CHAPTER 04 - RESEARCH METHODOLOGY

4.1 Chapter Overview

This study focusses on performing a thorough assessment of WCM efficiency in the Indian manufacturing sector. The current research aims to estimate the prevailing levels of WCM efficiency and its trends in manufacturing firms of India. Further, the study explores the determinants that impact the WCM efficiency along with identifying the variable wise importance of the significant variables. This study follows a multi-stage approach, as shown in Figure 4.1, wherein first stage assesses the WCM efficiency, its trends and changes throughout the study period using SBM-DEA approach. This stage offers a sector-wise efficiency for a better comparison among inter and intra manufacturing firms of India. The second stage delve into the determinants (both firm-level and macro-economic) that impact the Indian manufacturing firm's WCM efficiency using panel data fixed effect model. The third stage identifies the relative importance of the significant determinants resulting from the second stage using ANN and sensitivity analysis approach. Since varied samples, determinants, models and techniques have been utilized at each stage, hence, the respective research designs have been debated in distinct subsections as per its analysis stage.

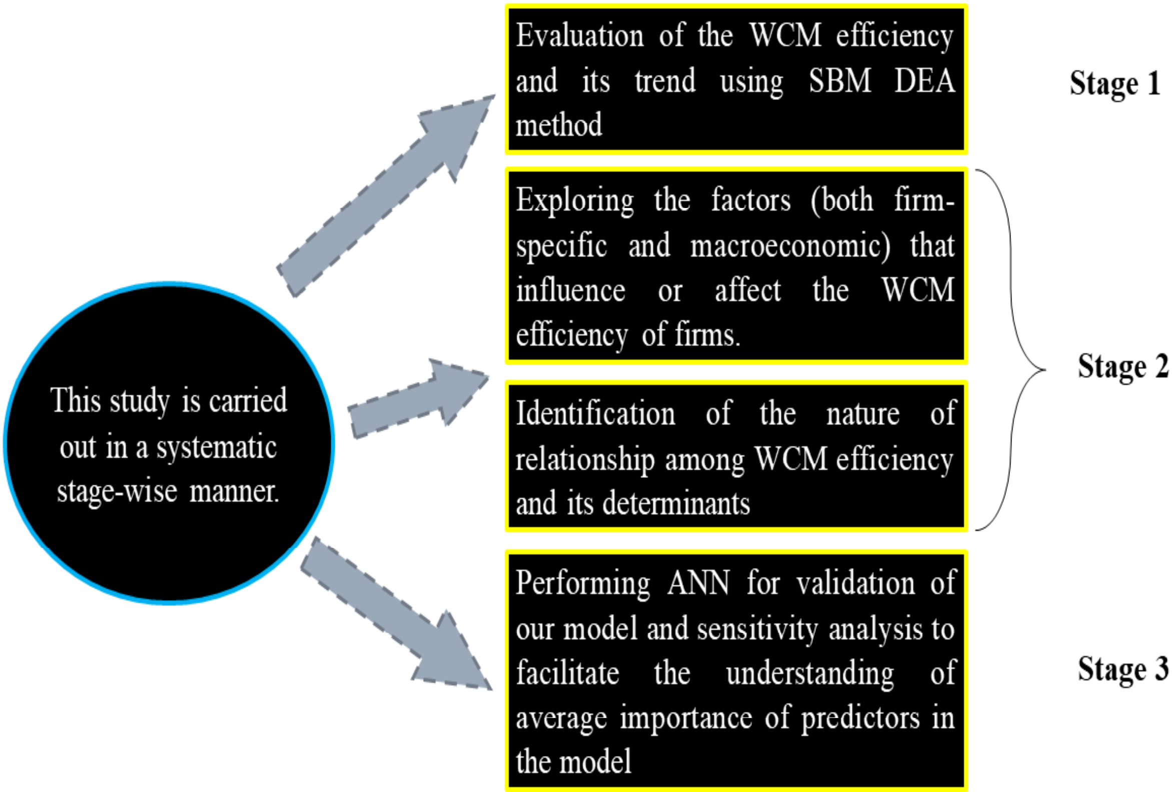

Figure 4.1: Brief of the Stages Involved in Research

Figure 4.2 offers a comprehensive flow of the stage-wise research performed comprising of the data explanation, methodology adopted, variables interpretation, empirical model and tools used for validating the proposed model along with predictors of WCM efficiency.

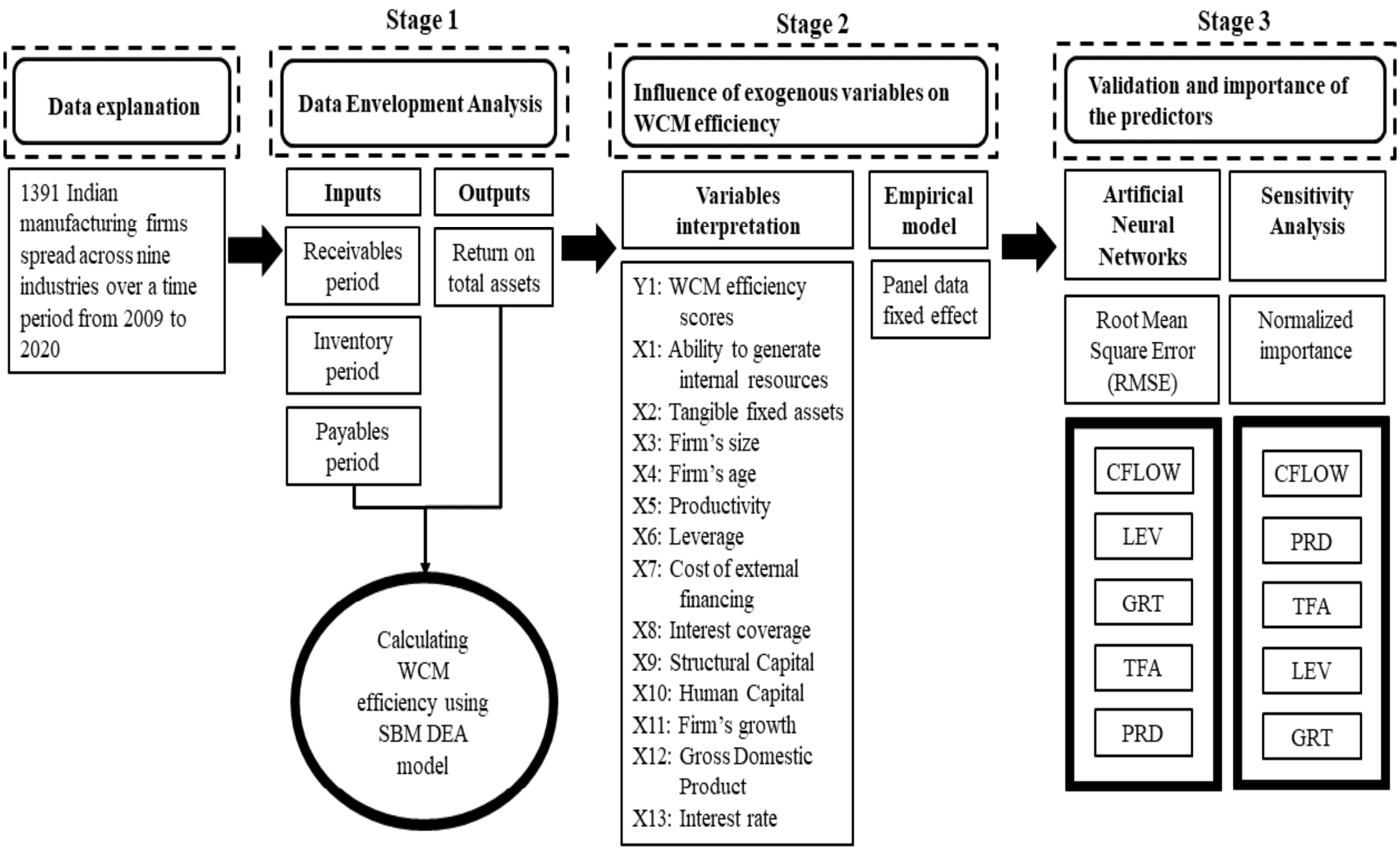

Figure 4.2: A Comprehensive Flow of Stage-Wise Research

4.2 Research Design

The current research adopted descriptive research design for identifying the associations among WCM efficiency and selected determinants of Indian manufacturing firms. Adopting descriptive research design in the domain of WCM have been earlier supported by (Deloof, 2003; Gill et al. 2010; Seth, Chadha and Sharma, 2020). The main purpose of descriptive research was to describe the situation as it is. Since we aim to examine the characteristics of manufacturing firms in terms of WCM efficiency highlighting their prevailing efficiency levels along with assessment of significant predictors of WCM efficiency, hence making descriptive research design apt for this study.

4.3 Data Explanation

As per the Annual Survey of Industries, the Indian manufacturing sector is categorized into organized and unorganized industries. Pradhan and Saluja (1998) discussed that for unorganized manufacturing industries, follow-up surveys of the economic censuses do not provide reliable estimates in terms of value-added, employment, inputs, outputs and so on. However, Pradhan and Saluja (1998) and Saluja (2004) mentioned that a fairly reliable data is available annually for organized manufacturing industries.

The current study employs 1391Bombay Stock Exchange–listed firms belonging to the organized manufacturing industries only using Prowess database. This database is sourced through the Centre for Monitoring Indian Economy (CMIE) and is generated from a varied set of sources that involves continual update cycles and abides by distinct standards (Seth et al., 2020); hence, reducing the probability of occurrence of an error in the database to a minimum. The earlier researchers (Elango and Pattnaik, 2007; Seth et al., 2020) have utilized this database for extracting firm level financial information of listed Indian firms, and the relative accuracy and available information of Prowess database are viewed as correct (Shukla, 2020). Also, studies have mentioned Prowess as the most comprehensive and reliable database of Indian listed firms that provides a credible source of information, especially for empirical research (Heaton et al.,2020). For warranting additional validity and reliability of this database, the authors of the current study have randomly cross-checked 20% of the collected financial information taken from Prowess database with other sources that are available publicly, such as the website of the firm or their annual reports.

Additionally, the current study also examined macroeconomic determinants, such as GDP and interest rate, for which the data is extracted from the website of Reserve Bank of India. The sample of the current study includes 1391 listed manufacturing firms spread over nine industries over a period from 2009 to 2020. The current study uses Indian manufacturing firms as a sample and considering the aftereffects of varying economic conditions such as demonetization and recent financial crisis, which might impact the economic condition and especially the manufacturing sector drastically, justifies the time period used for the current study.

Previous research has signified the varying effect of industries regarding working capital determination (Goel and Sharma, 2015a, b). Hence, for analyzing the industry effect, we have alienated the whole manufacturing sector into nine key manufacturing industries. Table 4.1 shows the bifurcation of the manufacturing sector into nine key industries and the number of firms in each of them. A list of all the firms is provided in Appendix.

Table 4.1: Sector-Wise List of Indian Manufacturing Firms Taken for this Study

Industry	Number of firms
Chemicals & chemical products	356
Construction materials	68
Consumer goods	59
Food & agro-based products	137
Machinery	172
Metals and metal products	181
Miscellaneous manufacturing	69
Textiles	212
Transport equipment	137
Total	**1391**

*Source: CMIE Prowess

While applying DEA technique, one of the major requirements for its correct application is the sample size. Since DEA is sensitive about the sample size along with the quantity of inputs and output used for the study due to its relativity of efficiency with its peers, hence, proper attention must be given to the adequacy of sample size before estimating the efficiency. For assessing the adequate sample size, Cooper et al. (2007) proposed rule of thumb for estimating efficiency through DEA, which are as follows:

$$N \geq max\{x * y, 3(x + y)\}$$

Where

N is the number of decision-making units (DMUs)

X is the number of inputs used

Y is the number of outputs used

The current research has used 3 inputs and 1 output which means x = 3 and y = 1, hence, x*y = 3 and 3(x+y) =12. Therefore, each industry must have at least 12 firms for estimating efficiency through DEA technique. Table 4.1 highlights the number of firms in each industry wherein the number of firms are greater than 12 for all the industries.

4.4 Stage 1: Data Envelopment Analysis (DEA) and its Slacks-Based Measure (SBM)

Since the formation of Data envelopment analysis (DEA) by Charnes, Cooper and Rhodes (1978; CCR), it is widely used in the field of multi-criteria decision making (MCDM). One of the uses of the DEA is to assess the relative efficiency of decision-making units (DMUs) by taking multiple inputs and outputs simultaneously. Precisely, DEA is a non-parametric linear programming-based technique, which uses the frontier analysis to evaluate the relative efficiency of DMUs. The most prominent feature of this technique is that it allows every DMU to select the most favorable weights for the inputs and outputs to compute the relative efficiency. Thus, the obtained efficiency is the best that a respective DMU can attain.

Banker, Charnes and Cooper (1984; BCC) extended the CCR model to variable return to scale (VRS) by adding the convexity condition. Specifically, the BCC model considered the VRS and, thus, calculate the pure technical efficiency by eliminating the effect of scale. Additionally, the DEA models are split into three categories, input-oriented, output-oriented, and non-oriented.

Considering the constantly evolving economy, industries such as manufacturing can have negative attributes in form of cash conversion cycle, and profit after tax; and hence, for dealing with such negative data, a DEA model must have a translational invariant property which is present in slack based measure (SBM) DEA model. The SBM DEA model is unit invariance and monotonic decreasing with the slacks. It also computes efficiency and slacks in one single step, unlike CCR DEA and BCC DEA models.

For better understanding of SBM DEA model, the following LP model is articulated. Consider, there are p inputs and q outputs for the n DMUs. The inputs, outputs, and intensity variables for DMU$_m$ are denoted as $\boldsymbol{x}_m = (x_{1m}, x_{2m}, \ldots, x_{pm})^T$, $\mathbf{y}_m=(y_{1m}, y_{2m}, \ldots, y_{qm})^T$, and $\boldsymbol{\lambda}_m=(\lambda_{1m}, \lambda_{2m}, \ldots, \lambda_{km})^T$, respectively. Then, the SBM DEA model for a DMU$_m$ is defined as,

Min $$\rho_m = \frac{1-\frac{1}{p}\sum_{i=1}^{p}\frac{s_{im}^-}{x_{im}}}{1+\frac{1}{q}\sum_{j=1}^{q}\frac{s_{jm}^+}{y_{jm}}}$$

Subject to (1)

$$\sum_{k=1}^{n}\lambda_{km}x_{ik} + s_{im}^- = x_{im} \qquad \forall i = 1, \ldots, p$$

$$\sum_{k=1}^{n} \lambda_{km} y_{jk} + s_{im}^{+} = y_{jm} \qquad \forall j = 1, \ . \ . \ . \ , q$$

$$\lambda_{km} \geq 0, s_{im}^{-} \geq 0, \ s_{jm}^{+} \geq 0, \qquad \forall m = 1, \ . \ . \ . \ , n.$$

Model (1) has a fractional objective function, and therefore it cannot be solved. Therefore, the objective function of model (1) is normalized by multiplying it by a scalar positive number (t>0) which is as follows:

Min $$\rho_m = t + \frac{1}{p} \sum_{i=1}^{p} \frac{S_{im}^{-}}{x_{im}}$$

$$t + \frac{1}{q} \sum_{j=1}^{q} \frac{S_{jm}^{+}}{y_{jm}} = 1$$

Subject to (2)

$$\sum_{k=1}^{n} \Lambda_{km} x_{ik} + S_{im}^{-} = t x_{im} \qquad \forall i = 1, \ . \ . \ . \ , p$$

$$\sum_{k=1}^{n} \Lambda_{km} y_{jk} + S_{im}^{+} = t y_{jm} \qquad \forall j = 1, \ . \ . \ . \ , q$$

$$\Lambda_{km} \geq 0, S_{im}^{-} \geq 0, \ S_{jm}^{+} \geq 0, \text{and } t > 0 \qquad \forall m = 1, \ . \ . \ . \ , n.$$

Here, $S_{im}^{-} = t s_{im}^{-}, \ S_{jm}^{-} = t s_{jm}^{-}, \ \Lambda_{km} = t \Lambda_{km}$.

In the current study, WCM efficiency is calculated using three inputs i.e. X1: (Receivables / Sales) *365; X2: (Inventories / Raw materials purchased) *365; and X3: (Trade payables / Raw materials purchased) *365 and one output i.e. Y1: (Earnings before interest and taxes / Total assets). Then, model (2) becomes,

Min $$\rho_m = t + \frac{1}{3} \sum_{i=1}^{3} \frac{S_{im}^{-}}{x_{im}}$$

$$t + \frac{S_{1m}^{+}}{y_{1m}} = 1$$

Subject to $\sum_{k=1}^{n} \Lambda_{km} x_{ik} + S_{im}^{-} = tx_{im}$ $\forall i = 1, \ . \ . \ . \ , 3$ (3)

$$\sum_{k=1}^{n} \Lambda_{km} y_{1k} + S_{1m}^{+} = ty_{1m}$$

$$\Lambda_{km} \geq 0, S_{im}^{-} \geq 0,\ S_{1m}^{+} \geq 0, \text{and } t > 0 \qquad \forall m = 1, \ . \ . \ . \ , n.$$

Some of the components of data used in this study comprise of negative values. So, for handling such negative data, we have transformed it to positive values using following translation:

$$\bar{x}_{3k} = (-(min\, x_{3k}) * 1.01) + x_{3k} \qquad \forall k = 1, \ . \ . \ . \ , n$$

$$\bar{y}_{1k} = (-(min y_{1k}) * 1.01) + y_{1k} \qquad \forall k = 1, \ . \ . \ . \ , n.$$

Thus, the model (3) is transformed into the model (4) as,

Min $\rho_m = t + \frac{1}{3}\sum_{i=1}^{2} (\frac{S_{im}^{-}}{x_{im}} + \frac{S_{3m}^{-}}{\bar{x}_{3m}})$

$$t + \frac{S_{1m}^{+}}{\bar{y}_{1m}} = 1$$

Subject to $\sum_{k=1}^{n} \Lambda_{km} x_{ik} + S_{im}^{-} = tx_{im}$ $\forall i = 1, \ . \ . \ . \ , 2$ (4)

$$\sum_{k=1}^{n} \Lambda_{km} \bar{x}_{3k} + S_{3m}^{-} = t\bar{x}_{3m} \qquad \forall m = 1, \ . \ . \ . \ , n$$

$$\sum_{k=1}^{n} \Lambda_{km} \bar{y}_{1k} + S_{1m}^{+} = \overline{ty}_{1m}$$

$$\Lambda_{km} \geq 0, S_{im}^{-} \geq 0, S_{3m}^{-} \geq 0,\ S_{1m}^{+} \geq 0, \text{and } t > 0 \qquad \forall m = 1, \ . \ . \ . \ , n.$$

The model (4) is a linear programming function, and we have used MATLAB software for assessing the WCM efficiency using this model.

4.5 Stage 2: Determinants Influencing Working Capital Management Efficiency

This section offers the proposition that WCM efficiency in manufacturing firms of India is substantially influenced by firm-level and macro-economic determinants. The current global scenario comprises of severe threats to be faced by the firms in terms of tight customer's demand, ever-changing fashion, and updated technology but at the same time offers prospects for higher growth. Firms continuously engage in curtailing their flaws and make use of their strengths for competing in the market. Hence, a mix of both internal as well as external factors influence the functioning and performance of firms that can add to or become obstacle in firm's way of achieving its objectives. Put differently, firm's performance and efficiency are impacted by a mix of firm specific and macro-economic conditions. Therefore, firm's WCM efficiency cannot be solely defined by only inputs and outputs but other factors might also significantly impact it. Mainly two categories i.e., firm-level determinants and macro-economic determinants are the factors influencing WCM efficiency. Thus, a proper investigation into the assessment of these factors would lead to an efficiency management of working capital.

4.5.1 Variables Definition

Table 4.2 discusses the independent and dependent variables along with their formulas and sources. These variables have been comprehensively discussed in the literature review section along with the hypotheses formulation for assessing the relationship of selected independent variables with the dependent variables. These variables were shortlisted from the previous literature based upon their importance in working capital decisions.

Table 4.2: Variables Explanation

Variable	Definition	Measurement	Source
Independent variable			
WCME	Working Capital Management Efficiency	Efficiency scores calculated as per the SBM DEA model	Bajec and Tuljak-Suban (2019)
Dependent variables			
CFLOW	Capacity to generate internal resources	(Net profit + Depreciation)/Total assets	Chiou, Cheng and Wu (2006)
TFA	Tangible fixed assets	Tangible fixed assets / Total assets	Banos-Caballero et al. (2010)
SIZ	Size of the firm	Natural logarithm of total assets	Banos-Caballero et al. (2010)
AGE	Age of the firm	Current year-Incorporation year	Goel and Sharma (2015)
PRD	Productivity	Sales/Wages	Seth et al. (2020)
LEV	Leverage	Debt/Total assets	Abbadi and Abbadi (2013)
CEF	Cost of external financing	Financial expenses/Total debt	Banos-Caballero et al. (2014)
IC	Interest coverage	Earnings before interest and tax/Financial expenses	Banos-Caballero et al. (2014)
SC	Structural capital	Research and development expenses/Profit after tax	Bayburina and Golovko (2009)
HC	Human capital	Staff welfare and training expenses	Sapra and Jain (2019)
GRT	Growth	(Current year sales-previous year sales)/previous year sales	Naser et al. (2013)
GDP	Gross Domestic Product	Final value of goods and services produced in an economy at a given period	Seth, Chadha and Sharma (2019)
INT	Interest rate	Mean interest rates of (Indian) central government securities	Palit (2013)

Source: Literature

4.5.2 Panel Data Regression Model for Assessing the Relationship of Determinants with Working Capital Management Efficiency

Panel data is a data consisting of a pool of observations on a cross-section of households, industries, countries, individuals over several periods (Baltagi, 2008). Generally, panel data is defined as longitudinal data that illuminate the cross-sectional observations such as individual's observations in time-series (Goel and Sharma, 2015). Hence, panel data involves a dataset on various units at two or more points in time. Panel data enhances the sample's deterministic power as it obtains numerous observations on each unit in the sample by way of incorporating two elements of data set which are time-series and cross-sectional. Additionally, it represents a convoluted cluster or hierarchical composition of multilevel data (Hsiao and Hsiao, 2006).

Unobserved heterogeneity and random error are accounted in panel data as they are tricky for precise measurement. Cultural aspects, socio-economic features and other facets that change with time but not among cross-sections (such as qualitative monitoring procedures, inflation rates, GDP) are complicated to measure. Since panel data offers multi-level assemblies for hierarchical molding so it incorporates various benefits over the single time-series or cross-sectional data (Hsiao, 2005). Panel data is widely used by the researchers in social sciences and economics due to its numerous advantages and precise measurement. Additionally, Panel data technique was employed for this research due to its various advantages such as it minimize measurement errors and bias of the sample arising from the existence of individual effects (Gujarati, 2009). Also, modelling dynamic responses with micro data and testing implicit assumptions in cross-sectional analysis is possible through panel data methodology (Hsiao, 1985).The current study tries to correlate unobserved individual specific effects with the regressors and rely on strict exogeneity assumption which includes that idiosyncratic errors and regressors to be uncorrelated for all periods, which makes panel data methodology opt for this study.

Panel data is classified as balanced panel and unbalanced panel wherein data where cross-sectional units and time-series observations are same then it is balanced panel. However, variation in the number of cross-sectional units and time-series observations signifies unbalanced panel. The current study has adopted balanced panel approach by collecting data that have equal number of cross-section units and time-series observations.

A relationship among dependent and independent variables is established using regression model. A simple panel regression model is stated as under:

$$Y_{it} = \alpha + \beta X_{it} + u_{it}$$

i = 1,2,3,4,…………., N

t = 1,2,3,4,…………., T

where,

i signifies individual entity

t symbolizes time period

β is a vector of coefficient which is to be estimated

Y_{it} embodies dependent variable of entity i at time t

X_{it} represents independent observation on cross-section i in time t

N is the total number of entities

T is the number of time periods

u_{it} denotes an error component of the model.

On the basis of error term "u_{it}", panel data regression model has two classifications named as random effect model and fixed effect model. Random effect model is applied when there is an indication that dependent variable is affected by difference in entities across cross section and its takes time invariant variables into consideration. Fixed effect model is employed in case objective is to examine the effect of variables that vary with time and are invariant across cross section. Additionally, it assumes that the regressor's slope coefficients does not vary across cross-sections (Gujarati, 2003).

In this stage after the efficiency scores were calculated using SBM DEA model, the scores obtained were used to entwine the exogenous variables affecting efficiency. This study prominences on the relation of WCM efficiency with exogenous variables of the firm and the set of independent variables used are capacity to generate internal resources, tangible fixed assets, size, age, productivity, leverage, cost of external financing, interest coverage, structural capital, human capital, growth, gross domestic product, and interest rate, which have been used in research in earlier studies in working capital context or associate these with firms' working capital performance. Following model is used in this study for the analysis:

$$\text{WCME} = \alpha + \beta_1 CFLOW_{it} + \beta_2 TFA_{it} + \beta_3 SIZ_{it} + \beta_4 AGE_{it} + \beta_5 PRD_{it} + \beta_6\, LEV_{it} + \beta_7\, CEF_{it} + \beta_8\, IC_{it} + \beta_9\, SC_{it} + \beta_{10}\, HC_{it} + \beta_{11}\, GRT_{it} + \beta_{12}\, GDP_{it} + \beta_{13}\, INT_{it} + \varepsilon_{it} \quad (1)$$

where,

WCME = The efficiency values of working capital management obtained by applying SBM DEA model

β_k = Unknown parameters for estimation

$\mathcal{E}_{it}$ = Random disturbance

For checking the reliability of all the explanatory variables in this study in the equation, the redundant test is taken for all of them. The redundant test results showed all the explanatory variables to be statistically significant and must become a part of the equation. Variance Inflation Factor (VIF) is applied for checking the multicollinearity (Habib and Huang, 2018). The VIF test values are less than 2 respectively, hence indicates that no serious correlation exists among the independent variables (Makori and Jagongo, 2013). Table 4.3 shows the multicollinearity test results of explanatory variables. Additionally, Table 4.3 also presents the summary statistics (mean, median, standard deviation) for the independent variables taken in the current study. This table 4.3 specifies considerable variability in the sample that may well be supporting better analysis.

Table 4.3: Summary Statistics at Firm Year Level and Variance Inflation Factor (VIF)

Variable	**Mean**	**Median**	**Maximum**	**Minimum**	**Standard Deviation**	**VIF**
CFLOW	0.063	0.063	0.824	-0.213	0.062	1.086
TFA	0.345	0.344	0.778	0.016	0.144	1.201
SIZ	3.375	3.325	6.555	1.435	0.461	1.056
AGE	1.470	1.435	2.098	0.816	0.217	1.072
PRD	19.332	18.806	35.349	10.604	0.223	1.008
LEV	0.386	0.342	0.973	0.000	0.147	1.085
CEF	0.15	0.10	5.23	0.02	0.37	1.128

IC	8.26	3.75	131.96	-0.34	14.42	1.072
SC	0.13	0.05	6.99	-7.17	0.84	1.026
HC	254.82	54.27	9122.95	1.40	841.50	1.072
GRT	0.144	0.112	0.691	-0.220	0.101	1.083
GDP	0.068	0.067	0.093	0.044	0.016	1.054
INT	0.079	0.080	0.085	0.071	0.004	1.021

Note: This table presents summary statistics of the independent variables used in the current study. The sample consists of BSE listed 1391 Indian manufacturing firms covering data for a period from 2009-2020

Source: CMIE Prowess and Eviews 10

The current research is to measure the impact of determinants that change with time, i.e. less attention is to be paid in time invariant factors. Furthermore, Hausman (1978) developed a test for testing the suitability of fixed effect or random effect model. The underlying null hypothesis is that there is no significant difference between random and fixed effects estimates. In case of rejection of null hypothesis, it is stated that fixed effect model is suitable to be applied and random effect is not suitable.

In consideration to the above-mentioned benefits of panel data regression model, the current research applied it for examining the impact on WCM efficiency from several firm-level and macro-economic determinants. Further, the study used Hausman test for choosing between random and fixed effects model.

4.6 Stage 3: Artificial Neural Networks and Sensitivity Analysis

For a robust analysis and to support the results of fixed effects model, ANN was performed. ANN is a vastly adopted technique in management science (Abubakar et al., 2019) due to its ability to draw inferences from normal and non-normal data which surpasses the assumptions of other methods such as regression and modelling. The reason for this is the capability of ANN to distinguish relationships which are linear and nonlinear (Abubakar et al., 2018). ANN is applied for training and testing the models' precision and estimating the symmetric and asymmetric patterns in the data accurately (Abubakar *et al.*, 2019).

Some of the characteristics of ANN involve accuracy and validity in predictions, higher reliability than regression or modelling, no assumptions for normality, homoscedasticity, sample size, factor loadings, sample error, tolerance for greater differences in data, and competence for generalizing the findings (Göçken et al., 2016). ANN's estimate symmetric and asymmetric patterns in the data with complete accuracy. ANN is used for modelling and testing the precision of the model (Abubakar et al., 2017).

ANN multi-layer perceptron feature with resilient backpropagation was deployed. The accuracy of models assessed through ANN is checked for using the measure of root mean square error (RMSE). In addition, a sensitivity analysis is performed to underscore the importance of variables selected in WCM efficiency models. A sensitivity analysis reveals the order of importance in which the inputs (independent variables) influence the outputs (dependent variables). For the above-mentioned analyses, IBM SPSS Statistics-version 20 and Amos-version 20 were utilized. A detailed analysis of the statistics is presented and discussed in the next chapter.