CHAPTER 3

TOOLS, TECHNIQUES, AND METHODOLOGY

In the first chapter, four research objectives have been discussed under section 1.5. For each research objective, there are many methodologies available. This chapter briefly explained the methods that are used to achieve the goals. Further, reasons to select the particular methodologies are discussed for specific objectives.

For assessing the customer value perception and their effect on customer satisfaction, structural equation modeling (SEM) is used. A structural equation model is a method that estimates a series of causal relationships among multiple observed variables, and these relationships are modeled in pictorial form. SEM model is the a priori hypothesis for a set of observed and latent variables. The SEM method aims to find out the a priori model valid rather than suitable (Shah and Goldstein, 2006).

ISM and MICMAC are used to identify the factors that can help a firm achieve a competitive position and establish contextual relationships among these factors. MICMAC uses binary numbers for the relationship, which failed to explain the strength of relationships. Thus, Fuzzy-MICMAC (FMICMAC) is used. However, these methodologies are old but still have the center of focus among researchers due to their validated consistency, fewer expert involvements for decision-making, easy applicability, applicability on any complex problems, etc. Some researches that used ISM methodology from reputed journals are as follows: Li et al. (2019), Sindhwani and Malhotra (2016), Raut et al. (2018a; 2017; 2018b), Dube and Gawande (2016), and Kumar and Dixit (2018).

Quality function deployment is the method that involves planning services to satisfy the customers more efficiently. For this tool, customer requirement is the first step or, say, driver force. In the manufacturing sector, the customer requirements are fixed and documented. While in the retail industry, it is tough to fix the requirement; therefore, customer value perception is used at the place of the requirement that assessed from the first objective of the research. Further, the design requirements are taken from the second objective of the study. QFD starts with the construction of supertanker cargo ships in the 1960s from Japan and moves to the automotive industry. Further, this tool is adopted by aerospace, defense, education, lifecycle analysis, logistics, software, process engineering, telecommunications, and health care (Bolar et al., 2014). In the retail sector, QFD is adopted by some authors like Simons and Bouwman (2006), Hsu and Lin (2006), and Seker (2019).

To establish the relationship among factors in terms of cause and effect, DEMATEL is used as the method. DEMATEL is used for the objective type of data, but it is popular for subjective data in this decade. The wide acceptability of DEMATEL can be revealed from its reported applications in various fields of decisions such as barriers of smart energy city (Addae et al., 2017), Website parameters (Cebi, 2013), Technology adoption (Lu et al., 2013), Hospital service quality criteria (Shieh et al., 2010). DEMATEL method used to handle and structure the complicated causal relationship model. The science and Human Affairs Program of the Battelle Memorial Institute of Geneva introduced DEMATEL to solve complex problems (Hsu et al., 2013). DEMATEL, in subjective judgment, has much ambiguity. To overcome this problem, the Grey theory is used. Grey theory was proposed by Deng (1982) from a grey set. Grey system consider the condition of fuzziness which give an advantage over fuzzy (Khompatraporn and Somboonwiwat, 2017; Xia et al., 2015; Li et al., 2007). Grey theory is not limited to only engineering problems only it has been used in management, barriers identification in implantation as well as adoption, risk management, advertisement agencies, project portfolio selection, supplier selection and so forth (Bhattacharyya, 2015; Xia et al., 2015; Rajesh et al., 2014, Thakur and Anbanandam, 2015). The Grey theory method can handle many ambiguities generated from the human decision (Li et al., 2007; Fu et al., 2001). Grey's theory can easily be used with any decision-making process to improve the judgments (Tseng, 2009). Grey numbers are usually pigeonholed as numbers with incomplete information. Grey numbers can convert into crisp numbers with the modified CFCS (converting fuzzy values into crisp scores) method, integrating a three-step procedure (Fu et al., 2012). DEMATEL allows the researcher to assign the weight to the experts involved in the decision-making.

3.1 Structural equation modeling

Mehrotra et al. (2017) define Structural equation modeling (SEM) as “a procedure for estimating a series of dependence relationships among a set of concepts or constructs represented by multiple measured variables and incorporated into an integrated model”. Structural equation modeling (SEM) is the combination of multiple regression and factor analysis. It takes a confirmatory approach to analyze the structural theory (Byrene, 2010). This theory is structured in pictorial form with observed variables, latent variables, and hypothesis relations. The relations are expressed in series of structural equations. Further, the structural equation uses parameters to analyze the observed variables and latent variables (Jöreskog and Sörbom 1993).

3.1.1 Terms involved in the pictorial presentation of SEM

Figure 3.1 shows the following terms that are involved in the graphical representation of SEM:

- **Observed variables**: These variables are directly asked the respondents. Observed variables have other names like statements and items.

- **Latent variables**: These variables are surmised indirectly. Latent variables have other names like construct and factor. These variables are unobservable and represented by multiple items.
- **Endogenous variables**: Endo is a Greek word that means 'in'. Thus, the variables that contain an arrow that heads towards them are known as endogenous variables or, say, a variable caused by other variables.
- **Exogenous variables**: Exo is a Greek word that means 'out'. Thus, the variables that contain an arrow which heads going outside from them is known as exogenous variable or say a variable that is not caused by other variables.
- **Disturbance**: it is also known as error terms or residual. It is treated like a latent variable and is associated with endogenous variables as an unspecified cause of effect variable.
- **Dependence relationship:** A regression type of relationship represented by a straight arrow-headed from independent construct towards dependent construct.
- **Correlation relationship:** It is a relationship among exogenous constructs. The theory speculates that there is no dependent relationship. The relationship among constructs shows by the two-headed curved arrow.
- **Path diagram:** A graphical representation of dependence and correlation relationship among construct.
- **Structural equation model:** It is a combination of factor analysis and multiple regressions. It examines the series of dependent relationships among the observed variables and constructs as well as between other constructs.

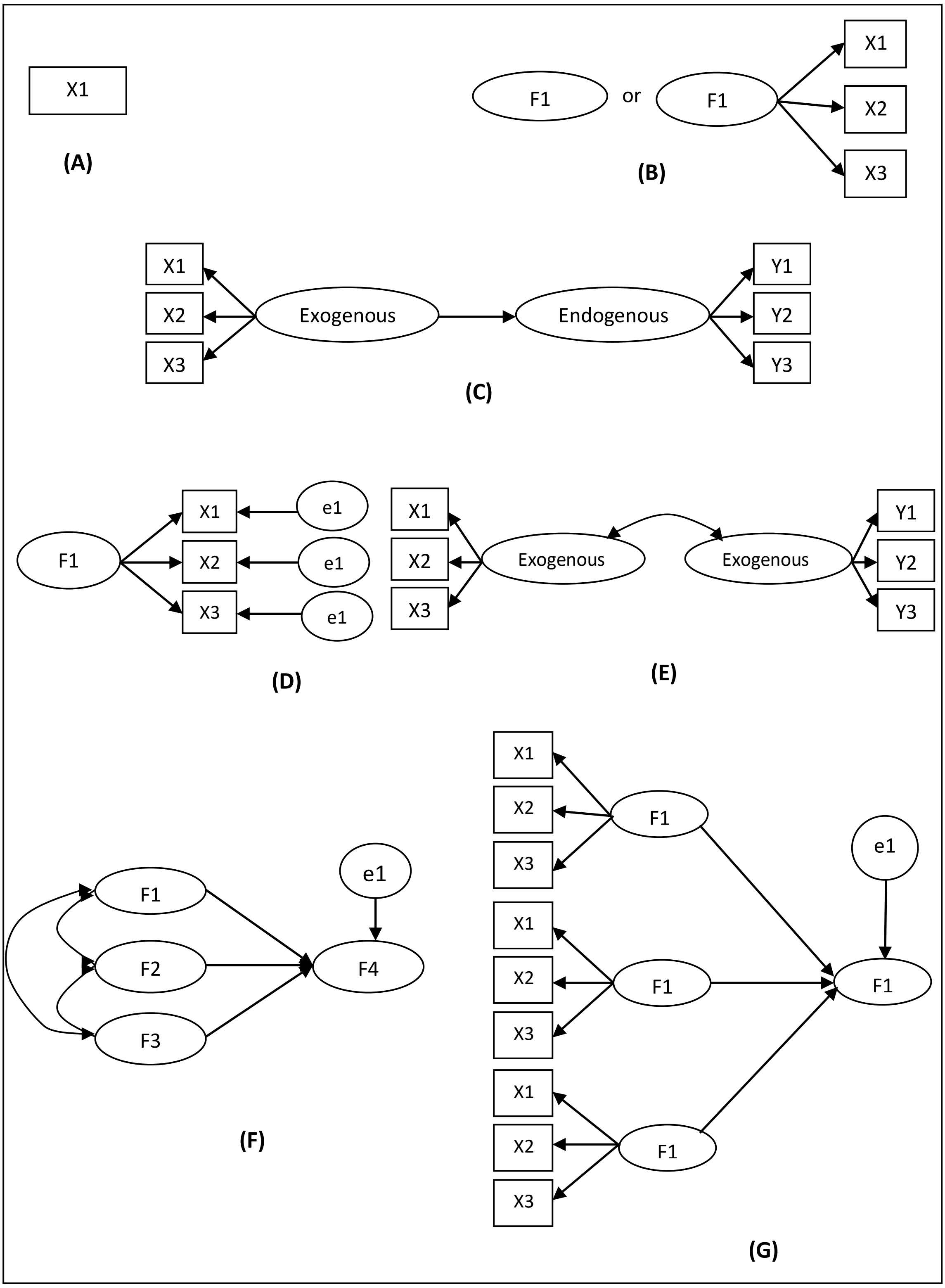

Figure 3.1: (A) shows the observed variable, (B) indicates the latent variable, (C) shows the exogenous, endogenous variable and dependence relationship, (D) here, e1, e2, and e3 shows the disturbance/error, (E) correlation relationship, (F) path diagram and (G) shows the structural equation model.

3.1.2 Steps involved in SEM

There are few steps involved in the SEM process (as shown in Figure 3.2). These steps

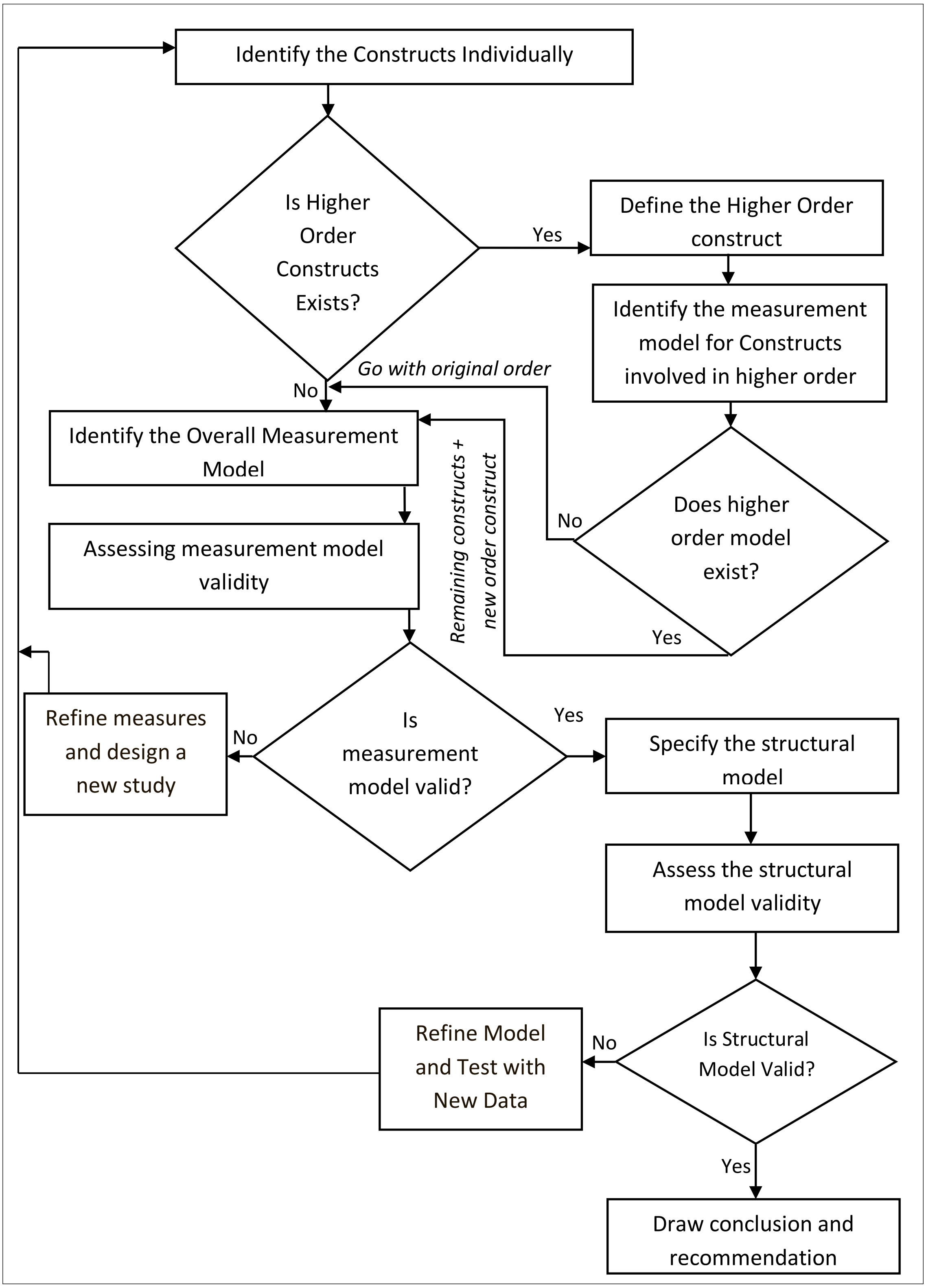

Figure 3.2 The process of structural equation model

are: (1) Identify the Constructs Individually, (2) Define higher-order construct if higher-order construct exists and find the measurement model for factors involved in the higher-order construct, (3) Identify the Overall Measurement Model, (4) Assessing overall measurement model validity, (5) if measurement model valid then specify the structural model, (6) Assess the structural model validity and (7) if structural model valid then draw conclusion and recommendations.

3.1.2.1 Identify the constructs Individually

This step starts with an excellent theoretical understanding of the constructs involved. Further, the scale type and items are selected from the literature that performed well or developed new scale items if rich history is not available. Before going to the next step, it is essential to test the validity issues like content validity and construct validity. Content validity is validated by research literature and expert opinion. In contrast, construct validity is checked by convergent validity (composite reliability (CR) and average variance extracted (AVE)) and discriminant validity.

3.1.2.2 Check higher-order constructs

If covariates of all measurable items are explained at the first level or layer construct, it is known as the first order construct. In second-order constructs, two or more first-order constructs are treated as indicators or measurable items. In a third-order construct, two or more second-order constructs are treated as measured or observed variables.

To check the higher-order constructs, the defined initial constructs (i.e., first-order constructs for second-order construct) should be theoretically related to higher-order constructs. If the assumed higher-order (e.g., most common second-order) model is not reasonable in the measurement model, the first-order model is preferred. If the model is reasonable, then higher-order constructs and the remaining constructs will go for the overall measurement model. The first-order, second-order, and third-order constructs are given in figure 3.3.

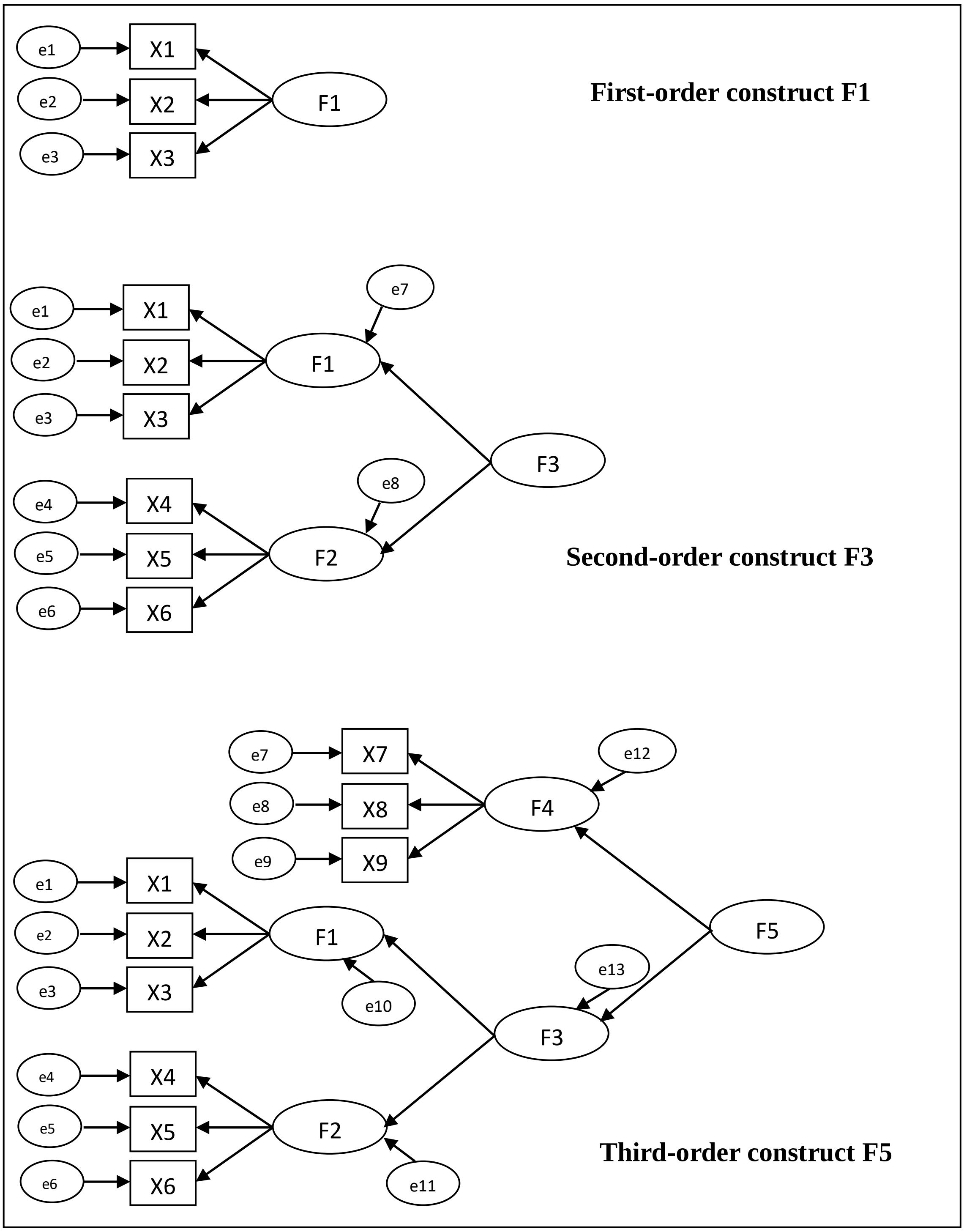

Figure 3.3: Different order constructs

3.1.2.3 Identify the Overall Measurement Model

Once the constructs and order have been defined, and then move to develop and specify the overall measurement model. This model is represented with a diagram (Figure 3.4).

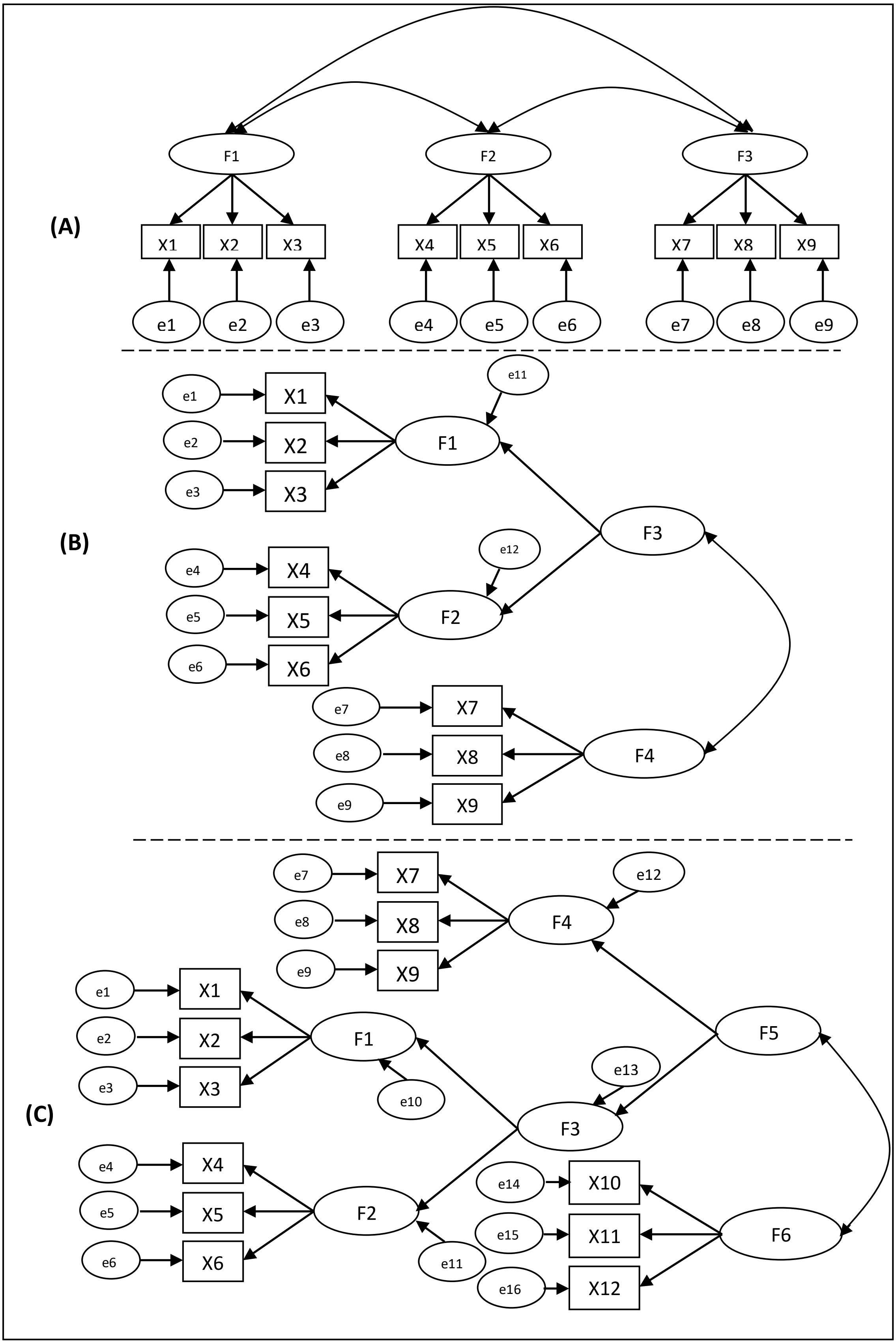

Figure 3.4: Measurement models: (A) simple (B) Second-order model and (C) Third-order model

3.1.2.4 Assessing measurement model validity

In the early measurement model fit, chi-square (χ^2) was the only indicator for model validity. With the extensive data, χ^2 comes under satisfaction. Thus, to overcome this issue, some more fit indices were needed. These fit indices are extracted from χ^2 and divided into the goodness of fit and badness of fit. Further goodness of fit is categorized into three categories: absolute fit indices, incremental fit indices, and parsimony fit indices (figure 3.5; Source: Malhotra et al., 2017).

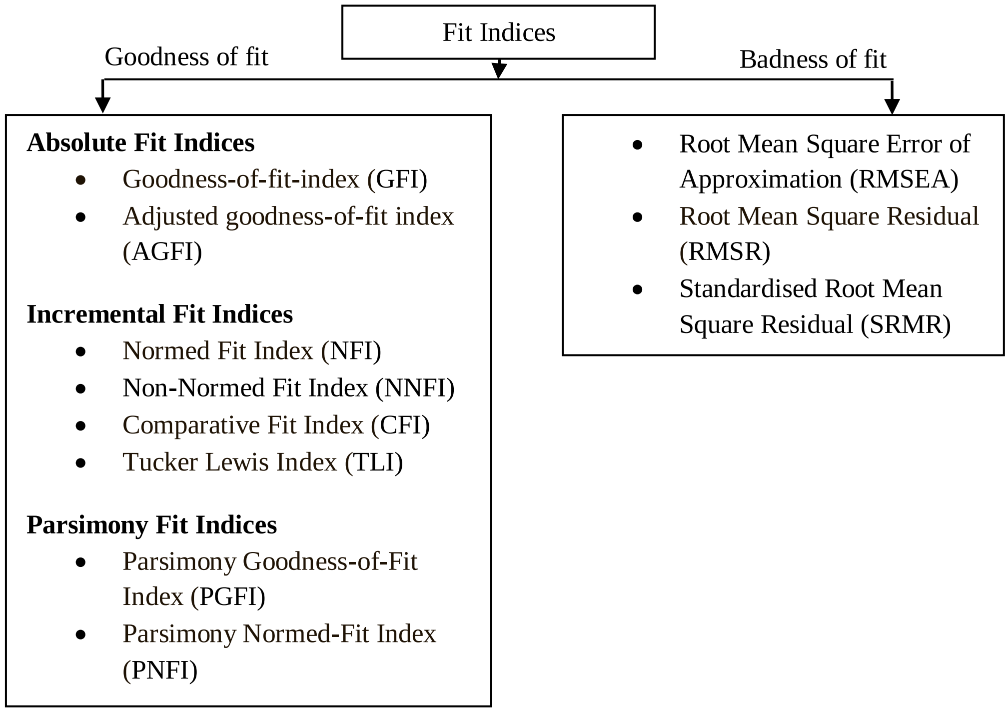

Figure 3.5: Classification of Fit indices

3.1.2.5 Specify the structural model

After the successful establishment of the measurement model, the next step is to specify the structural model. In this step, the relationship from one construct to another are assigning based on the theoretical model. The structural model mainly focuses on the dependence relationship that is hypothesized. This hypothesized relation is represented with the help of a single-headed arrow from one construct to another. Figure 3.6 shows the specification of the structural model.

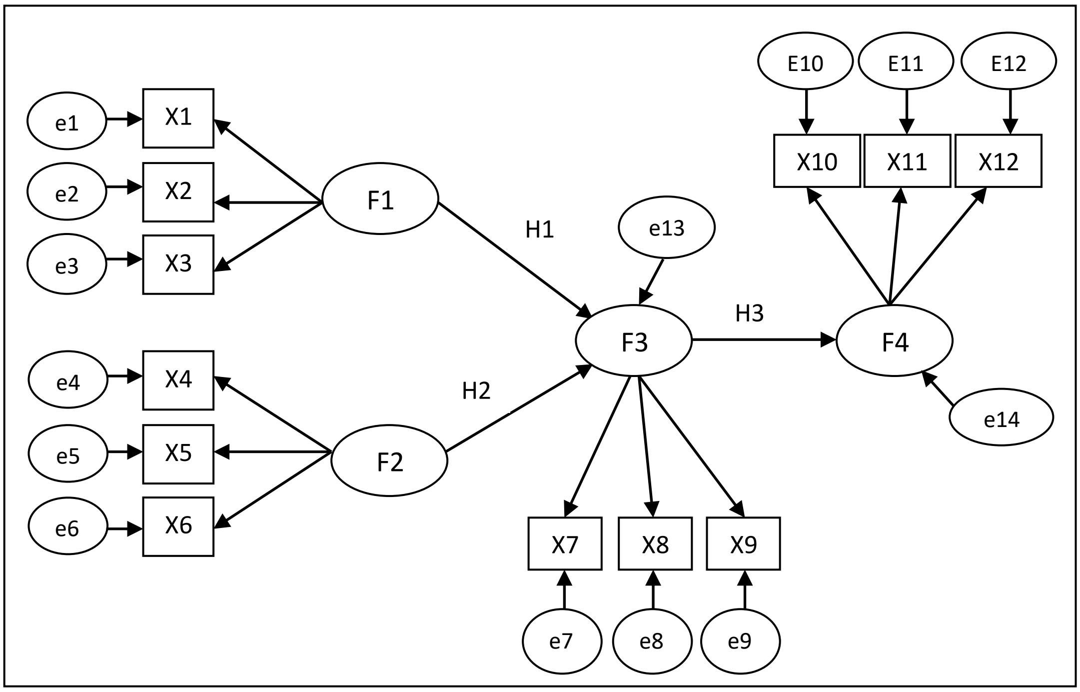

Figure 3.6: Structural Equation Model

3.1.2.6 Assess the structural model validity

After the specification of the structural model, it is required to test the model's validity and hypothesized relationships (e.g., H1, H2, and H3 in figure 3.6). Before reaching this step, the measurement model and its validity should be passing. The structural model validity is different from the measurement model in two ways, as Hair et al. (2014) suggested. First, compare the proposed model with an alternative or competing model. Second, test the hypothesized relationships that came from empirical evidence.

3.2 Interpretive structural modeling (ISM)

John Nelson Warfield proposed the ISM in 1974. ISM enables a group of experts (Warfield, 1974) and individuals (Ravi and Shankar 2005, Faisal et al. 2007, Alawamleh and Popplewell, 2011) to solve the complex problem with some basic concepts of graph theory. ISM is a methodology involved in identifying items and summarizing their relationship (Mandal and Deshmukh 1994) for an issue. It is a structural model to identify the items and define relationships among items for unclear or poorly limpid mental models and visualize it in a hierarchical model. ISM is interpretive as it depends on experts' judgment to establish the relationship between variables (Patel et al., 2014). These relationships create structures extracted from a complex set of variables. The structure form from the relationship portrays in the digraph. The steps involved in ISM have shown in figure 3.7.

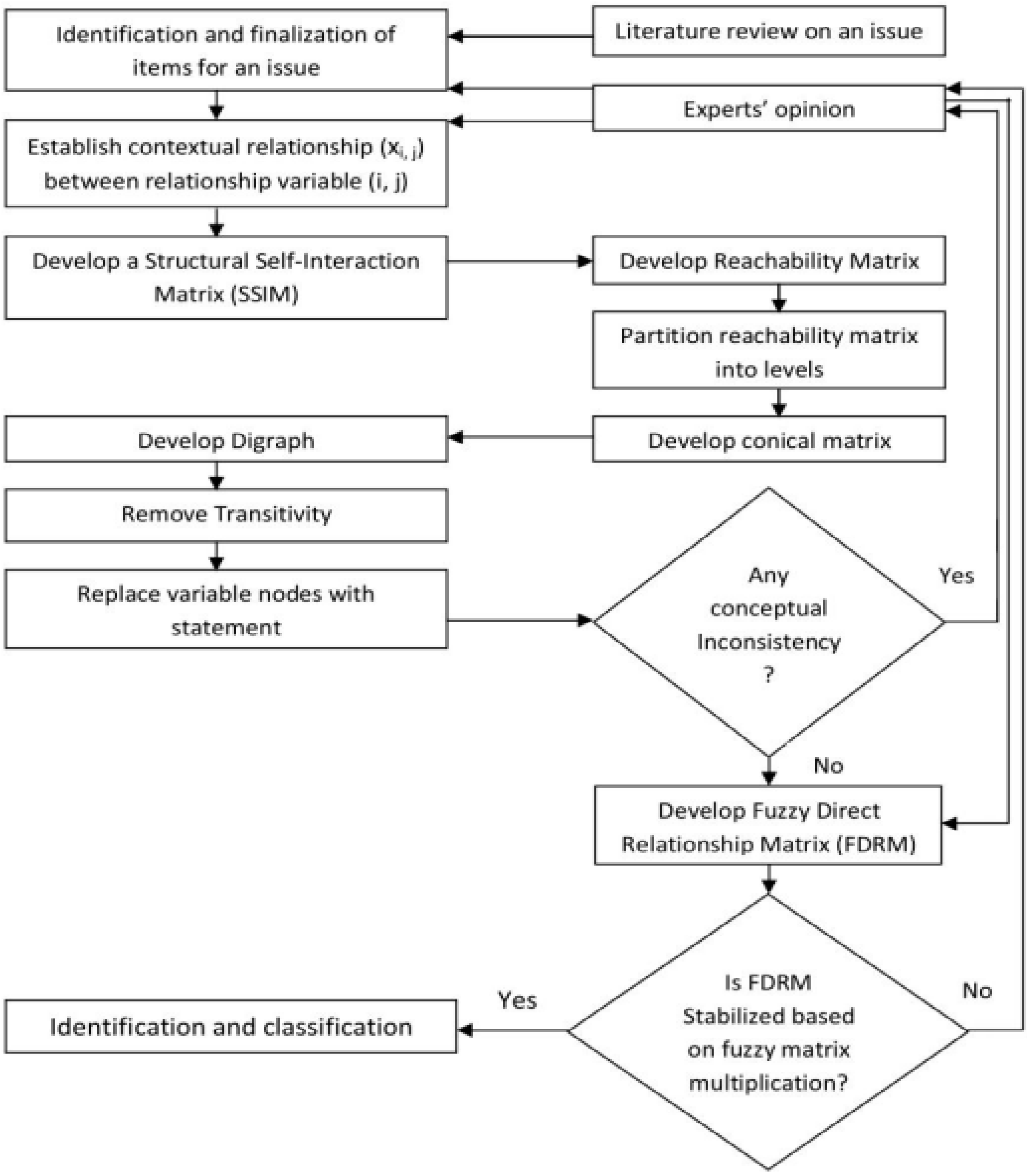

Figure 3.7: Flow chart showing ISM methodology for identifying SFs

3.2.1 Identification and finalization of items

For an issue, identification of factors and finalization of potential factors is the first step in ISM methodology. Identification of factors can be extracted from the extensive literature survey related to the issue. After identifying a list of factors, it is essential to finalize the crucial factors for a particular issue. Here, a group of experts is involved in finalizing the factors through different group problem-solving techniques like Brainstorming, the Delphi method, and so on.

3.2.2 Establish the contextual relationship and develop SSIM

A semi-structured questionnaire has been developed using finalized factors from the previous section. If N factors finalize from experts' suggestions, the total possible relationships will be N*(N-1)/2. For example, if the total factor is five, then possible relationships will be 10 (Table 3.1). ISM helps groups or individuals to structure their knowledge and model interrelationships to enhance the ability to understand complexity.

Table 3.1: Possible relationships for 5 factors

Factors	Factor5	Factor4	Factor3	Factor2	Factor1
Factor1	V	X	V	A	
Factor2	V	V	A		
Factor3	V	O			
Factor4	V				
Factor5					

To develop structural self-interaction matrix (SSIM), the questionnaire has been presented before the experts. Experts have compared each row with each column and opt one value from the set (V, A, X, or O). In this session, the relationship between two factors (i, j) denoted by the four symbols are as follows:

- V: i influences j (direction i → j)
- A: j influences i (direction j → i)
- X: i and j influences each other (direction i ←→ j)
- O: i and j have no relation

3.2.3 Develop the reachability matrix

To get the initial reachability matrix, substituting the symbols V, A, X, O into the binary digit 0 and 1. The conversion from symbol to binary digit is based on some rules, which are given below:

- If the (i, j) symbol in the SSIM is V, then the (i, j) value in the reachability matrix becomes 1, and the (j, i) value becomes 0.
- If the (i, j) symbol in the SSIM is A, then the (i, j) value in the reachability matrix becomes 0, and the (j, i) value becomes 1.
- If the (i, j) symbol in the SSIM is X, then the (i, j) value in the reachability matrix becomes 1, and the (j, i) value also becomes 1.
- If the (i, j) symbol in the SSIM is O, then the (i, j) value in the reachability matrix becomes 0, and the (j, i) value also becomes 0.

Based on the above rule, the initial reachability matrix has been formed. In the relationship matrix, one factor 'A' leads to factor 'B', and factor 'B' leads to factor 'C', then factor 'A' leads to factor 'C'. This relation is known as transitivity. Therefore, it is essential to identify all possible transitivity from the initial reachability matrix. To achieve the transitivity from the initial matrix, a method is used that was proposed by Malone (1975) and explained again by Ojha et al. (2014). The steps involved in this method are as follows:

- **Step 1**: Initial reachability matrix multiplied by itself.
- **Step 2**: Replace values that are greater than one with one from the formed matrix.
- **Step 3**: Check the similarity from the obtained matrix of step 2 with the previous matrix. If the obtained matrix is the same as the previous matrix, the transitivity

matrix is achieved, which is known as the final reachability matrix. If the obtained matrix is not the same as the previous matrix, repeat the above processes until transitivity is achieved.

3.2.4 Partition the reachability matrix into levels

The hierarchical structure formation starts with this section. The obtained final reachability matrix from the previous section is used partitioned the factors into different levels. For this, the reachability set and antecedent set should be extracted from the final reachability matrix. The reachability set for each factor consists of the factor itself and other factors on which the particular factor impacted. In short, all row items for particular factors in the final reachability matrix are the reachability set. The antecedent set for each factor consists of the factor itself and other factors that impact a particular factor. In short, all column items for particular factors in the final reachability matrix are the antecedent set.

Further, the interaction set for each factor is formed from the reachability set and antecedent set. If the reachability set and intersection set are the same for particular factors, then the level number is assigned to remove the factor and number from further processes. This process is repeated till all levels are formed. The first level factor is at the top of the hierarchical model that cannot help achieve other factors. These identified levels help to build the hierarchical model. For better understanding, the application of this section can be seen in Chapter 5.

3.2.5 Developing the conical matrix

This matrix is the step just before the formation of a digraph (Poduval et al., 2015). The arrangement of factors in this matrix is as follows: the factors that have the most zero in rows are put at the top of the matrix, whereas the factors that have the most unitary in rows are put at the down of the matrix.

3.2.6 Formation of Model

ISM model building starts from the canonical matrix that helps in the generation of a digraph. In the digraph, the relationship shows by an arrow from i to j or j to i (Hasan et al., 2009). Based on the discussion, the initial digraph has direct and indirect relations among factors. For example, if factor 'A' is related to factor 'B' and factor 'B' related to factor 'C', then factor 'A' is related to factor 'C'. A to B and B to C directly relate in this relation, but A to C is an indirect relation and also known as transitivity. For the digraph, set the factors according to their levels (that found from section 3.2.4) and establish the relation with the conical matrix's help. After removing the transitivity and replace the node with statements, the final ISM model has been formed. The developed model should be checked for conceptual inconsistency and necessary modifications.

3.2.7 MICMAC analysis

The MICMAC is stands for Matrice d'Impacts Croises Multiplication Applique' an Classment (Yadav and Barve, 2015). The final reachability matrix is used for the MICMAC analysis, and driving and dependence power is analyzed. The sum of row elements is known as the driving power of a particular factor. In contrast, the sum of column elements is known as the dependence power of a particular factor. The factors are divided into autonomous, dependent, linkage, and driver (or independent) based on driving and dependence power. Figure 3.8 shows that the autonomous cluster has weak driving and weak, dependent power, the dependent cluster has weak driving and strong dependent power, the linkage cluster has strong driving power and strong dependent power, and the independent cluster has strong driving power and weak, dependent power.

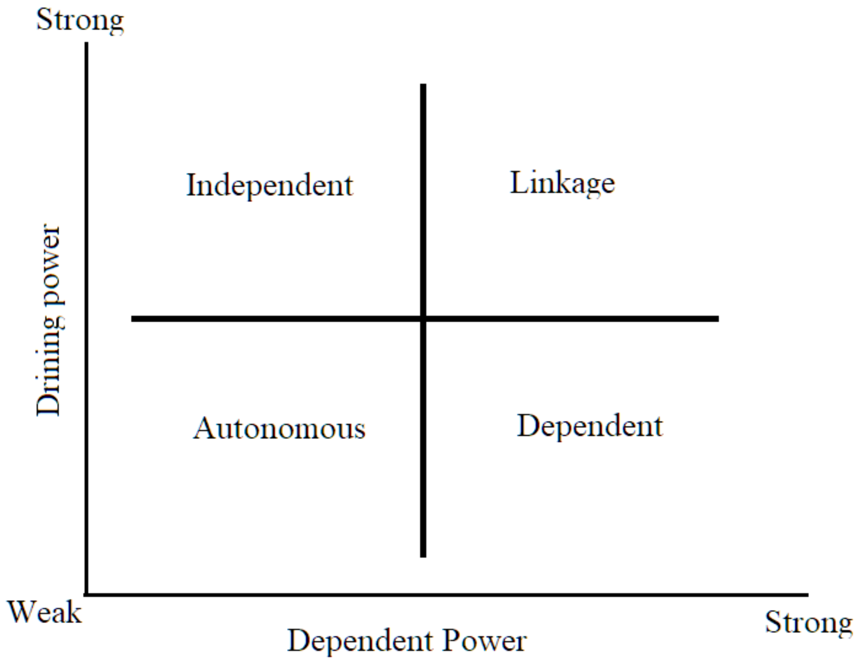

Figure 3.8: Clusters based on driving and dependent power

3.2.8 FMICMAC analysis

The FMICMAC analysis stands for Fuzzy Matrice d'Impacts Croises Multiplication Applique' an Classment. The MICMAC analysis uses binary numbers (0 and 1) for the relationships that cannot show the relationship's strength (Gorane and kant, 2015). Therefore, factors can be divided into clusters, as mentioned earlier, based on binary relationships. There is no scope for discussion about the strength of the relationship between two variables in terms of weak, weak, no relation, strong, and very strong. To overcome this problem, the FMICMAC is used (Dubey and Ali, 2014). The result can be better if the strength of the relationship was considered. Another reason to use the FMICMAC is that MICMAC uses the only binary relationship between identified strengthening factors, whereas the Fuzzy-MICMAC approach provides sensitive analysis related to driving and dependence behavior of strengthening factors (Gorane and kant, 2015). In the FMICMAC, several steps are as follows. In the first step, a direct relationship matrix (DRM) should be obtained by ignoring the transitivity and converted all diagonal unitary numbers into zero. Further, experts should be contacted again to get the strength of the relationship among factors. The obtained matrix is known as the fuzzy direct relationship matrix.

Zimmermann (1991) stated the three types of fuzzy composition to determine the fuzzy indirect relationship's strength with element i to j: max-min, max-average, and max-product. For this research, the max-min is most suitable since the fuzzy relationships represent the relationship's strength (Pfohl et al., 2011). To obtain the indirect relationships, the FDM was modified based on the computational steps given in Yenradee and Dangton (2000). In the n × n matrix, the convergence of matrix has obtained through the fuzzy multiplication as stated by (Zadeh, 1965). Matrix multiplication will continue until the stabilization of hierarchies of driver and dependence power. According to fuzzy set theory, the resultant matrix from the multiplication of two fuzzy matrices is also a fuzzy matrix.

$$\mu_c = \max [\min \{\mu_a, \mu_b\}] \quad \text{... 3.1}$$

Where, $\mu_a = [a_{ik}]$ and $\mu_b = [b_{kj}]$

3.3 Quality function deployment

QFD took VoC and is deployed throughout all-new service development stages (Griffin & Hauser, 1993). Shigeru Mizuno and Yoji Akao instigated the QFD in the 1960s, and QFD applied first in 1972 at Mitsubishi Heavy Industries Limited in the Kobe Shipyard, Japan. QFD is a powerful technique to satisfy customers in a more significant way (Cherif et al., 2010). QFD was founded as a TQM tool to develop a product but had significant support for the service, too (Debata, 2012).

QFD can apply to any planning process (Cohen, 1995). Cristiano et al. (2001) surveyed 400 companies in America and Japan and reported that QFD could minimize the initial internal problems. DiMingo (1988) suggested two types of positioning:

market positioning and psychological positioning. In market positioning, the firm controls the processes and activities to achieve the marketing position or, say; this positioning is related to firms' oriented outcome. In psychological positioning, the firm tries to create perceptual distinction in the customers' minds. For the service-centric firms, there are limited researches available. Day (2006) stated that service-centric firms could compete based on relationship, performance, and price rather than '4P'. Based on DiMingo (1988), Day (2006), and Amonini et al. (2010) theory, here, an effort was made to combine the customers' perspective and firms' design requirements with satisfying customers and to position the stores in the customers' mind. House of quality (HOQ) framework use here as the most recognized form of QFD.

A typical HOQ has six main elements, as shown in figure 3.9. Structured and systematic way of transformation of the customers' requirement into prioritizing functional design requirements make HOQ is an integral part of QFD. The presentation way of HOQ can be different in various presentations (Griffin & Hauser, 1993; Cohen, 1995; Cherif et al., 2010).

The six main elements are customer requirements, design requirements, the relationship between customer requirements and design requirements, planning matrix, design requirements correlation matrix, and design matrix. Some authors use the customer requirements correlation matrix (Debata et al., 2012) as the seventh part of QFD. All seven parts are explained below:

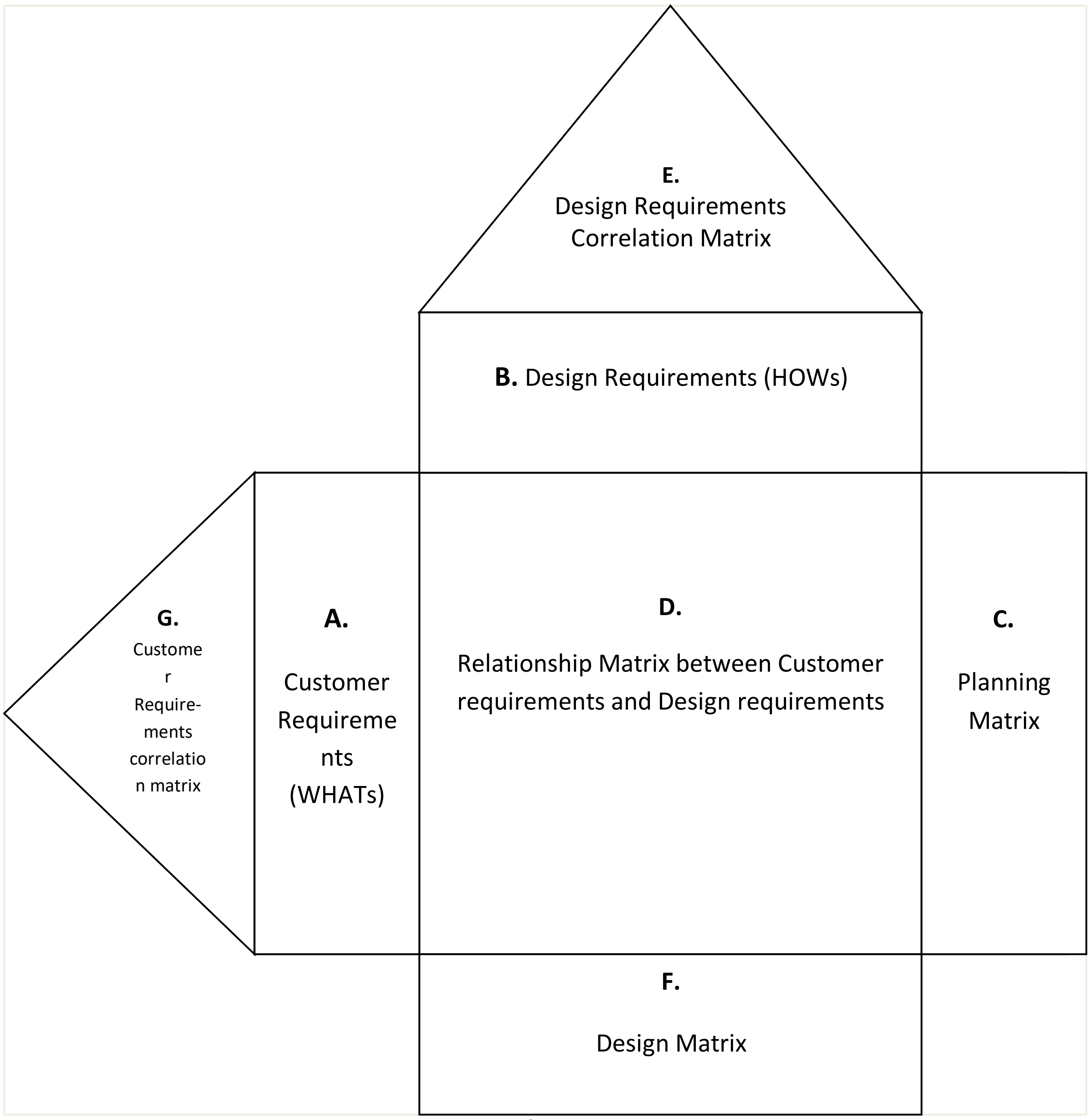

Figure 3.9: House of quality: Framework

- *Customer requirements (WHATs)*: QFD is a customer-centric tool and starts with customers. Customers are of three types: Internal (Shareholders, managers, and employees), Intermediate (Wholesale people and retailers), and Ultimate (service recipients, purchasers) (Chan et al., 2002). Generally, the ultimate customer can be the main focus of the survey. After customer identification next step is to find their list of requirements with the help of various methods. Here, the survey method is used to collect the list of requirements. This section also requires the relative importance of customer requirements (CRs).

- *The relative importance of the customer requirements*: Collected data from customer survey usually contain simultaneous requirements; they must be included relative importance of requirements.

- *Design requirements (HOWs)*: This section deals with the list of design requirements gathered from the experts. A structured set is formed to fulfill the customer requirements with relevant and measurable design requirements.

- *Relationship matrix between WHATs and HOWs*: The purpose of QFD is to determine the degree of relationship between customer requirements and design requirements. It is very tough to trace the relationship due to the reason of multiple dependencies on design requirements for each customer requirements. The symbolic scale has been used to fill this portion.

- *Inner dependence among the Customer requirements*: Customer requirements have inner dependence and can support each other. These relations can be identified through the inner dependence triangular matrix.

- *Interrelationship among design requirements*: The triangular matrix on the top of HOQ shows the design requirements' relationship. Here symbols are used to show the strength of interrelationships; for example:

    - A solid dot (●) represents a strong relationship.
    - A theta (ϴ) represents a moderate relationship.
    - A hallow dot (○) represents a weak relationship.
    - A triangle (Δ) represents a very weak relationship.

- *Overall priorities of design requirements and additional goals (Design Matrix)*: The results obtained from the preceding steps can be calculated here to find the final rank of HOWs. This is also known as design requirement ratings.

3.4 Grey-DEMATEL

ISM and DEMATEL are methods that can solve complex problems. Both have several similarities like cause and effect relationship among the factors (Chauhan et al., 2018) involved in the problem. In ISM, the relationship is shown by ‘0’ or ‘1’, and it does not allow the weighting of experts’ values. Therefore, some authors used fuzzy ISM to overcome this drawback in their sensitivity analysis (Gorane et al., 2015). Now, again a group of researchers opposes the fuzzy ISM. According to them, if ISM implemented successfully, then what is the use of fuzzy? Many authors used the fuzzy ISM in their study and used the questionnaire method at the place of brainstorming. It adds strength to the ISM. If the ISM is implemented via brainstorming, then the use of fuzzy ISM cannot have much importance, whereas if the questionnaire method is used then to overcome the vagueness in decisions, the fuzzy IMS should be used as sensitivity analysis.

In the decision-making, the Grey theory and DEMATEL method used to solve the complex problem. Grey theory was proposed by Deng (1982) from a grey set. Grey system consider the condition of fuzziness which give an advantage over fuzzy (Khompatraporn and Somboonwiwat, 2017; Xia et al., 2015; Li et al., 2007). Grey theory is not limited to only engineering problems only it has been used in management, barriers identification in implantation as well as adoption, risk management, advertisement agencies, project portfolio selection, supplier selection and so forth (Bhattacharyya, 2015; Xia et al., 2015; Rajesh et al., 2014, Thakur and Anbanandam, 2015). The Grey theory method can handle many ambiguities generated from human decisions (Li et al., 2007; Fu et al., 2001). Grey's theory can easily be used with any decision-making process to improve the judgments (Tseng, 2009). Grey numbers are usually pigeonholed as numbers with incomplete information. Grey numbers can convert into crisp numbers with the modified CFCS (converting fuzzy values into crisp scores) method, integrating a three-step procedure (Fu et al., 2012). DEMATEL allows the researcher to assign the weight to the experts involved in the decision-making.

Wide acceptability of DEMATEL can be revealed from its reported applications in various fields of decisions such as barriers of smart energy city (Addae et al., 2017), Website parameters (Cebi, 2013), Technology adoption (Lu et al., 2013), Hospital service quality criteria (Shieh et al., 2010). DEMATEL method used to handle and structure the complicated causal relationship model. The science and Human Affairs Program of the Battelle Memorial Institute of Geneva introduced DEMATEL to solve complex problems (Hsu et al., 2013). DEMATEL is a structural modeling method that tries to determine interdependence amongst a system's elements through a causal diagram (Wu et al., 2010; Tseng, 2009; Kim, 2006). There are several steps to solve the complex problem through the Grey-DEMATEL method. Figure 3.10 shows the flow diagram of the Grey-DEMATEL approach. The steps involved in the Grey theory are the identification of initial relation matrices, finding of Grey relation matrices, average Grey relation matrix, and find the crisp relation matrix from average Grey matrix. The steps involved in the DEMATEL method are a calculation of normalized direct, crisp relation matrix, compute the total relation matrix and obtain the cause and effect parameter. Here, the factors will identify from the literature and with the help of experts' opinions. The systematic procedure of Grey-DEMATEL is as follows.

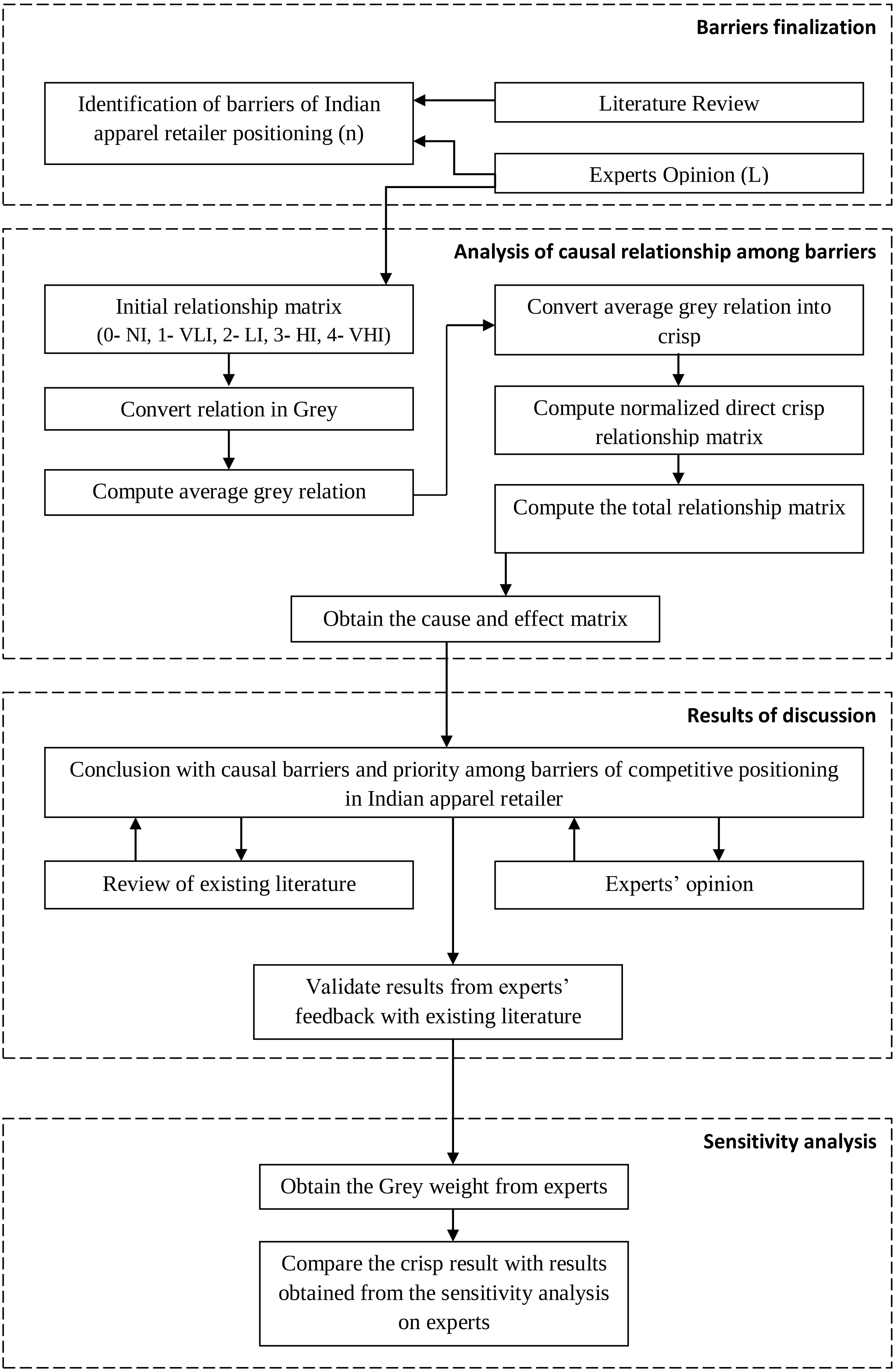

Figure 3.10: Flow chart for the Grey-DEMATEL methodology

3.4.1 Initial Relationship matrix

Total *L* respondents (Experts) have chosen *N* barriers of competitive retail position. Each respondent *K* participated in evaluating the direct influence of barriers *i* over barriers *j*. Therefore, *L* initial relation matrices have been established. The evaluation is based on a scale varying from zero to four. Scale with its linguistic term and associated Grey values will be available in chapter 7.

3.4.2 Conversion of initial relationship matrix in Grey relationship matrix

The initial relationship matrix contains the integer values that will convert into Grey relationship matrix using the Grey values. Grey scales have an upper and a lower range of values (Deng, 1982, 1989). i. e.

$$\otimes X_{ij}^{K} = \left(\underline{X}_{ij}^{K}, \overline{X}_{ij}^{K} \right) \qquad \dots (3.2)$$

Where, $\otimes X_{ij}^{K}$ shows the grey relation matrix for each expert k individually, $\underline{X}_{ij}^{K}$ shows the lower range of values for barrier i over j, $1 \leq K \leq L$; $1 \leq i \leq N$; $1 \leq j \leq N$.

The initial relationship values were converted into the Grey values with the help of Table 3.2. Therefore, the modified relationship matrices i.e. $[\otimes X_{ij}^{1}], [\otimes X_{ij}^{2}], [\otimes X_{ij}^{3}], \dots \dots \dots [\otimes X_{ij}^{L}]$ have obtained.

3.4.3 Computation of average Grey relationship matrix

The average Grey relation matrix (equal weight for each expert) $[\otimes \widetilde{X}_{ij}]$ obtained through the equation (Kose et al., 2013; Liu et al., 2012; Rajesh and Ravi, 2015) that has given below.

$$\otimes \widetilde{X}_{ij} = \left(\frac{\sum_K \underline{X}_{ij}^{K}}{L}, \frac{\sum_K \overline{X}_{ij}^{K}}{L} \right) = \left(\underline{\otimes} \widetilde{X}_{ij}, \overline{\otimes} \widetilde{X}_{ij} \right) \qquad \dots (3.3)$$

Where, $\otimes\widetilde{X}_{ij}$ stands for average grey relation value for barrier i over j and K is range from 1 to L (Number of experts).

The weighted average Grey relation matrix $\left[\otimes_{w}\widetilde{X}_{ij}\right]$ (different weight assigned for each expert based on their experience and expertise) obtained through the equation that has given below

$$\otimes_{w}\widetilde{X}_{ij} = \left(\frac{\sum_{K} W^{K}\underline{X}_{ij}^{K}}{\sum_{K} W^{K}}, \frac{\sum_{K} W^{K}\overline{X}_{ij}^{K}}{\sum_{K} W^{K}}\right) = \left(\underline{\otimes_{w}}\widetilde{X}_{ij}, \overline{\otimes_{w}}\widetilde{X}_{ij}\right) \quad .... (3.4)$$

Where, $\otimes_{w}\widetilde{X}_{ij}$ stands for weighted average grey relation value for barrier i over barrier j and W^{K} is the weight assigned for each expert k. There is no need for any modification in the case of the weighted average grey relation matrix in further steps.

3.4.4 Conversion of average Grey relation matrix into the crisp relation matrix

This is the three steps procedure using the CFCS method (Arikan et al., 2013, Rajesh and Ravi, 2015).

(i) Grey value normalization

Here, the normalization of the Grey value for the upper range and lower range will be found with the given formula.

$$\underline{\otimes}\dot{X}_{ij} = \left(\underline{\otimes}\widetilde{X}_{ij} - {}^{\min}{}_{j}\underline{\otimes}\widetilde{X}_{ij}\right)/\Delta_{\min}^{\max} \quad \ldots (3.5)$$

Where, $\underline{\otimes}\dot{X}_{ij}$stands for the normalized lower limit value of average Grey relation $\otimes\widetilde{X}_{ij}$

$$\overline{\otimes}\dot{X}_{ij} = \left(\overline{\otimes}\widetilde{X}_{ij} - \min_{j}\overline{\otimes}\widetilde{X}_{ij}\right)/\Delta_{\min}^{\max} \quad \ldots (3.6)$$

Where, $\overline{\otimes}\dot{\mathrm{X}}_{\mathrm{ij}}$ stands for the normalized upper limit value of average Grey relation $\otimes\widetilde{\mathrm{X}}_{\mathrm{ij}}$ and $\Delta_{\min}^{\max}$ can find by the given below.

$$\Delta_{\min}^{\max} = \max_{j} \overline{\otimes}\widetilde{\mathrm{X}}_{\mathrm{ij}} - \min_{j} \underline{\otimes}\widetilde{\mathrm{X}}_{\mathrm{ij}} \qquad \ldots (3.7)$$

(ii) Calculating the total normalized crisp values

$$\mathrm{Y}_{\mathrm{ij}} = \left(\frac{\left(\underline{\otimes}\dot{\mathrm{X}}_{\mathrm{ij}}(1-\underline{\otimes}\dot{\mathrm{X}}_{\mathrm{ij}}\right) + \left(\overline{\otimes}\dot{\mathrm{X}}_{\mathrm{ij}} \times \overline{\otimes}\dot{\mathrm{X}}_{\mathrm{ij}}\right)}{\left(1-\underline{\otimes}\dot{\mathrm{X}}_{\mathrm{ij}} + \overline{\otimes}\dot{\mathrm{X}}_{\mathrm{ij}}\right)} \right) \qquad \ldots (3.8)$$

(iii) Calculating the final crisp values and matrix

$$Y_{ij}^{*} = \left(min\, \underline{\otimes}\widetilde{\mathrm{X}}_{\mathrm{ij}} + \left(\mathrm{Y}_{\mathrm{ij}} \times \Delta_{\min}^{\max} \right) \right) \qquad \ldots (3.9)$$

Y_{ij}^{*} Shows the crisp values and to find the crisp matrix the equation is given below.

$$Y = \left[Y_{ij}^{*} \right] \qquad \ldots (3.10)$$

3.4.5 Generating the crisp relationship matrix

The normalized direct crisp relation matrix, Z, will calculate with the help of the given equation.

$$Z = \frac{Y_{ij}^{*}}{\max\limits_{1 \le i \le n} \sum_{j=1}^{n} Y_{ij}^{*}} \qquad \ldots (3.11)$$

Each element in Z falls between 0 and 1.

3.4.6 Calculating the total relationship matrix

The total relationship matrix, T is calculating with the help of the equation that is given below.

$$\mathrm{T} = \mathrm{Z} \times (\mathrm{I} - \mathrm{Z})^{-1} \qquad \ldots (3.12)$$

Where, ‘I’ is the identity matrix.

3.4.7 Obtain the causal diagram

Assume t_{ij} stands for T. Let R and C be defined as the sum of row elements and column elements for T, respectively.

$$R_i = \sum_{j=1}^{n} t_{ij} \ \forall i \qquad \text{… (3.13)}$$

$$C_j = \sum_{i=1}^{n} t_{ij} \ \forall j \qquad \text{… (3.14)}$$

3.4.8 Set up threshold and plot digraph

Matrix T shows the information on how one barrier affects another. A threshold value is required to avoid negligible effects. Threshold value usually set by the mean (μ) and standard deviation (σ) of all elements of matrix T (= μ + σ). In the causal digraph, the horizontal axis (prominence) is determined by (C + R), and the vertical axis (relation) is determined by (C – R). When (C – R) value is positive, it is in the cause category, while negative, it is in the effect category.

3.5 Summary of Methodologies

The use of methodologies, strengths and weaknesses are discussed in table 3.2.

Table 3.2: Summary of methodologies

Methodology	Used to	Strength	Weakness	Used for apparel retailing
Structural Equation modelling	Analyzing the structural relationships among latent constructs that are indicated by multiple measures (Lei and Wu, 2007) .	• Allows conducting a complex, multidimensional, and more precise analysis of empirical data (Tarka, 2017). • Simultaneously analyze data sets with many series of different linkages (Tarka, 2017). • It helps in theory building.	• The ultimate goal is to maximize the model fit to the data instead of carefully differentiated research plans and careful substantive considerations on the grounds of theory (Tarka, 2017).	Ong et al., 2018; Lin and Lin, 2017; Carpenter and Fairhurst, 2005; Bouzaabia et al., 2013; Chang et al., 2015; Kumar and Kim, 2014
Interpretive Structural Model	Identifying and summarizing relationships among factors for a problem or an issue (Sage, 1977).	• Take some elementary graph theory to explain the complex relations between factors of an issue. • It allows individuals and groups to make a decision for an issue. • It transforms unclear, poorly articulated mental models into visible, well-defined models (Jadhav et al., 2014).	• It is a subjective judgement, and any biasing can affect the final result. • It is a qualitative-based analysis.	Deshmukh and Mohan, 2017; Ramesh et al., 2010; Mishra, 2021; Suresh et al., 2019
Quality Function Deployment	Address the strategic and operational decisions to prioritize the functional requirements to maximize the output value with minimum resources.	• Prioritization of functional requirements concerns customers' voices. • Maximize the output value and minimize the resources used. • Reduce implementation	• Need large data for customer requirements. • Difficulty to cooperation among multidisciplinary team. • Time consuming process. • In retail there is no fix	Seker, 2019; Hsu and Lin, 2006; Trappey et al., 1995; Akao, 1990

		time.	customer requirements. Thus use customer value perception and need a survey to collect potential requirements.	
Grey theory	Deals with the ambiguities caused from human judgments (Rajesh and Ravi, 2015)	• Generate possible outcomes with a small amount of data (Xia et al., 2015). • It overcome the vagueness and imprecise judgements. • It uses range due to insuffufficiency and incompletness of crisp values (Lin et al., 2008)	• It is a subjective judgement, and any biasing can affect the final result. • It is a qualitative-based analysis.	----
DEMATEL	Explains interdependence relationships and influential effect values between relevant factors in the form of a digraph and a cause and effect diagram (Lin, 2013).s	• Powerful method to visualize the structure of complex causal relationships. • Able to turn decisions and unclear judgments into exact numerical values using the information provided by each of the decision makers. • It shows the direction of influence from one factor to other by an arrow.	• DEMATEL can not overcome the vagueness and imprecise judgement itself.	Mishra, 2021;