpretation of Results and Drawing Conclusions

Measurement Model – It is necessary to distinguish between reflective and formative measurement models to evaluate them. Reflective measurement models should be assessed with regard to their reliability and validity. Construct reliability assessment routinely focuses on composite reliability as an estimate of a construct’s internal consistency. Unlike Cronbach’s alpha, composite reliability does not assume that all indicators are equally reliable, making it more suitable for PLS-SEM, which prioritizes indicators according to their reliability during model estimation. Composite reliability values of 0.60 to 0.70 in exploratory research and values from 0.70 to 0.90 in more advanced stages of research are regarded as satisfactory (Nunnally and Bernstein 1994), whereas values below 0.60 indicate a lack of reliability. Likewise, each indicator’s reliability needs to be taken into account, whereby each indicator’s absolute standardized loading should be higher than 0.70. Generally, indicators with loadings between 0.40 and 0.70 should only be considered for removal from the scale if deleting this indicator leads to an increase in composite reliability above the suggested threshold value. Another consideration in the decision to delete indicators is the extent to which their removal affects validity. Weaker indicators are sometimes retained on the basis of their contribution to content validity. Indicators that exhibit very low loadings of 0.40 and
lower should, however, always be eliminated from reflective scales. Reflective measurement models’ validity assessment focuses on convergent validity and discriminant validity.

For convergent validity, researchers need to examine the average variance extracted (AVE). An AVE value of 0.50 and higher indicates a sufficient degree of convergent validity, meaning that the latent variable explains more than half of its indicators’ variance. For the assessment of discriminant validity, two measures have been put forward—the Fornell–Larcker criterion and cross loadings. The Fornell–Larcker criterion (Fornell and Larcker 1981) postulates that a latent construct shares more variance with its assigned indicators than with another latent variable in the structural model.

In statistical terms, the AVE of each latent construct should be greater than the latent construct’s highest squared correlation with any other latent construct. The second criterion of discriminant validity is usually a bit more liberal: an indicator’s loading with its associated latent construct should be higher than its loadings with all the remaining constructs (i.e., the cross loadings).

Traditional statistical evaluation criteria for reflective scales cannot be directly transferred to formative indices. In a formative measurement model, indicators represent the latent construct’s (potentially) independent causes and thus do not necessarily correlate highly. Furthermore, formative indicators are assumed to be error free. Consequently, the concepts of internal consistency reliability and convergent validity are not meaningful when formative indicators are involved. Instead, theoretical rationale and expert opinion play a more important role in the evaluation of formative indexes. Nevertheless, PLS-SEM also offers some statistical criteria for assessing formative measurement models’ quality. At the indicator level, the question arises whether each indicator indeed
contributes to forming the index in accordance with its intended contents. Two specific issues require a critical analysis and careful decisions with respect to the index’s contents. First, an indicator that was theorized to contribute to a formative index can be irrelevant.

The feature called ‘bootstrapping’ available in SmartPLS® is the very useful. The bootstrapping procedure allows the significance of formative indicators’ coefficients to be tested. In addition to considering the significance of the indicator’s weight, researchers should also evaluate an indicator’s absolute importance for its construct (i.e., the loading). When both weight and loading are non-significant, there is no empirical support for the indicator’s relevance in providing content to the formative index. It has to be decided whether to retain or delete a non-significant indicator, which is always crucial for the theoretical underpinnings and interpretation of empirical results. If the theory-driven conceptualization of the measure strongly supports the indicator’s inclusion (e.g., by means of face, expert, and content validity), it should be kept in the formative measurement model and the researcher should focus on explaining the empirical outcome. In the present research no such decision was required as the eliminated indicators were not significant in comparison to the retained ones. Moreover the SEM theory also suggests that the researcher can also interpret the empirical finding as countering the conceptual foundations that support the indicator’s inclusion and thus decide to exclude the non-significant indicator from further analysis. Even though this step usually has almost no effect on the parameter estimates when re-estimating the model, one has to bear in mind that eliminating formative indicators can have adverse consequences for the derived measure’s content validity (Diamantopoulos and Siguaw 2006). While non-significant indicators may simply imply a lack of theoretical relevance, another potential reason for their lack of significance may be the existence of heterogeneous data structures. If parameter estimates are affected by heterogeneity, a formative indicator may
not be significant when solely evaluated on the aggregate data level. But there may be one or more subpopulation(s) in which an indicator is significantly related to the construct while this is not the case in another subpopulation. Therefore, researchers should examine whether heterogeneity affects the coefficients in formative measurement models significantly before eliminating non-significant indictors. This can be done by either partitioning the data on the basis of a priori information (e.g., demographic variables; Rigdon et al., 2010) and estimating distinct models or by using the finite mixture PLS.

Second, an indicator’s information can become redundant due to high levels of multicollinearity in the formative measurement model which can cause indicators to be non-significant. To determine redundancy, it is necessary to examine the degree of multicollinearity in the formative indicators.

**Structural Model** - The primary evaluation criteria for the structural model are the $R^2$ measures and the level and significance of the path coefficients. Because the goal of the prediction-oriented PLS-SEM approach is to explain the endogenous latent variables’ variance, the key target constructs’ level of $R^2$ should be high. The judgment of what $R^2$ level is high depends, however, on the specific research discipline. Whereas $R^2$ results of 0.20 are considered high in disciplines such as consumer behaviour, $R^2$ values of 0.75 would be perceived as high in success driver studies. In marketing research studies, $R^2$ values of 0.75, 0.50, or 0.25 for endogenous latent variables in the structural model can, as a rule of thumb, be described as substantial, moderate, or weak, respectively.

The individual path coefficients of the PLS structural model can be interpreted as standardized beta coefficients of ordinary least squares regressions. Just as with the indicators’ weights and loadings, each path coefficient’s significance can be assessed by means of a bootstrapping procedure. Paths that are non-significant or show signs contrary
to the hypothesized direction do not support a prior hypothesis, whereas significant paths showing the hypothesized direction empirically support the proposed causal relationship. Another important aspect of structural model evaluation is heterogeneity of observations, which can be a threat to the PLS-SEM results’ validity, that is, different population parameters are likely to occur for different subpopulations such as segments of consumers, firms, or countries. However, the true sources of heterogeneity can never be fully known a priori. As a result, situations arise in which differences are related to unobserved heterogeneity and cannot be attributed to any predetermined variable(s).

### 4.7.5 System Dynamics (SD) Modelling & Simulation

The SD modelling and simulation has invaded into management research several decades ago. The SD modelling makes the real-life situation visual through a computer based model and enables the visualization of multiple scenarios. Through these scenarios the user can study the ramifications on the variables of specific interest. The process of system dynamics model development is not simple because the variables are many and the relations need not be linear.

The SD is an approach for studying and modelling complex feedback systems in many areas like industrial, social, environmental, biological and business systems that are found to be dynamic in nature. SD is built upon traditional management of social system, cybernetics and computer simulation (Sushil, 1993). It is based on the philosophy that the behaviour of a system is principally caused by its structure based on policies and traditions; and the structure of an organization can be best represented in terms of underlying flows of various resources across the functional departments tracing across various feedback loops, delays and amplifications in the system.

The credit for pioneering the discipline of system dynamics belongs to Jay W. Forrester. He worked under Gordon S. Brown - the pioneer of feedback control systems
(servomechanism) at the MIT laboratory, after his B.S degree in electrical engineering in 1939. Later, Forrester lead a project of building a real time flight simulator which could predict the behaviour of air planes from wind tunnel test data prior to construction. This was after the World War II. The design of the Whirlwind digital computer was the result of this project (Forrester, 1989). He had by that time already pioneered the field of feedback control systems as well as digital computers, for which he was credited with a number of honours and patents. Forrester in his pursuit for a more practical approach developed a method that is now known as “System Dynamics”. This was based on a study of fluctuating production cycles in a GE household appliance manufacturing plant. He wrote books like “Industrial Dynamics” in 1961 and “Urban Dynamics” in 1969 followed by “World Dynamics” in 1973 to deal with broader social systems. System dynamics was thus, first developed as a management discipline to understand how the policies of corporations produce successes and failures (Forrester, 1989).

Forrester mentions that well-intentioned policies intended to help cure social problems often fail to do so as these policies were derived from unclear mental models. These mental models are insufficient for understanding complex social systems and decisions based on them are likely to do more harm than good. Computer simulation models are then offered as a method to understanding and approaching these systems. Policy makers have historically drawn from their own intuitions for their policies, but their intuitions often point to the wrong decisions. These mistakes are not necessarily caused by incompetence or malice, but because people cannot accurately simulate a complex system in their heads. With the world becoming increasingly complex, the need for new tools is clear. System dynamics is an effective tool to deal with such complex systems.

The challenge in SD modelling is to capture the appropriate causal relationships causing the problem of interest without portraying the model being too complex. Taking the
human cognitive incapability of dealing with complex nonlinear systems it becomes imperative to decide the significant relationships from the less significant ones through trial and error method. Identifying system boundaries of a model thus, is an iterative process. The more, the modeller understands the problem, the easier it becomes to be able to identify significant relationships from the less important ones. Computer simulations shed light on important social problems and may have a significant impact on how people view the systems around them.

There are various software tools which are now available for the modelling and simulation using SD principles. In this research VensimPLE 5.10e (Ventana Systems Inc., 2009), has been used. There are several software which are available which are briefly explained in the following paragraphs.

1. **Dynamo**: This is the first system dynamics simulation language. It was developed by Jack Pugh at MIT, the language was made commercially available from Pugh-Roberts in the early 1960s. DYNAMO today runs on PC compatibles under Windows. It provides an equation based development environment for system dynamics models.

2. **iThink/Stella**: This was introduced on the Macintosh in 1984, the Stella software provided a graphically oriented front end for the development of system dynamics models. The stock and flow diagrams, used in the system dynamics literature are directly supported with a series of tools supporting model development. Equation writing is done through dialog boxes accessible from the stock and flow diagrams. iThink is available for Macintosh and Windows computers. iThink guides business team through the creation of models that simulate business processes and scenarios.

3. **PowerSim**: The Norwegian government sponsored research aimed at improving the quality of high school education using system dynamics models in the mid 1980’s. This project resulted in the development of Mosaic, an object oriented system aimed
primarily at the development of simulation based games for education. PowerSim was later developed as a Windows based environment for the development of system dynamics models that also facilitates packaging as interactive games or learning environments. PowerSim's modelling and simulation tools are used to map formal mental models into models that can be simulated and analyzed on computers.

4. **Vensim**: It was developed in the mid-1980s for use in consulting projects, Vensim was made commercially available in 1992. It is an integrated environment for the development and analysis of system dynamics models. Vensim is the modelling software used by Venture Dynamics Group and runs on Windows and Macintosh computers. Vensim is used for developing, analysing, and packaging high quality dynamic feedback models. Models are constructed graphically or in a text editor. The features include dynamic functions, subscripting (arrays), Monte Carlo sensitivity analysis, optimization, data handling, application interface etc.

### 4.7.5.1 SD Modelling Procedure

The purpose of the SD approach used in the modelling and simulation of performance of organization in terms of the dimensions of OCB, KM and TQM is to investigate the dynamic interaction of various system variables in order to assess the influence on policy decisions. A system boundary is defined, and a model of the system is constructed in order to examine the system. The methodological steps used in this research are in accordance to the procedure recommended by Sterman (2000) as given below:
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1. Define the dynamic problem to be worked out and its scope;
2. Identify the variables involved and their relationship;
3. Select appropriate software to model the system;
4. Construct the stock and flow diagram;
5. Simulate the model;
6. Verify the model; and
7. Validate the model.

The modelling process was divided into five phases: problem articulation, formulating a dynamic hypothesis, formulating a simulation model, testing, and policy design and evaluation which is as shown in Figure 4.5.

**Phase 1: Problem Articulation (Boundary Selection)**

The model needs to address a problem, and should not try to model the whole complexity of a system. The analogy of a map better explains this requirement. A map is a model designed to solve the problem of location in that area and gives the information required in order to move from Point A to Point B. If the map does not have a purpose and tries to incorporate all the complexity of the area, the map may end up being too complex than the problem and will obviously be inadequate. Therefore, the model must have a goal, solve a need, and simplify rather than attempt to emulate a complete system in detail (Sterman 2000). The clear definition of the problem also identifies the model boundaries and scope of the research.

In the present research the system boundary is the performance of the organization. So, the system would consist of the dimensions of OCB as the inputs along with the KM and TQM dimensions acting along with the OCB dimensions. The system output would be the performance level of the organization.
Phase 2: Formulating a Dynamic Hypothesis

Using the available data and expertise of people associated to the service sector under consideration, a theory of the origin of the problem is to be formulated. Many different opinions arise, and the theory should capture as many of them as possible. Still, the model focuses almost exclusively on endogenous variables. Exogenous variables are either included with minor association or excluded totally. The approach is to fix the problem from within the workflow. Variables not related to the problem are excluded, as are variables that add too much complexity to the model without offering additional benefits.

In this phase, different SD tools are used, such as causal loop diagrams and stock and flow maps. The various parameters influencing the OCB, KM and TQM have been identified and its causal relationships are analysed in this research.
Phase 3: Formulating a Simulation Model

Once the dynamic hypothesis has been formulated (including different aspects and points of view); a simulation model is designed that tries to represent all the interrelations in a dynamic system. The idea is to connect the different explanations of the same problem into one particular model that simulates the different behaviours defined in Phase 2. This stage usually creates new insights and feedback to the previous ideas. This process is a constant iteration of modelling data against real world data (Sterman 2000). The model is modified and tested until a functional and full version is developed. Here, the identified variables are interrelated using the equations listed as follows:

\textbf{Governing equations:}

(01) \hspace{1em} \text{altruism} = 0.5; \text{ Units: Dmnl} [0,1]

(02) \hspace{1em} \text{civic virtue} = 0.5; \text{ Units: Dmnl} [0,1]

(03) \hspace{1em} \text{conscientiousness} = 0.5; \text{ Units: Dmnl} [0,1]

(04) \hspace{1em} \text{courtesy} = 0.5; \text{ Units: Dmnl} [0,2]

(05) \hspace{1em} \text{decline in } \text{PERF} = \frac{((0.409 + 0.092*(1\text{-sportsmanship}) + 0.192*(1\text{-conscientiousness}) + 0.184*(1\text{-civic virtue}) + 0.02*(1\text{-altruism}) - 0.002*(1\text{-courtesy}) + 0.113*(1\text{-KM}) + 0.31*(1\text{-TQM}))/1.318) \times \text{PERF}/\text{TIME STEP}}{\text{PERF/TIME STEP}}

\text{Units: Dmnl/Month}

(06) \hspace{1em} \text{decline in } \text{KM} = \frac{((1.165 + 0.114*(1\text{-sportsmanship}) + 0.132*(1\text{-conscientiousness}) + 0.153*(1\text{-civic virtue}) + 0.092*(1\text{-altruism}) + 0.092*(1\text{-courtesy}))/1.748)*(1\text{-organization culture})(\text{Time/TIME STEP})\times(\text{KM}/\text{TIME STEP}}{\text{KM/TIME STEP}}

\text{Units: Dmnl/Month [0,1]}
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(07) \( \text{decline in TQM} = \)
\[
\left( (0.028 + 0.068 \times (1 - \text{sportmanship}) + 0.896 \times (1 - \text{KM}) + 0.018 \times (1 - \text{altruism}) + 0.001 \times (1 - \text{courtesy}) - 0.057 \times (1 - \text{consciousness}) + 0.044 \times (1 - \text{civic virtue}) \right)/0.998 \times \text{TQM/TIME STEP}
\]
Units: Dmnl/Month [0,1]

(08) \( \text{FINAL TIME} = 48 \)
Units: Month; The final time for the simulation.

(09) \( \text{increase in KM} = \)
\[
\left( (1.165 + 0.114 \times \text{sportmanship} + 0.132 \times \text{consciousness} + 0.153 \times \text{civic virtue} + 0.092 \times \text{altruism} + 0.092 \times \text{courtesy})/1.748 \times (1 - \text{KM}) \times \text{organization culture} \times \text{TIME STEP} / \text{TILE STEP} \right)/\text{TILE STEP}
\]
Units: Dmnl/Month

(10) \( \text{increase in PERF} = \)
\[
\left( (0.409 + 0.092 \times \text{sportmanship} + 0.192 \times \text{consciousness} + 0.184 \times \text{civic virtue} + 0.02 \times \text{altruism} - 0.002 \times \text{courtesy} + 0.113 \times \text{KM} + 0.31 \times \text{TQM})/1.318 \times (1 - \text{PERF} \times \text{TILE STEP}/ \text{TILE STEP} \right)/\text{TILE STEP}
\]
Units: Dmnl/Month

(11) \( \text{increase in TQM} = \)
\[
\left( (0.028 + 0.068 \times \text{sportmanship} + 0.896 \times \text{KM} + 0.018 \times \text{altruism} + 0.001 \times \text{courtesy} - 0.057 \times \text{consciousness} + 0.044 \times \text{civic virtue} \right)/0.998 \times (1 - \text{TQM})/\text{TILE STEP}
\]
Units: Dmnl/Month

(12) \( \text{INITIAL TIME} = 0 \)
Units: Month
The initial time for the simulation.

(13) \( \text{KM} = \text{INTEG} \left( (\text{increase in KM} - \text{decline in KM}), 0 \right) \)
Units: Dmnl [0,1]
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(14) organization culture(
[[0,0)-(48,1),(1,0.01),(2,0.02),(3,0.03),(4,0.04),(5,0.06),(6,0.08),(7,0.1),
(8,0.125),(9,0.15),(10,0.2),(11,0.275),(12,0.35),(13,0.45),(14,0.53),(15,
0.63),(16,0.7),(17,0.75),(18,0.8),(19,0.85),(20,0.9),(21,0.93),(22,0.95),
(23,0.97),(24,0.98),(25,0.99),(26,0.99),(27,0.98),(28,0.97),(29,0.95),(30,
0.94),(31,0.92),(32,0.91),(33,0.88),(34,0.86),(35,0.84),(36,0.8),(37,0.72),
(38,0.79),(39,0.73),(40,0.78),(41,0.74),(42,0.77),(43,0.75),(44,0.76),(45,
0.75),(46,0.75),(47,0.75),(48,0.75))
Units: Dmnl [0,1]

(15) PERF = INTEG (increase in PERF-decline in PERF, 0)
Units: Dmnl [0,1]

(16) SAVEPER = TIME STEP
Units: Month [0,1]; The frequency with which output is stored.

(17) sportsmanship=0.5
Units: Dmnl [0,1]

(18) TIME STEP = 1
Units: Month [1,1]
The time step for the simulation.

(19) TQM = INTEG (increase in TQM-delcine in TQM,0)
Units: Dmnl [0,1]

Phase 4: Testing

Even though testing occurs continuously from the start of the modelling process, a tough
test must take place once there is a fully functional version. The test consists of extreme
conditions that do not normally occur in real life, but that have predictable outcomes of
exactly what the model should do in these situations. Extreme conditions may include the
OCB at its top level of operation or TQM at its best, say 100% efficiency (theoretical).
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Testing also includes the verification of equations and dimensional consistency of variables. The variables must also represent significant concepts in the real world (Sterman 2000). In the current research behaviour reproduction test has been considered to validate the model.

**Phase 5: Policy Design and Evaluation**

For studying the policy design an evaluation which forms the final phase of modelling and simulation it is necessary to consider the base run and the permitted variance in the exogenous variables of study. In this research the OCB parameters are varied from 20 percent efficiency to 80 percent efficiency to study their influence on the performance of the organization. The corresponding change in the endogenous variable is studied. At this stage, the model becomes an excellent learning tool and a strong simulator for developing entirely new strategies, structures, and decision rules. The resultant graphs form the basis for the policy decisions and evaluation.

The above procedure resulted in the following causal loop diagram and stock and flow diagram.

**4.7.5.2 Causal Loop Diagram**

The SD model is built on the basis of casual loop diagrams. They represent the synergies and cause-and-effect relations among the various system parameters (Lertpattarapong 2002). During model development, Causal loop diagrams acts as preparatory drafts of causal hypotheses, and they can clear up the representation of a model. A causal diagram comprises of variables connected by arrows indicating the causal influences among the variables. Variables are related by causal links, and arrows are used to describe the relations. Each causal link is designated a polarity, either positive (+) or negative (-) which denote how the dependent variable changes with variation in the independent variable. A loop identifier is used to ascertain whether it is a positive (reinforcing) or a
negative (balancing) feedback loop. In the context of this research, it is presumed that all the dimensions of OCB have positive influences on KM, TQM and OCB (Figure 4.6). In other words, an increase in altruistic approach of the employees will increase the efficiency of KM and so on. Ultimately, PERF will be the endogenous variable as shown.

**Figure 4.6:** Causal Loop Diagram of Performance of Organization
4.7.5.3 **Stock and Flow Diagram**

The causal loop diagrams led into the formation of the stock and flow diagrams. The mathematical relations in the developed causal loop diagram relates the variables in the stock and flow diagram. Thus, SD model developed in this research follows the generic research methodology suggested by Sterman (2000). Stock and flow diagram enables the use of ‘rate’ and ‘stock’ of the variables. Any variable which increases at a particular rate results in the stock or accumulation. In the context of this research each dimension of study constitutes the rate of increase of a variable which again contributes to the increase in the efficiency of the endogenous variable. Increase on KM and decrease in KM are the two rates and the remainder acts as the stock of KM (Figure 4.7). It is important to note that the exogenous variable of the study (OCB) have several dimensions which influence the rate of increase or decrease in the KM performance.

![Stock and Flow Diagram](image)

**Figure 4.7:** Stock and Flow – Knowledge Management
Figure 4.8: Stock and flow – Total Quality Management

Figure 4.9: Stock and Flow – Performance of the Organization
4.7.5.4 Model Validation Process

Validation is the way to ensure that the model is adequately precise (Stewart 1997). The two key concepts in validation are; the ideas of sufficient accuracy and models that are built for a purpose. There is no model that is 100% accurate; in fact, a model is not intended to be precise, but should give a simplified way for understanding and examining reality (Pidd 1992). The main difficulty faced by a simulation analyst is that to determine whether a simulation model is an accurate representation of the considered system for the objectives. System dynamics modellers have developed a large number of tests to dig up the defects and improve the model performance. The validity of a model cannot be greater than the objective set for it. Therefore, the model objective must be a justified representation of the values prevalent in the real system. A model could be proven valid by a series of methods, but the validation may be totally useless if the objectives are wrongly set (Sushil, 1993).

There are various tests for validating a SD model. They are classified as described in the following paragraphs.

A. Validating Model Structure

1. Test of Suitability

**Structure-Verification Test:** This test is meant to answer the following question: “Is the model structure not in contradiction to the knowledge about the structure of the real system, and have the most relevant structures of the real system being modelled?”

**Dimensional-Consistency Test:** “Do the dimensions of the variables in every equation balance on each side of the equation?”

**Extreme-Conditions Test:** “Does every equation in the model make sense even if subjected to extreme (but possible) values of variables?”
Boundary Adequacy Test: This test verifies whether the model structure is appropriate for the model purpose.

2. Tests of Consistency

Face Validity Test: “Does the model structure look like the real system? Does a reasonable fit exist between the feedback structure of the model and the essential characteristics of the real system?”

Parameter Verification Test: The numerical values of parameters should have real system equivalents.

3. Test of Utility and Effectiveness

Appropriateness for the Audience: The more the appropriate a model for the audience, the more will be the audience’s perception of model validity.

B. Validating Model Behaviour

1. Tests of Suitability

Parameter Sensitivity Test: “Do the modes of behaviour change with the parameter variations?”

Structural Sensitivity Test: “Is the behaviour of the model sensitive to reasonable structural reformulation?”

2. Tests of Consistency

Behaviour-Reproduction Test: Here, the generated model behaviour is judged with the historical behaviour pattern.

Behaviour-Prediction Test: “Whether or not the model generates patterns of future behaviour in terms of periods, shape or other characteristics?

Behaviour Anomaly Test: “What behaviour shown by the model is conflicting with the real system behaviour and how implausible behaviour arises if the assumptions are altered?”
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**Family Member Test:** Parameter values are chosen to depict a particular situation. By choosing a different set of parameter values can the model be applied to other situation as well?

**Surprising Behaviour Test:** “Does the model under some test circumstances produce dramatically unexpected or surprise behaviour, not observed in the real system?”

**Extreme-Policy Test:** If the model behaves in an expected fashion even under extreme policies, then it boosts confidence in the model.

**Boundary Adequacy Test:** If the extra model structure does not change the behaviour, then this extra structure is not necessary. Alternatively, if a model structure does not reproduce desired model behaviour, it calls for inclusion of additional model structure.

**Behaviour-Sensitivity Test:** “Does plausible shift in parameters cause model to fail behaviour tests previously passed?”

**Statistical tests:** “Does the model pass statistical tests based on the data from real system?”

3. **Test of Utility and Effectiveness**

**Counter Intuitive Behaviour:** “In response to some policies, does the model exhibit behaviour that at first contradicts intuitions, and later, with the aid of the model, is seen as a clear implication of the structure of the system?”

C. **Validating Policy Implications**

1. **Test of Suitability**

**Policy Sensitivity and Robustness Test:** “Does the model based policy recommendations change with reasonable changes in the parameter values, or reasonable alteration in the equations?”
2. Tests of Consistency

**Changed Behaviour Prediction Test:** “Does the model correctly predict how the behaviour of the system would change if the governing policy is changed?”

**Boundary Adequacy Test:** “Does modifying of the model boundary alter policy recommendations?”

**System Improvement Test:** “Are the policies found beneficial after working with a model?

3. Test of Utility and Effectiveness

**Implementable Policy Test:** “Can those responsible for policy making in the real system be convinced of the values of model-based policy recommendations?”

The Table 4.6 summarizes the main tests, the purpose of each, and the primary tools and methods used in each, which has been adopted in this research.

**Table 4.6:** Tests for Assessment of Dynamic Models (Source: Sterman, 2000)

<table>
<thead>
<tr>
<th>Test</th>
<th>Purpose of Test</th>
<th>Tools and Procedures</th>
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<tbody>
<tr>
<td>1. Boundary Adequacy</td>
<td>Are the fundamental thoughts for expressing the problem endogenous to the model? Does the performance of the model change significantly when boundary hypotheses are eased? Do the policy proposals change when the model boundary is stretched?</td>
<td>Use model boundary charts, subsystem diagrams, causal diagrams, stock and flow maps, and direct assessment of model equations. Use interviews, workshops to solicit expert opinion, archival materials, review of literature, direct inspection/participation in system processes, etc. Modify the model to include convincing additional structure; make constants and exogenous variables endogenous, then repeat sensitivity and policy analysis.</td>
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<tr>
<td>2. Structure Assessment</td>
<td>Is the model structure consistent with the descriptive knowledge of the system? Is the level of aggregation relevant? Does the model live up to basic physical laws such as conservation laws? Do the decision rules encapsulate the behaviour of the variables in the system?</td>
<td>Use policy structure diagrams, causal diagrams, stock and flow maps and direct inspection of model equations. Use interviews, workshops to solicit expert opinion, archival materials, direct inspection or participation in system processes, as in above. Conduct partial model tests of the intended rationality of decision rules. Conduct laboratory experiments to elicit mental models and decision rules of system participants. Develop disaggregate sub models and compare behaviour to aggregate formulations. Disaggregate suspect structures, and then repeat sensitivity and policy analysis.</td>
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<tr>
<td>3. Dimensional Consistency</td>
<td>Is each mathematical statement dimensionally consistent without the parameters having no logical implication?</td>
<td>Use dimensional analysis software. Inspect model equations for suspect parameters. In this model the variables are considered to be dimensionless.</td>
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<tr>
<td>4. Parameter Assessment</td>
<td>Are the parameter values consistent with relevant descriptive and numerical knowledge of the system? Do all parameters have real world counterparts?</td>
<td>Use statistical methods to estimate parameters (wide range of methods available). Use partial model tests to calibrate subsystems. Use judgmental methods based on interviews, expert opinion, focus groups, archival materials, direct experience, etc. (as above) Develop disaggregate sub models to estimate relationships for use in more aggregate models.</td>
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<tr>
<td>5. Extreme Conditions</td>
<td>Does each mathematical statement make logical sense even when its inputs take on extreme states?</td>
<td>Inspect each equation. Test response to extreme values of each input, alone and in combination. Subject model</td>
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<tr>
<td>6. Integration Error</td>
<td>Does the model answer plausibly when subjected to extreme policies, shocks, and parameters? to large shocks and extreme conditions. Carry out tests that assess conformance to basic physical laws.</td>
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<tr>
<td>7. Behaviour Reproduction</td>
<td>Are the results responsive to the selection of time step or numerical integration method? Cut the time step in half and test for changes in behaviour. Use different integration methods and test for changes in behaviour.</td>
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<tr>
<td>8. Behaviour Anomaly</td>
<td>Does the model reproduce the behaviour of interest in the system (qualitatively and quantitatively)? Does it endogenously induce the symptoms of difficulty motivating the study? Does the model generate the various modes of behaviour observed in the real system? Do the frequencies and phase relationships among the variables match the data? Compute statistical measures of correspondence between model and data e.g. descriptive statistics. Compare model output and data qualitatively, including modes of behaviour, shape of variables, asymmetries, relative amplitudes and phasing, unusual events.</td>
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<tr>
<td>9. Family Member</td>
<td>Do anomalous behaviours result when assumptions of the model are changed or deleted? Zero out significant effects (loop knockout analysis). Replace equilibrium assumptions with disequilibrium structures.</td>
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<tr>
<td>10. Surprise Behaviour</td>
<td>Can the model generate the behaviour observed in other instances of the same system? Calibrate the model to the widest possible range of related systems.</td>
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<td></td>
<td>Does the model generate previously unobserved or unrecognized behaviour? Does the model successfully predict the response of the system to novel conditions? Keep accurate, complete, and dated records of model simulations. Use model to simulate foreseeable future behaviour of system. Resolve all discrepancies between model behaviour and your understanding of the real system. Document participant and client mental models prior to the start of the modelling effort.</td>
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</tbody>
</table>
11. Sensitivity Analysis

| Numerical sensitivity: Do the numerical values of the parameters change significantly? |
| Behavioural sensitivity: Do the modes of behaviour generated by the model change significantly? |
| Policy sensitivity: Do the policy implications change significantly? When do assumptions about parameters, boundary, and aggregation are varied over the plausible range of uncertainty? |

| Perform univariate and multivariate sensitivity analysis. Use analytic methods (linearization, local and global stability analysis, etc.). Conduct model boundary and aggregation tests listed in (1) and (2). Use optimization methods to find the best parameters and policies. Use optimization methods to find parameter combinations, which will generate absurd results or reverse policy outcomes. |

12. System Improvement

| Did the modelling process help change the system for the better? |

| Design instruments in progress to assess the impact of the modelling process on mental models, behaviour, and outcomes. Design controlled experiments with treatment and control groups, random assignment, pre intervention and post intervention assessment, etc. |