CHAPTER 3

Methodology
3.A Research Framework

The current study aims to find out the psychosocial factors influencing the turnover intention in Indian IT employees. Based on the review of literature a turnover intention model is proposed for Indian IT employees. The research aims to explore how this model holds well in reality. This chapter details on the research questions, objectives of the study, the research hypothesis and the psychometric tools for assessment. Later this section details on the statistical tool employed for this research – structural equation modeling.

3.A.I Research Title

*Personal, Interpersonal and Job Correlates of Employee Turnover Intention in Indian IT Industry*

3.A.II Research Questions

The guiding norms of this research are the below research questions:

- What are the personal factors that influence the turnover intention of employees in Indian IT industry?

- What are the interpersonal factors that influence the turnover intention of employees in Indian IT industry?
What are the job characteristics that influence the turnover intention of employees in Indian IT industry?

Is there a difference among genders in the pathway to turnover intention observed in Indian IT employees?

3.A.III Objectives of the Study

Research questions were analysed at more depth and based on the review of literature the objectives of this study are defined as below:

- To identify the role of emotional intelligence in influencing turnover intention in Indian IT industry in Indian IT employees.

- To identify the level of influence of perceived manager support in determining turnover intention in Indian IT employees.

- To identify the level of influence of perceived manager status in determining turnover intention in Indian IT employees.

- To identify the level of influence of perceived colleague support in determining turnover intention in Indian IT employees.

- To identify the level of influence of social support in determining turnover intention in Indian IT employees.
To identify the level of influence of job interdependence in determining turnover intention in Indian IT employees.

To identify the level of influence of the degree of interaction outside organization in determining turnover intention in Indian IT employees.

To identify the level of influence of feedback in determining turnover intention.

To identify the level of influence of the degree of work to family conflict in determining turnover intention in Indian IT employees.

To compare the pathway of turnover intention among men and women who are Indian IT employees.

3.A.IV Research Hypothesis

The research hypotheses were formulated based on the results of the two preliminary studies conducted by the research in Indian IT industry and based on the review of literature. The research hypotheses are listed as below:

Manager plays a pivotal role in the job life of an Indian IT employee. Studies have proved that perceived manager support has negative influence on turnover intention. (DeConinck & Johnson, 2009)

H1: Perceived Manager support has significant negative influence on turnover intention.
Eisenberger et al. (2002) has established the moderating effect of perceived manager status on the relationship between perceived manager support and turnover intention. Further as India is a country where power is given high accord (Hofstede et al., 2010), this relationship is hypothesized.

H1a: Perceived Manager Status has a moderating effect on the relationship between perceived manager support and turnover intention.

The role of emotional intelligence is widely seen as a tool to cope up with non-supportive managers (Lubit, 2004). Moderating effect of emotional intelligence on negative work behaviours like turnover is established (Quebbeman & Rozell, 2002). Hence, the below hypothesis is proposed.

H1b: Emotional intelligence has a moderating effect on the relationship between perceived manager support and turnover intention.

Studies have established that colleague support helps to reduce turnover intention (Ducharme et al., 2007). Emphasis can be given on this finding as India is collectivist society (Hofstede et al., 2010). Therefore, the below hypothesis is formulated.

H2: Perceived colleague support has significant negative influence on turnover intention.

Emotional Intelligence is as tool for coping up with non-supportive colleagues (Lubit, 2004). Empirical studies have substantiated this (Elfenbein et al., 2008). So the below hypothesis is made.

H2a: Emotional intelligence has a moderating effect on the relationship between perceived colleague support and turnover intention.
Being a collectivist society social support can be expected play a role in Indian IT industry. The effect of social support on turnover intention is as well empirically verified in collectivist society (Lobburi, 2012). Hence the below relation is hypothesized.

**H3:** Social support has significant negative influence on turnover intention.

Buffering nature of emotional intelligence for social support is well established using empirical studies. (Balogun & Olowodunoye, 2012). Hence the below hypothesis is projected.

**H3a:** Emotional intelligence has a moderating effect on the relationship between social support and turnover intention.

In IT industry the nature of interdependence is ambiguous. Such interdependence will cause conflicts. (McShane & Glinow, 2007). Also a positive relationship between interdependence and turnover intention is proven. (Salancik et al., 1980). Hence the below hypothesis is made.

**H4:** Interdependence has significant positive influence on turnover intention.

Luca and Tarricone (2001) found there is strong correlation between emotional intelligence and team harmony while performing collaborative tasks. As the shaping tendency of emotional intelligence is the accepted norm (Baumeister et al., 2007), the below moderating hypothesis is formed.

**H4a:** Emotional intelligence has a moderating effect on the relationship between interdependence and turnover intention.
Getting timely constructive feedback can help employees to work towards positive outcomes. Empirically, studies have shown that a positive feedback environment contributes negatively to turnover intention (Sparr & Sonnentag, 2008). Hence, below hypothesis is set up.

H5: Feedback from Others has significant negative influence on turnover intention.

McEnrue et al. (2009) showed a positive relationship between feedback receptivity and emotional intelligence based on which below hypothesis is proposed.

H5a: Emotional intelligence has a moderating effect on the relationship between Feedback from others and turnover intention.

Indian IT professionals like to engage in client facing activities and lack of it can lead to turnover intention (Lacity et al., 2008). Based on this finding, the below hypothesis is formulated.

H6: Interaction outside organization has significant negative influence on turnover intention.

Carmeli (2003) has found that emotionally intelligent employees blames the organization less for frustrating events like in interaction outside organizational. Based on that the below moderating hypothesis is formed.

H6a: Emotional intelligence has a moderating effect on the relationship between interaction outside organization and turnover intention.

Studies have shown that work to family conflict lead to turnover intention (Blomme et al., 2010). In Indian context where family life has great significance, this bears greater importance and hence the below hypothesis.

H7: Work to Family Conflict has significant positive influence on turnover intention.
Emotional intelligence was shown to have a moderating effect on the stress caused by work to family conflict (Suliman & Al-Shaikh, 2007). The below hypothesis is found on this fact.

H7a: Emotional intelligence has a moderating effect on the relationship between work to family conflict and turnover intention.

The gender differences are to be explored for the groups separately based on the same set of hypothesis.

Figure 11: Hypothesized Model
All the variables represented inside circle, apart from yellow and red circles are independent variables. The yellow circles signify moderating variables and the red circle represents dependent variable. Line ending with an arrow mark represents a relation between the dependent variable with the independent variable. The dotted red line shows that the variable from which it originates moderates the relationship its arrow mark points.

3.A.V Operational Definitions

The operational definitions used for this study are as below:

Employee Turnover:
Mobley (1982) defines employee turnover as the voluntary cessation of membership in an organization by an individual who received monetary compensation from the organization.

Turnover Intention:
Tett and Meyer (1993) defines turnover intention as a conscious and deliberate willingness to leave the organization.

Emotional Intelligence:
Salovey and Mayer (1990) defines Emotional Intelligence (EI) as ‘one’s ability to recognize one’s own feeling and others’ feelings, to discriminate among them, and to use the information to guide one’s thinking and action’.
Perceived Manager Status:

Eisenberger et al. (2002) define perceived manager status as the degree to which employees identify the manager with the organization.

Perceived Manager Support:

Perceived manager support is the perception of employees on degree to which supervisors value their contributions and care about their well-being. (Eisenberger et al., 2002)

Perceived Colleague Support:

Perceived colleague support is the perception of employees on degree to which help, appreciation and care are provided by colleagues. (Ladd & Henry, 2000)

Social Support:

Morgeson and Humphrey (2006) defines social support as the degree to which a job provides opportunities for advice and assistance from others. In the current study ‘others’ refers to HR personnel, manager’s managers and colleagues who are not part of the same team.

Task Interdependence:

Kiggundu (1981) defines task interdependence as degree to which the job depends on others and others depend on it to complete the work. This comprises of initiated task interdependence and received task interdependence. Initiated task interdependence denotes the degree to which work flows from a particular job to one or more jobs. Received task interdependence denotes the degree to which a person in a particular job is affected by the workflow from one or more other jobs.
Feedback:
Morgeson and Humphrey (2006) defines feedback as the degree to which others in the organization provide information about performance.

Interaction outside Organization:
Morgeson and Humphrey (2006) defines Interaction outside the organization as the extent to which the job requires employees to interact and communicate with individuals external to the organization – i.e. suppliers, customers, or any other external entity.

Work to Family Conflict:
Netemeyer (1996) defines Work to Family conflict as the inter-role conflict in which the general demands of, time devoted to, and strain created by the job interfere with performing family-related responsibilities.

3.A.VI Variables Involved

3.A.VI.(a) Dependent Variable

Dependent variable is:

- Turnover Intention
Independent Variables

Independent variables are:

- Perceived Manager Support
- Perceived Colleague Support
- Social Context of Job Design
  - Social Support
  - Job Interdependence
  - Feedback
  - Interaction Outside Organization
  - Work to Family Conflict

Moderating Variables

The statistical model of moderator can be represented as follows:
“A common framework for capturing both the correlational and the experimental views of a moderator variable is possible by using a path diagram as both a descriptive and an analytic procedure. The model diagrammed in Figure 4 has three causal paths that feed into the outcome variable: the impact of the predictor (Path a), the impact of moderator (Path b), and the interaction or product of these two (Path c). The moderator hypothesis is supported if the interaction (Path c) is significant.” (Baron & Kenny, 1986)

Moderating Variables are

- Emotional Intelligence
- Perceived Manager Status

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9 Baron and Kenny (1986)
3.A.VI.(d) Control Variable

Perceived Utility of Possible Alternatives will be taken as a control variable. It is not directly possible to control the effect of this variable. Tenure, age, marital status and family origin will be controlled and the employees would be selected from two companies of the same nature. Also within these two groups, the research would ensure that the selected employees work in the same domain. This would ensure that the perceived utility and perceived availability of the employees are controlled. The only assumption here is that the levels of the employees’ awareness on job opportunities are the same, which of course will be determined also by their friend circles apart from their tenure, age and education, which are controlled. In addition, the awareness on job opportunities in IT sector is uniformly accessible largely as the opportunities are provided and spread through websites like naukri.com and monsterindia.com.

3.A.VII Research Design

Once the research problem was identified, a rigorous review of literature (Chapter 2) provided an indication for variables that are to be included in the study. Based on the understanding of the literature review, two case studies were undertaken. The first case study (J. Joseph & Shastri, 2013a) interviewed five HR personnel from 5 different organizations to understand employee turnover from their perspective. In the second case study (J. Joseph & Shastri, 2013b), 5 employees from the Indian IT industry who had actually quit their job were interviewed to understand employee turnover from their perspective. From the understanding based on these case studies and literature review a model for employee turnover intention in IT industry is proposed (Section 1.9). The hypotheses are also formulated based on the
proposed model (Section 3.1.4). In the research design, the sampling design, observational design and the statistical design are established. The sampling design deals with the method of selecting items to be observed for the study. The observational design relates to the condition under which the observations are to be made. The statistical design concerns with the question of how many items are to be observed and how the data and information gathered are to be analysed. (Kothari, 1990)

3.A.VII.(a) Research Design Phases

The study first analyses whether the proposed model stands good for the entire data collected. Further, the study examines whether the proposed model stands good for both the groups of gender.

3.A.VII.(b) Sampling Design

3.A.VII.(b).i Sample Selection

A stratified random sampling will be used to select the subjects (Indian IT employees) of a single IT organization.

In total, at least 300 employees will be given questionnaires to measure turnover intention, emotional intelligence, perceived manager support, perceived manager status, perceived colleague support, social context of work design and work-family conflict.
3.A.VII.(b).ii Inclusion Criteria

- Tenure with the company 2-8 years: Employees with experience of up to five years had the highest attrition rate of 39 per cent, while it was 27 per cent for those with 5-10 years of experience and 22 per cent in the 10-15 years' experience bracket. (PTI, Jul 19, 2011) Employees having tenure less than 2 years may still be in the honeymoon period of new employment and more than 8 years may have the hangover effect. (Boswell et al., 2005)

- Total experience 2-10 years: As we consider employees with tenure 2-6 years in the current company the total experience of 2-10 years is chosen.

- Age group to be considered is 23-31. On an average for the said tenure, this should be the age group. This is added as an extra condition to weed out extreme cases.

- The study is done in a single geographical location (Hyderabad, India)

- An attempt is given to ensure almost equal number of men and women

3.A.VII.(b).iii Exclusion Criteria

- People from outside Andhra Pradesh were not considered.

- Companies that do not belong to the ‘prospectors’ strategy group are not selected. This is to avoid the influence of strategy in the proposed model.
• Companies having a very flat hierarchical structure are avoided. This is to ensure that the organizational structure does not influence the model.

• Companies that do not belong to the ‘growth’ categorization based on life cycle and size of organization are not selected. This is to avoid the influence of strategy in the proposed model.

• Companies having scrum methodology of practice are avoided. This ensures that uniform human resource practices are there for employees whose data is collected.

• Employees who do not involve in tactical consulting for ERP software either SAP or Oracle are avoided. This is to ensure a uniform IT work process.

3.A.VIII Tools of Assessment

The below sub sections give a brief on the psychometric tools used in this study and the penultimate section gives the reliability measures of all the psychometric tools. The last sub section details on the demographic questionnaire used in this study.
Turnover Intention:

Turnover Intention is measured by 5 items using 7-point Likert-type scale (1 - strongly disagree, 7 – strongly agree) (Wayne et al., 1997). This was originally prepared by adding first three items from Landau & Hammer (Landau & Hammer, 1986) and fourth item was added from the Michigan Organizational Assessment Questionnaire (Nadler, Jenkins, Cammann, & Lawler, 1975) and the last item was newly introduced (Wayne et al., 1997).

The items in the questionnaire can be categorized into two categories – actions showing turnover intention and thoughts on turnover intention.

Figure 13: Turnover Intention Subscales
Items 1 & 2 of the questionnaire (given in Appendix A: Questionnaire 1) fall into the category of actions showing turnover. These items show the search for alternative jobs. Items 3, 4 & 5 denote thoughts on turnover. Item 5 is reverse scored and the same is mentioned in the questionnaire as well.

3.A.VIII.(b) Psychometric Measure for Emotional Intelligence

There are many popular measures for Emotional Intelligence (EI) like:

- Emotional Quotient Inventory -EQ-i (Bar-On, 2004)
- Emotional and Social Competence Inventory –ESCI. (Boyatzis, 2007)
- Mayer, Salovey, Caruso Emotional Intelligence Test -MSCEIT (Mayer et al., 2003)
- The Wong and Law Emotional Intelligence Scale -WLEIS (Law et al., 2004)
- The Schutte Self-Report Inventory (Schutte et al., 1998)
- The Swinburne University Emotional Intelligence Test. (Palmer & Stough, 2001)

In this study Emotional Intelligence is measured using the 16 item WLEIS (Law et al., 2004). WLEIS is a 7-point Likert-type scale (1 – strongly disagree to 7 – strongly agree).

The reasons for choosing WLEIS is as below:

- This measure of EI has a proven predictive validity for turnover intention
- This measure of EI is specifically designed for organizational psychology
- It has good validity and reliability
- It is a short measure which is also free of cost
- A number of research studies have utilized this scale especially the ones concerning to turnover intention.
- Measurement equivalence of this scale is already proved. (Libbrecht, Lievens, & Schollaert, 2010)
The Wong and Law Emotional Intelligence Scale (WLEIS):

Law et al. (2004) depicts EI by adapting and modifying from the conceptualization of emotional intelligence given in MSCEIT (Salovey & Mayer, 1990). The details of the scale are as below:

The categorization into these sub scales is given along with the questionnaire itself (Appendix A: Questionnaire 2).

3.A.VIII.(c) Psychometric Measure for Perceived Manager Status

Perceived Manager Status is measured by 12 items using 7-point Likert-type scale (1 - strongly disagree, 7 – strongly agree) 7-point Likert-type scale (1 - strongly disagree, 7 – strongly agree). (Eisenberger et al., 2002).
The term ‘Supervisor’ in the original questionnaire is changed to “Manager” to adapt to the terminology in vogue in Indian IT industry.

Figure 15: Perceived Manager Status Subscales

Eisenberger et al. (2002) states that the value of manager represents the how the organization value the manager and positive regard the organization has for the manager. Influence of manager designates manager’s influence in important organizational decisions. Authority of manager designates supervisor’s authority and autonomy in carrying out job responsibilities.

Items 1,3,11 & 12 in the questionnaire (Appendix A : Questionnaire 3) denote value of manager; items 2, 6, 7 & 9 denote influence of manager and items 4, 5, 8 & 10 denote authority of manager.(Eisenberger et al., 2002)
Perceived Manager Support is measured by 8 items using 7-point Likert-type scale (1 – strongly disagree, 7 – strongly agree) (Eisenberger et al., 2002).

The term ‘Supervisor’ in the original questionnaire is changed to “Manager” to adapt to the terminology in vogue in Indian IT industry.

Manager support comprises of the appreciation provided by the manager and the care provided by the manager. (Kottke & Sharafinski, 1988). Items 1, 2, 5 & 8 in the questionnaire (Appendix A: Questionnaire 4) denote appreciation provided by manager and items 3, 4, 6 & 7 denote care provided by manager. Items 2, 3, 5 & 7 are reverse scored and the same is mentioned in the questionnaire.
Ladd and Henry (2000) prepared a questionnaire for perceived colleague support which is used in this study. The questionnaire has nine items based on a 7 point Likert scale (1 - strongly disagree, 7 – strongly agree). This questionnaire was in turn based on the perceived organizational support measure developed by Eisenberger et al. (Eisenberger et al., 1986).

The term “coworker” is changed to “colleague” to adapt to the terminology in vogue in Indian IT industry.

Perceived colleague support can be said to consist of the help, appreciation and care provided by colleagues. (Ladd & Henry, 2000). Items 1, 2 & 4 in the questionnaire (Appendix A: Figure 17: Perceived Colleague Support Subscales

Perceived colleague support can be said to consist of the help, appreciation and care provided by colleagues. (Ladd & Henry, 2000). Items 1, 2 & 4 in the questionnaire (Appendix A:
Questionnaire 5) denote help provided by colleagues. Items 3, 6 & 7 denote appreciation provided by colleague. Items 5, 8 & 9 denote appreciation provided by colleagues.

3.A.VIII.(f)  Psychometric Measure for Social Support

Morgeson and Humphrey (2006) prepared the work design questionnaire (WDQ). The social support factor has two factors – opportunity for socializing and support provided by HR managers, manager’s manager and colleagues outside the current team. The questionnaire (Appendix A: Questionnaire 6) has six items all of which are measure using 7 point Likert scale (1 - strongly disagree, 7 – strongly agree). Items 1, 2 & 3 in the questionnaire represent socializing opportunity. Items 4, 5 & 6 represent support provided by HR managers, manager’s manager and colleagues outside the current team. The wordings of the items 4, 5 & 6 were adjusted to impart the questions clearly. Later a written approval was obtained from Morgeson through personal communication. The original question of item 4 had mentioned manager, which was changed to HR manager. Items 5 & 6 had simply mentioned colleagues, which were changed to colleagues outside the team. This was done to include a wider aspect of social support.
3.A.VIII.(g) Psychometric Measure for Job Interdependence

Job interdependence is also measured using the Work Design Questionnaire (WDQ) (Morgeson & Humphrey, 2006). Job interdependence consists of two factors- initiated interdependence (others having tasks that can start only after finishing the task in hand) and received interdependence (waiting for others to complete their tasks). The categorizations of items are mentioned in the questionnaire itself (Appendix A: Questionnaire 7). Each category has three items each and each item is measured using a 7 point Likert scale (1 - strongly disagree, 7 – strongly agree).
3.A.VIII.(h)  **Psychometric Measure for Feedback**

Feedback was measured using the Work Design Questionnaire (WDQ) prepared by Frederick P. Morgeson and Stephen E. Humphrey in 2006. (Morgeson & Humphrey, 2006). The questionnaire (Appendix A: Questionnaire 8) has three items measured using 7 point Likert scale (1 - strongly disagree, 7 – strongly agree). Each of the three items represent 3 factors viz., feedback on job performance, feedback on job performance effectiveness and feedback on overall performance.
3.A.VIII.(i) Psychometric Measure for Interaction outside Organization

Interaction outside organization was measured using the Work Design Questionnaire (WDQ) was prepared by Frederick P. Morgeson and Stephen E. Humphrey in 2006. (Morgeson & Humphrey, 2006). The questionnaire (Appendix A: Questionnaire 9) has four items measured using 7 point Likert scale (1 - strongly disagree, 7 – strongly agree). Each of the three items represents three factors viz., time spent, involvement and communication. Time spent is assessed by item 1. Items 2 & 4 measure the level of involvement. Item 3 represents the extent of communication.
3.A.VIII.(j) Psychometric Measure for Work to Family Conflict

Netemeyer (1996) developed the work to family conflict questionnaire. Work to family conflict is seen as two types of conflict—time based conflict and stress based conflict. There are five items in the questionnaire (Appendix A: Questionnaire 10). Each of the items are measured by 7 point Likert scale (1 - strongly disagree, 7 – strongly agree). The three items denote time based conflict and the last two items denote stress based conflict.
3.A.VIII.(k)  Reliability and Validity of Psychometric Tools

Reliability measures (Cronbach’s alpha) for the questionnaires used are as below:

Turnover Intention (Wayne) $\alpha = 0.89$

Perceived Manager Support $\alpha = 0.97$

Perceived Colleague Support $\alpha = 0.97$

Perceived Supervisor Status $\alpha = 0.89$

Work Design $\alpha = 0.87$
Work to Family Conflict $\alpha = 0.91$

Emotional Intelligence $\alpha = 0.81$

3.A.VIII.(l) Survey Measure for Demographics

The questionnaire for demographics has 21 questions (Appendix A: Questionnaire 11). Information on various factors like gender, nature of the work, technology domain, hometown etc. was collected using this questionnaire.

3.A.IX Ethical Consideration

Informed consent is obtained from each and every participant.

3.B Data Analysis Using Descriptive Statistics

Sample characteristics of the data collected and comparative analysis between various groups of individuals as per the demographic details obtained will be analysed to understand the nature of the data collected.
3.C Data Analysis Using Structural Equation Modeling

Overview of Structural Equation Modeling:

Hoyle (1995) defines structural equation modeling as a comprehensive approach for testing hypothesis about relations among observed and latent variables. The observed variables are the questions that are posed to the participants and the variables that are determined from the answers of those questions are called latent variables. For example, let us take the variable perceived manager support. In fact, perceived manager support is determined by posing several questions to the participants. For parsimony, item parceling is used. Items or questions posed to the participants are grouped to form parcels and then parcels are treated like a directly observed variable.

Choice of Moderation Analysis

For analysing the moderation effect many methods are available like constrained approach (Marsh, Wen, & Hau, 2004), residual centring (Little, Bovaird, & Widaman, 2006) and Latent moderated structural equation (LMS) (Klein & Moosbrugger, 2000).

Following recommendation by (Weiss, 2010a) this study uses LMS method using MPlus software.

Choice of SEM Software:

The software for structure equation modeling in the study is MPlus (Muthén & Muthén, 1998-2012).
Sample Size Consideration:

SEM models can perform well even with small samples (e.g. 50 to 100) (Iacobucci, 2010). Typical sample sizes in SEM is 200-300 (Kline, 2011)

Advantage of SEM over Multiple Regression and ANOVA

- SEM has the ability to model latent variables – all psychological variables measured as perceived variables are in essence latent variables and not as directly observed variables. For e.g., perceived manager support, perceived stress
- Confirmatory factor analysis helps to correct measurement error.
- SEM is the only analysis that allows complete and simultaneous tests of all the relationships (Tabachnick & Fidell, 2013)
- Error terms are modelled and are not ignored in the analysis.

3.C.I Item Parcelling

The proposed model is studied using structural equation modelling. In item parceling, items or questions posed to the participants are grouped to form parcels and then parcels are treated like a directly observed variable rather than treating each individual items or questions as the directly observed variable. Item parceling offers parsimony with respect to the sample size (Little, Lindenberger, & Nesselroade, 1999). Hence item parcelling is recommended in structural equation modeling (Little, Rhemtulla, Gibson, & Schoemann, 2013). This is line with existing literature (Matsunaga, 2008). Item parceling can be seen as an ideal approach
while dealing with lengthy scales. (Yang, Nay, & Hoyle, 2010). Parceling helps to analyse models as latent model as against a mere path analysis without adding too much complexity (Coffman & MacCallum, 2005). Monte Carlo studies have proved the efficiency of item parceling (Nasser & Wisenbaker, 2003). Item parceling is a good substitute to second order constructs as it does not compromise on quality while simplifying the approach (Hall, Snell, & Foust, 1999). Human research management studies have extensively relied on item parceling (Williams & O'Boyle, 2008). Item parceling paves way for optimum models (Holt, 2004). Item parceling is a useful approach to develop a more parsimonious model and improve model fit without losing information (Wang & Wang, 2012). Even the greatest critics of item parceling, mandates the usage of item parceling when uni-dimensionality is preserved. (Bandalos & Finney, 2001). Questions of each inventory were compartmentalized as per their dimensionality as described in the conceptual framework section. Thus, the uni-dimensionality was preserved. The technique used for parceling in this study is facet-representative parcels (Little et al., 2013). The scales are analysed to understand the facets or sub scale it measures and each sub scale is represented as a parcel. Generally 3 parcels are recommended (Little, Cunningham, Shahar, & Widaman, 2002). However 2 to 6 parcels are also considered good (Yang et al., 2010)

**Formation of Item Parcels:**

Based on the sub scales, item parcels were formed for each of the variables. The variables were parcelled as below based on the facets that were already discussed earlier:

- Turnover Intention – Actions reflecting turnover intention, Thoughts of turnover
- Emotional Intelligence – Use of emotion, regulation of emotion, self-emotions appraisal and others emotions appraisal
- Perceived Manager Status - Valuation, Influence and Authority
- Perceived Manager Support – Manager Appreciation, Manager Care
- Perceived Colleague Support- Help, Appreciation and Care from colleagues
- Social Support – Socializing opportunity, HR & Other Employee Support
- Interdependence – Initiated interdependence and received interdependence.
- Feedback – Feedback on job performance, feedback on job performance effectiveness and feedback on overall performance
- Interaction outside organization - Time spent, Involvement and communication
- Work to Family Conflict – Time based conflict and stress based conflict.

The proposed model can be depicted with the details of these parcels as in below figure:

![Detailed Hypothesized model](image)

*Figure 23: Detailed Hypothesized model*

*(Ellipses in yellow represent moderating variables)*
3.C.II Confirmatory Factor Analysis

A two-step structural equation modeling is the recommended process (J. C. Anderson & Gerbing, 1988). Confirmatory factor analysis (CFA) forms the first step followed by the full structural equation modeling. ‘A confirmatory factor analysis model specifies the posited relations of the observed variables to the underlying constructs, with the constructs allowed to intercorrelate freely’ (Anderson & Gerbing, 1988). By using confirmatory factor analysis we ensure that the measurement model fits well before we proceed to the structural model (Anderson & Gerbing, 1988). Consistency of this approach is well established (Anderson, Gerbing, & Hunter, 1987). Confirmatory factor analysis aims at proving the unidimensionality of factors (Gerbing & Anderson, 1988). Recent reanalysis on the matter has also propounded for a 2-step approach in structural equation modeling. (Iacobucci, 2009). Critique is also there against 2 step approach (Fornell & Yi, 1992a) and the same authors furthered their argument against two step approach. (Fornell & Yi, 1992b). All the claims made by the critiques were later dismissed (Anderson & Gerbing, 1992)

The specification of CFA is strongly driven by theory or prior research evidence (Brown, 2006). The CFA model here is determined after the item parcelling. We try to establish how well the latent variable explains the observed variables. In fact, it is a validation of the measurement instruments. Later for multi group analysis, confirmatory factor analysis is done separately for men and women.

Regardless of the complexity of the model, latent variables must be scaled by either specifying marker indicators or fixing the variance of the factor (usually to a value of 1.0) (Brown, 2006). Throughout this analysis, variance is fixed to one. In this approach all factor loadings are freely estimated (Byrne, 2012). Maximum likelihood algorithm is used for estimation. ‘The term maximum likelihood describes the statistical principle that underlies the derivation of parameter estimates; the estimates are the ones that maximize the likelihood
(the continuous generalization) that the data (the observed covariances) were drawn from this population. It is a normal theory method because multivariate normality is assumed for the population distributions of the endogenous variables’ (Kline, 2011) However some of the data we analysed could possibly be non-normal. It is best not to ignore the multivariate normality assumption of default maximum likelihood estimation (Curran & Bauer, 2007). Discrepancy may occur if normality assumption is not met (Olsson, Foss, Troye, & Howell, 2004) as cited in (Kline, 2011). For this reason, normality test will be carried out to ensure normality. If the data is non-normal then it can be addressed by Satorra-Bentler correction (Satorra & Bentler, 1994). ‘A scaled $\chi^2$ is obtained as a result of this, which can be considered to be adjusted for the degree of kurtosis’ (West, Finch, & Curran, 1995). Estimator MLR in MPlus provides Satorra-Bentler (S-B) corrected $\chi^2$. When degree of non-normality is high S-B $\chi^2$ performs well (Finney & DiStefano, 2006) but over rejects true models at $N \leq 250$ under moderate non-normality (Yu, 2002). For this reason if the data is normal, this study intends to use the ML estimator.

This study analyses the hypotheses for the entire sample first and then does the multi group analysis based on gender. Therefore, the full cycle of process for the entire data will be done first and it will be followed up by multi group analysis. In conducting the confirmatory factor analysis, there is no much difference between the CFA for the entire data (Appendix B: MPlus Code 5) and the gender based multi group analysis. For multi group analysis as well, confirmatory factor analysis is executed per group i.e. CFA will be run separately for men and women (Appendix B: MPlus Code 17 & 18).
3.C.II.(a) General Explanation of MPlus Code

Each of the MPlus codes (viz., Appendix B: MPlus Code) presented in this study, follows a common way of coding wherever possible. Differences mandated by the scenario are explained in those respective sections.

**Title** gives a title to the MPlus code and is informational only.

**Data** specifies from which file the program for the analysis takes the data. Comma separated value (CSV) text files are supplied for the analysis. The parcelled items are arranged from columns 1 to 26 (when the CSV file is opened in Microsoft Excel). The last column specifies whether that particular row of data belongs to men or women group. Value “1” signifies men group and value “2” signifies women group.

Under the command **Variable**, first with the command “Names are”, all the columns present in the CSV files are labelled by a variable name in a sequence. For example, the first variables names given are A1-A2 (i.e. A1 to A2). This means that the first two columns in the CSV file will have the data A1 and A2 respectively. See MPlus Code: Representation, to know the details of each variable. With the command USEVARIABLES all the variables (columns of CSV) that will be used in the analysis are mentioned. USEOBSERVATIONS mentions which all rows will be used in the analysis. For the condition ‘k EQ 1’ (read as ‘k equals one’), all the rows from group men will be selected for analysis and for the condition ‘k EQ 2’, all the rows from group women will be selected.

Under the **Model** command, the latent variables are defined through BY statements. For instance the statement A BY A1* A2*; implies that A causes A1 and A2. The asterisk (*) beside A1 and A2 denotes that these parameters are freely estimated. Free estimation is required as the variance is kept at 1. (e.g., A@1). The value of estimator in Analysis is determined based on the test of normality. The value for “iterations” is default value and for convergence a tighter value is given compared to the default value of .0001 (Muthén & Muthén, 1998-2012) Type = General is used for regular confirmatory factor analysis and
structural equation modelling and it is the default option. The Output option specifies which
all output should be printed and the Plot command specifies which graphs should be made
available along with output.

3.C.II.(b) Test for Outliers

Before the actual CFA, univariate and multivariate outliers are to be found. Univariate
outliers can be found by standardized z score, \(|z| > 3\) is an outlier (Kline, 2011). Multivariate
outlier is identified through Mahalanobis distance p-value < 0.001 (Kline, 2011). Mahalanobis
distance p-value can be directly computed from MPlus using the command
OUTLIERS: MAHALANOBIS in SAVEDATA section. The p-values can be stored into
separate file using the FILE IS option in the same section. (Muthén & Muthén, 1998-2012)
recommends that the entries that are identified as outliers are to be deleted from further
analysis (Wang & Wang, 2012). Outliers are tested in a group specific manner only - i.e.
separately for men and women.

MPlus Code 1: Outliers (Men) provides the MPlus code for identifying multivariate outliers in
the men group and MPlus Code 2: Outliers (Women) serves to identify multivariate outliers in
the women group. The only difference in both the file is the value of USEOBSERVATIONS.
The input file is “full_data_with_outliers.csv” which contains all the observations collected
apart from the missing data. Observations, for which there are missing data, are to be
completely avoided. Even though MPlus has the capability to impute values for missing data
this study intends to avoid the missing data entries completely for better precision. The
Estimator option given is that of MLR as test of normality is not yet done. The savedata
option asks for the Mahalanobis distance and its p-value. In addition, the file with these
values is saved in the specified file name.
3.C.II.(c) Test of Normality

MPlus provides Mardia multivariate skewness and kurtosis tests (Mardia, 1974). This helps to establish the normality and robustness of data (Mardia, Kent, & Bibby, 1979) as mentioned in (Wang & Wang, 2012). The estimator MLR will be used in the analysis—the default estimator when mixture modeling is done in MPlus. Depending on this result, test estimator ML (if data is normal) or MLR (if data is non-normal) will be chosen. There is no need of univariate normality information when there is multivariate normality. If multivariate normality is proved then there is univariate normality as well (Hayduk, 1987) as cited in (Wang & Wang, 2012). The test of normality is carried out in a group specific manner only.

MPlus Code 3: Normality (Men) gives the code for normality test for men group and MPlus Code 4: Normality (Women) gives the corresponding program for women group.

3.C.II.(d) Test for Censored Data

We need to understand whether there is high end or low end censoring that is present and make amendments (like including the command CENSORED in MPlus so that it treats the variables are censored variables. (Muthén & Muthén, 1998-2012)) . Whether the data is piled up in the corners can be analysed through histogram frequency plot. This is directly obtained in output for MPlus with the plot command PLOT1. (Wang & Wang, 2012). Also on the plot obtained on normality, we can see whether the values are censored towards the end.
3.C.II.(e) Construct Validity

Construct Validity is the extent to which a set of measured items actually reflects the theoretical latent construct those items are designed to measure. Construct validity is comprised of convergent validity, discriminant validity, nomological and face validity. (Hair, Black, Babin, & Anderson, 2010)

![Figure 24: Construct Validity](image)

Convergent validity can be determined by factor loading of items (item reliability), average variance extracted (AVE) and construct reliability (or composite reliability).(Hair et al., 2010).
AVE (Average Variance Extracted for a factor) = (Sum of the squared factor loadings of all the items of that factor)/ (Number of items) (Hair et al., 2010)

Construct or composite reliability of a factor (CR) is calculated as:

CR = (Square of the sum of factor loadings of the items of that factor)/ (Square of the sum of factor loadings of the items of that factor + Sum of error variances of all the indicators of that factor) (Hair et al., 2010).

Hair et al. (2010) recommends composite reliability (CR) due to the tendency of Cornbach’s alpha to understate reliability (Sijtsma, 2009) as cited in (Teo, 2011).

Discriminant validity specifies how different a construct is from other construct and is said to exist when the AVE of a construct is greater than any of the squared correlation of the indicator.(Fornell & Larcker, 1981)

Face validity is the appearance of validity in the absence of empirical testing.(Cook & Beckman, 2006) and nomological validity is tested by examining whether the correlations among the construct make sense.(Hair et al., 2010)
### Table 1: Construct Validity Cut Off Criteria

<table>
<thead>
<tr>
<th>Validity</th>
<th>Cut Off</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Construct Validity</strong></td>
<td></td>
</tr>
<tr>
<td>Convergent Validity</td>
<td>Factor Loading: Should be 0.5 or higher and ideally 0.7 or higher. (Hair et al., 2010)</td>
</tr>
<tr>
<td></td>
<td>Average Variance Extracted (AVE): Should not be less than 0.5 (Fornell &amp; Larcker, 1981)</td>
</tr>
<tr>
<td></td>
<td>Construct Reliability (CR): 0.7 or higher. Reliability between 0.6 and 0.7 acceptable if other indicators of the model's construct validity are good. (Hair et al., 2010)</td>
</tr>
<tr>
<td>Discriminant Validity</td>
<td>AVE vs. Other Square Correlation: AVE of the factor should be greater than any of the squared correlation between its indicators (Fornell &amp; Larcker, 1981)</td>
</tr>
</tbody>
</table>

R Square is multiple correlations squared. It shows how much variance a factor account for in an observed variable (Albright & Park, 2009)

#### 3.C.II.(f) Model Fit

Below are the indexes used to assess the model fit:

Chi-Square ($\chi^2$): ‘Assesses the magnitude of discrepancy between the sample and fitted covariances matrices’ (L. t. Hu & Bentler, 1999). ‘With small samples, the computed $\chi^2$ may not be distributed as $\chi^2$, leading to inaccurate probability levels’ (Tabachnick & Fidell, 2013)

Normed Chi-Square ($\chi^2$/df) Chi square is divided by the degrees of freedom which seeks to minimize the effect of sample size on chi-square (Hooper, Coughlan, & Mullen, 2008)
Root Mean Square Error of Approximation (RMSEA): ‘Estimates the lack of fit in a model compared to a perfect (saturated) model’ (Tabachnick & Fidell, 2013)

Standardized Root Mean Square Residual (SRMR): Here again lower values indicate better fit.

Tucker-Lewis Index (TLI) or Non-normed Fit Index (NNFI) and Comparative Fit Index (CFI): TLI and CFI are incremental fit indices. (L.-t. Hu & M.Bentler, 1995) ‘which does not use chi-square in its raw form but compare the chi-square value to a base line model’. (Hooper et al., 2008)

Schermelleh-Engel, Moosbrugger, and Müller (2003) evaluated the cut off criteria for the fit indices and below is the recommendation from them:

<table>
<thead>
<tr>
<th>Fit Measure</th>
<th>Good Fit</th>
<th>Acceptable Fit</th>
<th>Based On</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\chi^2$ p value</td>
<td>$0.05 &lt; p \leq 1.00$</td>
<td>$0.01 \leq p \leq 0.05$</td>
<td>(Hooper et al., 2008) ; (Hayduk, 1996)</td>
</tr>
<tr>
<td>$\chi^2$/df</td>
<td>$0 \leq \chi^2$/df $\leq 2$</td>
<td>$2 &lt; \chi^2$/df $\leq 3$</td>
<td>(Tabachnick &amp; Fidell, 2013)</td>
</tr>
<tr>
<td>RMSEA (Root Mean Square Error Of Approximation)</td>
<td>$0 \leq \text{RMSEA} \leq 0.05$</td>
<td>$0.05 &lt; \text{RMSEA} \leq 0.08$</td>
<td>(Browne &amp; Cudeck, 1993) ; (Savalei, 2012)</td>
</tr>
<tr>
<td>p value for test of close fit (RMSEA $&lt; 0.05$)</td>
<td>$0.10 &lt; p \leq 1.00$</td>
<td>$0.10 &lt; p \leq 1.00$</td>
<td>(Chen, Curran, Bollen, Kirby, &amp; Paxton, 2008)</td>
</tr>
<tr>
<td>RMSEA Confidence interval (CI)</td>
<td>close to RMSEA, left boundary of CI = .00</td>
<td>close to RMSEA</td>
<td></td>
</tr>
</tbody>
</table>
**Table 2: Model Fit Cut Off Criteria**

<table>
<thead>
<tr>
<th>Metric</th>
<th>Cutoff Criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>SRMR</strong> (Standardized Root Mean Square Residual)</td>
<td>$0 \leq \text{SRMR} \leq 0.05$</td>
</tr>
<tr>
<td><strong>CFI (Comparative Fit Index)</strong></td>
<td>$0.97 \leq \text{CFI} \leq 1.00$</td>
</tr>
<tr>
<td><strong>TLI (Tucker Lewis Index) or NNFI</strong></td>
<td>$0.97 \leq \text{NNFI} \leq 1.00$</td>
</tr>
</tbody>
</table>

3.C.III Test for Invariance for Multi group Analysis

3.C.III.(a) Measurement Invariance

Measurement invariance is established when configural invariance, metric invariance, scalar invariance and residual invariance are established. Measurement invariance proves that the measuring instruments measure the same thing across both the groups. In configural invariance, all parameters are set free across groups. Only variance is fixed to one across both the groups. Model fit parameters like the p-value of chi-square, CFI, TLI, etc. are used to ascertain whether configural invariance holds. As we proceed from configural model to residual invariance model, factor loadings, intercepts and residuals are incrementally constrained across both the groups. A LR (loglikelihood) chi-square difference test will indicate whether these incrementally constrained models are statistically different from the configural model if the p-value $> 0.05$ (Wang & Wang, 2012). Moreover, if $\Delta\text{CFI}$ (change in
CFI) between the models are less than 0.01 then it denotes no difference between the models (Cheung & Rensvold, 2002).

**Configural Invariance**

Wang and Wang (2012) defines configural measurement invariance is defined as the same number of factors and the same patterns of free and fixed factor loadings across groups without equality restrictions on any other model parameters. The corresponding MPlus code is given in Appendix B (MPlus Code 19).

**Metric Invariance**

Weak measurement invariance is defined as invariance of factor loadings across groups. (Wang & Wang, 2012). The corresponding MPlus code is given in Appendix B (MPlus Code 20).

**Scalar Invariance**

Wang and Wang (2012) defines scalar invariance or strong measurement invariance is defined as invariance of both factor loadings and indicator/item intercepts across groups. The corresponding MPlus code is given in Appendix B (MPlus Code 21).

**Residual Invariance**

Residual invariance or strict measurement invariance requires metric (factor loadings) invariance, scalar (indicator/item intercepts) invariance, and error variance invariance. (Wang & Wang, 2012). The corresponding MPlus code is given in Appendix B (MPlus Code 22).
Once the measurement invariance is established, we proceed to test the structural invariance. Two tests are carried out here—inequality of factor covariances and inequality of factor means. Inequality of factor variances is not tested as it is of no particular interest (Wang & Wang, 2012). For testing inequality of factor covariance, it is constrained across groups and the model’s chi-square difference with configural model is checked for significance. Also, residual variance are not constrained across groups as it was already done in residual invariance model (Wang & Wang, 2012). We cannot determine the mean of the latent factors but can only find the difference of the mean of the latent factors between both groups (Byrne, 2012).

**Invariance of Factor Covariances**

‘A covariance between two factors represents the association between the two factors. Invariance of factor covariances establish that the relationships between factors under study remain unchanged in different populations’ (Wang & Wang, 2012). The corresponding MPlus code is given in Appendix B (MPlus Code 23).

**Invariance of Factor Means**

Since factor means cannot be identified in all the groups, one of the groups must be treated as the reference group, and then differences in factor means between other groups and the reference group are estimated as recommended by (Byrne, 2012) as referenced in (Wang & Wang, 2012). Then this difference is tested for statistical significance to establish invariance of factor means. The corresponding MPlus code is given in Appendix B (MPlus Code 24).
3.C.III.(c) SEM Without Interaction

Structural Model:

In the single group analysis, the full structural model will be specified without the interaction effects. A model fit has to be obtained before proceeding with further analysis.

In multi-group analysis, the full structural model is run with the measurement invariance – i.e. factor loadings, intercepts and residuals are kept equal across groups. Freeing these parameters across groups improves model fit, but a tighter approach is envisaged here. In MPlus multi group analysis, residuals are not constrained equal by default hence this constraint is mentioned explicitly. The target here is model fit. If model fit is obtained even if certain paths are found to be not significant, they are not avoided in the name of parsimony at this point as these variables could be used for further analysis. However if model fit is not there, an attempt for model fit will be made as per the modification indices suggested by MPlus output.

3.C.IV Single Item LMS

3.C.IV.(a) Latent Moderated Structural Equation

Klein and Moosbrugger (2000) defined the latent moderated structural for the study of moderation effects. (Moosbrugger, Schermelleh-Engel, Kelava, & Klein, 2009).

“The Latent Moderated Structural Equations (LMS) approach is a new method developed for the analysis of the general interaction model that utilizes the mixture distribution and
provides a ML estimation of model parameters by adapting the EM algorithm”. (Klein & Moosbrugger, 2000).

“The term maximum likelihood (ML) describes the statistical principle that underlies the derivation of parameter estimates; the estimates are the ones that maximize the likelihood (the continuous generalization) that the data (the observed covariances) were drawn from this population. It is a normal theory method because multivariate normality is assumed for the population distributions of the endogenous variables”. (Kline, 2011)

“A common approach to the ML estimation of parametric models with mixture densities is the application of the EM (expectation maximization) algorithm (Redner & Walker, 1984). Under fairly general conditions, the EM algorithm provides an iterative estimation procedure that converges to a maximum likelihood estimation of the model parameters (Dempster, Laird, & Rubin, 1977)” (Klein & Moosbrugger, 2000)

LMS can be carried out through the application MPlus. (Muthén & Muthén, 1998-2012). LMS method is recommended to be the most promising by various studies (Weiss, 2010b)

As multiple moderation effects have to be studied, the effects are studied individually and then the significant ones are combined together.

Significance of each moderated relation is individually studied by the code in Appendix B (MPlus Code 7 to 14 – for entire sample) and if the relation is non-significant then that moderated relation is avoided from further study. This code is run as many times as moderated relations exist in the proposed model. For multi group analysis, this individual moderation runs are made with invariance (Appendix B- MPlus Code 26-33)
3.C.IV.(b) Process for Single Item LMS

When three interaction effects are mentioned in MPlus, then there will be more than 50,000 integration points and that will run indefinitely. Therefore, the option is to reduce the integration points by explicitly specifying the number of integration points say for e.g. 6000. However, to have high precision it is recommended to test for the interactions separately. All the significant interactions are then combined together to have a full blown LMS whose integration point is fixed to 6000. (Muthén, 2013) as per MPlus recommendation (Muthén & Muthén, 1998-2012).

Single interaction effect will be introduced to the model having model fit from the full structural equation modeling. The case is same for single group analysis and multi group analysis.

However, with interaction option, multi group option is not available in MPlus. But the same can be achieved through using latent class approach with the KNOWNCLASS option and analysis type as MIXTURE RANDOM. (Muthén & Muthén, 1998-2012). The test for each moderation effect is done with the measurement invariance and the effects of both the classes are obtained in the output separately. ‘Est./S.E. = z’ helps to identify the significance. If |z| > 1.96, then the interaction effect is said to be significant.

3.C.V Full Blown LMS

From the individual runs of LMS, the significant interactions are identified. The full model is run without non-significant interaction effects and |z| > 1.96 denotes a significant moderation effect.
In multi group analysis, the full model is run with the latent class approach and all the significant interactions, which are significant for either or both class, are mentioned in the XWITH (interaction effect) statements. If the respective class where the interaction effect is not there, the regression path of the interaction effect is set to zero. Again, in this \(|z| > 1.96\) denotes a significant moderation effect. Based on this, the model is rerun by setting the non-significant paths both moderation and otherwise to zero. This model with interaction is compared to a model without interaction that has all the interaction effect paths set to zero. The model with interaction has to be statistically different from this model without interaction as the model without interaction is parsimonious. The statistical difference is determined through loglikelihood difference chi-square test. \(\chi^2\) difference \(TRd\) (Muthén & Muthén, 2013) is given as \(-2(Lo-L1)\) (Rupp, Templin, & Henso, 2010) where \(Lo\) is the H0 value for nested model (with less free parameters- \(p0\)) and \(L1\) is the H0 value of the comparison model (with more free parameters- \(p1\)). The difference \(\chi^2\) (\(TRd\)) value is tested at degrees of freedom \(p1-p0\) for significance. If the data is non-normal, Satorra-Bentler correction has to be done. For this purpose, \(TRd\) is divided by \(cd\), given by the formula:

\[
cd = \frac{(p0*c0 - p1*c1)}{(p0 - p1)}
\]

--where \(c0\) is correction factor for nested model and \(c1\) is the correction factor for comparison model

Once the model with interaction is proved better, the same model is replicated in the multi group setting even without defining the interaction effects. This will enable us to get the model fit for interaction model. There is no separate model fit for interaction model hence the model fit from the model without interaction is used.

Standardized Coefficients are not reported with the latent moderated structural equation in MPlus. (Muthén, 2012) provides the formula to calculate the standardized values. For a simple MPlus Code shown below:

\[
A \ BY \ A1* \ A2*;
\]

\[
P \ BY \ P1* \ P2* \ P3*;
\]
Y BY Y1* Y2*;
AxP | A XWITH P;
Y ON A P AxP;
A@1;P@1;Y@1;

So as to make the notations similar to standard notations:

A \rightarrow \eta_1
P \rightarrow \eta_2
Y \rightarrow \eta_3

\beta_1^* = \beta_1 \sqrt{V(\eta_1)} / \sqrt{V(\eta_3)}
\beta_2^* = \beta_2 \sqrt{V(\eta_2)} / \sqrt{V(\eta_3)}
\beta_3^* = \beta_3 \sqrt{V(\eta_1) \cdot V(\eta_2)} / \sqrt{V(\eta_3)}

---- \beta_1^*, \beta_2^* and \beta_3^* are the standardized coefficients
---- \beta_1, \beta_2 and \beta_3 are the non-standardized coefficients
---- V is the variance

V(\eta_3) = \beta_1^2 V(\eta_1) + \beta_2^2 V(\eta_2) + 2 \beta_1 \beta_2 \text{Cov}(\eta_1, \eta_2) + \beta_3^2 ((V(\eta_1) V(\eta_2) + [\text{Cov}(\eta_1, \eta_2)]^2))
+ V(\zeta_3) (Muthén, 2012)
By modelling,

\[ V(\eta_1) = 1 \]
\[ V(\eta_2) = 1 \]
\[ V(\zeta_3) = 1 \]

Hence \( V(\eta_3) \) can be re-written as:

\[ V(\eta_3) = \beta_1^2 + \beta_2^2 + 2 \beta_1 \beta_2 \text{Cov}(\eta_1, \eta_2) + \beta_3^2 (1 + [\text{Cov}(\eta_1, \eta_2)]^2) + 1 \]

---Equation (1)

R Square is given by \[ \frac{V(\eta_3) - V(\zeta_3)}{V(\eta_3)} \]

\[ \Rightarrow \frac{V(\eta_3) - 1}{V(\eta_3)} \]

---Equation (2)

Proportion of \( V(\eta_3) \) contributed by the interaction term can be quantified as below as stated in (Mooijaart & Satorra, 2009) as cited in (Muthén, 2012)

\[ \beta_3^2 \frac{V(\eta_1) V(\eta_2) + [\text{Cov}(\eta_1, \eta_2)]^2}{V(\eta_3)} \]

\[ \Rightarrow \beta_3^2 \frac{1 + [\text{Cov}(\eta_1, \eta_2)]^2}{V(\eta_3)} \]

---Equation (3)

Mean of \( \eta_3 \) is given as \( E(\eta_3) = \beta_3 \text{Cov}(\eta_1, \eta_2) \) (B. O. Muthén, 2012)

---Equation (4)
Hence, the formula for all standardized slope can be obtained from unstandardized slope as below:

\[ \beta_1^* = \frac{\beta_1}{\sqrt{V(\eta_3)}} \]

\[ \beta_2^* = \frac{\beta_2}{\sqrt{V(\eta_3)}} \]

\[ \beta_3^* = \frac{\beta_3}{\sqrt{V(\eta_3)}} \] (Muthén, 2012)

---Equation (5)

Muthén (2012) as well provides equations for plotting interaction at mean of \( \eta_2 \), one SD above the mean of \( \eta_2 \) and one SD below the mean of \( \eta_2 \). (Porzio & Vitale, 2007)

\[ E(\eta_3^* | \eta_1^*, \eta_2^* = 0) = \beta_1^* \eta_1^* , \]

\[ E(\eta_3^* | \eta_1^*, \eta_2^* = 1) = (\beta_1^* + \beta_3^*) \eta_1^* + \beta_2 \]

\[ E(\eta_3^* | \eta_1^*, \eta_2^* = -1) = (\beta_1^* - \beta_3^*) \eta_1^* - \beta_2 \]

---Equation (6)

3.C.VI  Invariance Testing at SEM level for Multi group Analysis

Invariance at SEM level also follows a similar method to invariance at CFA level. First, a configural model is devised with all the parameters free. It is important here to establish that the interaction effects as hold in the configural model. However to establish the model fit, the model without interaction using multi group option is run. Then the fully constrained model with factor loadings, intercept and structural regression paths constrained equal is run. (Byrne, 2012) Invariance at SEM level is established if the configural model (with
interaction) is found to be statistically same as the fully constrained model. A loglikelihood chi-square difference test is used for this purpose.

**Configural Invariance**

In testing the configural invariance of full structural equation model, factor loadings and intercepts are not constrained equal across groups. As the intercepts are free across groups factor means are fixed to zero. (Byrne, 2012)

**Structural Path Invariance**

In testing the structural path invariance of full structural equation model, factor loadings, intercepts and structural paths are constrained equal across groups. Also, so as to obtain an identifiable model, factor means are fixed to zero. (Byrne, 2012)

**Summary**

This chapter introduced the research questions and then the objectives of the study. The hypotheses that have to be tested in the study were established. Operational definitions used in the study were enunciated and the details of the research design were described along with the details of psychometric tools used in the study. Finally, the data analysis strategy was described in detail.