Mapping and Predicting Capital Structure Efficiency of Sustainable Green MSMEs: Evidence from an emerging country

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Abstract

This study evaluates the capital structure efficiency (CSE) of green micro, small, and medium enterprises (MSMEs) in India, employing a hybrid approach combining Data Envelopment Analysis (DEA) and Gene Expression Programming (GEP). The research aims to assess the efficiency levels across different MSME categories, identify significant determinants of CSE, and develop predictive models to enhance financial decision-making. The study addresses key questions on the current efficiency levels, influential factors, and the effectiveness of various predictive models in forecasting CSE. Utilizing data from the CMIE Prowess database, the analysis reveals that micro-sized green MSMEs exhibit higher capital structure efficiency compared to medium and small enterprises due to lower operational costs and greater flexibility in decision-making. Significant factors influencing CSE include the Debt-to-EBITDA ratio, Debt-to-Asset Ratio, and Return on Equity. Comparative analysis shows that the DEA-GEP model consistently outperforms other models, particularly in predictive accuracy and reliability, as validated by Monte Carlo simulations. Key findings suggest that efficient debt management and profitability enhancement are crucial for improving CSE in green MSMEs. This research contributes to the theoretical understanding of capital structure in sustainable enterprises and offers practical implications for managers and policymakers to foster financial and environmental sustainability.

Keywords: Capital structure efficiency (CSE), Data envelopment analysis (DEA), Gene expression programming (GEP), Micro small and medium enterprises (MSMEs).

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1. Introduction

The triple bottom line approach advocates for sustainability across three dimensions: people, planet, and profits, suggesting that firms should prioritise environmental and social concerns alongside financial considerations. The question arises: "Is it possible?" Can firms achieve environmental, social, and financial sustainability simultaneously? Yes, the transition towards sustainable development has placed green Micro, Small, and Medium Enterprises (MSMEs) at the forefront of both economic and environmental transformation. These enterprises, characterised by their commitment to sustainable practices and innovation, are crucial drivers in the global effort to address climate change and promote eco-friendly industrial practices (Tripathi et al., 2013). (Xu et al., 2024) advocated that sustainability has been linked to higher operational and market performance levels.

The World Economic Forum (2018) provided empirical evidence that environmental resource preservation improves the organisation's financial metrics. As a result, businesses are now either fundamentally building their business in the green sector or embracing greener practices in their existing business, such as investment in energy efficiency, sustainable supply chains, carbon offsetting and many more. They are crucial in advancing the transition towards a greener economy while addressing environmental concerns. However, implementing green technologies and practices requires significant upfront investment costs (C. Chen et al., 2016). (Brahmbhatt, 2021) states that green initiatives have long payback periods, which can create liquidity challenges and hinder cash flow for green firms, especially those operating in industries with tight profit margins. (Desalegn & Tangl, 2022) advocated that green firms encounter difficulties accessing financing, as traditional lenders and investors perceive sustainability projects as risky or unproven. This poses serious limitations for green firms, the majority of which are small and unorganised (Bouchmel et al., 2024). Additionally, such challenges have contributory effects on financial performance, which could also influence the firms' financing options and their capital structure. In an impact market, leverage can have uncertain and complex effects on firms' efficiency. Hence, it is important for firms to utilise whatever funds are with them judiciously (Li et al., 2020). In other words, firms should efficiently utilise every component (debt and equity) of their capital structure.

Furthermore, most studies, such as those by (Rao et al., 2019; Seth, Sharma, et al., 2020; Zheng & Luo, 2023) have focused on larger firms in a general context without delving into the specific challenges faced by green enterprises. These studies typically apply traditional theories and techniques for efficiency analysis. However, the applicability of theories to green MSMEs, which operate under different constraints and opportunities, remains underexplored. Additionally, Green enterprises often have different operational and financial structures compared to conventional firms, influencing their efficiency and capital structure decisions. Hence, the primary aim of this research is to evaluate the capital structure efficiency of green MSMEs in India using advanced analytical models. Specifically, the study intends to:

1. Assess the current levels of capital structure efficiency among green MSMEs of different sizes (micro, small, and medium).
2. Identify and analyse the key factors that influence capital structure efficiency in green MSMEs.
3. Develop predictive models that can be used to forecast capital structure efficiency based on identified influencing factors.

To achieve these aims, the study is guided by the following research questions:

1. What are the current levels of capital structure efficiency among different types of green MSMEs in India?
2. Which factors most significantly affect capital structure efficiency in green MSMEs, and how do these factors interact?
3. How can predictive models be developed to forecast capital structure efficiency in green MSMEs?

Addressing these questions is critical for several reasons:

First, the current study contributes to the academic understanding of how sustainability influences financial management practices. It extends traditional finance theories into the context of environmentally focused enterprises, offering new insights into the dynamics of efficiency in this sector. Second, for managers of green MSMEs, understanding the factors that drive capital structure efficiency is essential for optimizing their financial strategies and navigating the challenges of balancing financial as well as environmental objectives, ultimately enhancing their competitiveness and sustainability. Third, by identifying the key factors that influence capital structure efficiency, the study provides a basis for developing financial and regulatory policies that foster the growth and sustainability of these enterprises.

To address research questions, we adopted a novel methodology, i.e. DEA, along with gene expression programming. This offers various advantages over earlier research methods. First, DEA being non-parametric, does not require assumptions about data distribution and is capable of handling multiple inputs and outputs, making it ideal for complex efficiency evaluations (Amirteimoori et al., 2022). Second, GEP on the other hand, provides flexibility in modelling complex relationships and effectively addresses overfitting and multicollinearity issues that are common in traditional linear models (Peng et al., 2014). The robustness tests, including DEA-SEM, DEA-Regression, DEA-MLPNN, and DEA-RF, each bring unique strengths: DEA-SEM integrates structural equation modelling to account for latent variables; DEA-Regression checks linear relationships; and DEA-MLPNN and DEA-RF use machine learning techniques to capture non-linear patterns and interactions. Third, the generation of decision rules is based on the efficient frontier. Additionally, traditional DEA models may not account for dynamic changes over time and are often limited to cross-sectional data (Seth et al., 2024).

The remaining sections of this article are structured as follows: Section 2 presents a literature overview on capital composition and the application of DEA and machine learning in evaluating firm performance. Section 3 outlines the research methodology, encompassing data origins, variables, and model specifications. Section 4 unveils the findings of the analysis and explores their significance for MSMEs in India. Lastly, Section 5 offers the final remarks and suggestions for future research.

2. Theoretical Framework and Literature Review

2.1 Theoretical Framework

The capital structure decisions of firms have long been analysed through various theoretical lenses, each offering unique insights into the determinants and implications of these decisions. This study leverages the Efficiency and Resource-based theory to explore capital structure efficiency in green MSMEs. These theories explain how firms strategically allocate their resources and optimise their capital structure to achieve competitive advantage and sustainability goals.

Efficiency Theory posits that firms strive to minimise the cost of capital by efficiently utilising debt and equity to achieve an optimal capital structure(Ahmed et al., 2020). In the context of green MSMEs, this theory suggests that these firms seek to minimise the cost of financing their environmentally sustainable projects and initiatives.

Resource-based theory, on the other hand, emphasises the internal resources and capabilities of a firm as sources of sustainable competitive advantage(Vicente-Lorente, 2001). In the case of green MSMEs, this theory suggests that firms may leverage their unique environmental assets, such as renewable energy technologies or eco-friendly production processes, to access specialised sources of financing or attract socially responsible investors, thereby achieving an efficient capital structure.

2.2 The capital structure of the small business

Capital structure efficiency or management refers to how effectively a company or organisation manages its mix of financing sources (such as debt and equity) to optimize its financial performance and maximise shareholder value. It involves striking a balance between debt and equity financing that minimises the cost of capital while maximising shareholder returns (Gentzoglanis, 2007; Gill & Wilson, 2021; Margaritis & Psillaki, 2007; Nadu, 2013; Nan & Wen, 2012).

Multiple studies have investigated the relationship between capital structure and firm performance, as well as the variables that impact firms' financing decisions, but there are very few studies that have studied the efficiency of capital structure. (Akhtar et al., 2016)discovered a favourable relationship between ownership structure and leverage and a beneficial effect of leverage on productivity in the Pakistani textile sector. (Koralun-Bereźnicka, 2018) examined the influence of major determinants on leverage across various business sizes and loan maturity structures in eleven EU nations. He discovered that small companies adhere to the pecking-order theory, while medium- and large-sized enterprises adhere to the trade-off theory. (Fernandes et al., 2018) examined the drivers of debt financing in Portuguese small and midsize enterprises & observed that short-term leverage is positively correlated with productivity and that businesses prefer to adhere to the pecking-order hypothesis.

Other studies have explored the impact of different financing options on technical efficiency and financing efficiency, such as (Odeleye & Olohunlana, 2019; Sun & Geng, 2019) in the Nigerian agro-allied industry and Chinese listed companies in strategic emerging industries. while (Rahim & Shah, 2019) examined the link between business efficiency and debt in Pakistani non-financial organisations,

More recent studies continue to provide valuable insights into the determinants of firm financing decisions and efficiency. For example, (Xiaomei et al., 2023) examined the impact of tax enforcement on debt policy and capital structure of Chinese listed firms, while (Atta Mills et al., 2022) evaluated the operating efficiency of real estate companies in China and its effect on stock returns., whereas (Neville & Lucey, 2022) investigated the capital structure of high-tech SMEs in Ireland.

These studies have employed various methods to analyse the relationship between financing alternatives, firm efficiency, and leverage. Varied financing choices have different implications on business efficiency and leverage, which may be impacted by firm size, risk, growth rate, and institutional ownership. In addition, contextual variables such as legal systems, information-sharing methods, and social capital may influence the capital structure choices of businesses.

2.3 Machine Learning in Finance

Recent research has investigated the capacity of machine learning techniques to enhance financial decision-making and risk management. (Manjunath et al., 2023) proved the efficacy of integrating technical indicators, PCA, and machine learning algorithms for accurate prediction of stock market trend. (N. Chen, 2023)investigated the visual recognition impact of the CNN-LSTM technique based on neural network optimization with respect to China's real estate index and stock movement.

Moreover, a number of studies have proved the applicability of neural networks in forecasting and assessing financial performance and risks in a variety of finance and management domains. (Charef, 2023) used a hybrid GARCH-NN model to forecast currency rates in Tunisia and found that it outperformed individual models. Using an ensemble neural network technique, (Yeh & Chen, 2022) determined that social and human capital metrics are good predictors of crowdfunding project success. (De Clerk & Savel'ev, 2022) ANN approach for estimating GARCH parameters demonstrates considerable time savings in comparison to maximum likelihood estimation techniques.

Additionally, Numerous researchers have investigated the capability of ANNs to enhance portfolio performance and forecast default rates in P2P online lending. For example, (Liang & Cai, 2020) investigated the default rate of monthly new loans in the US P2P lending platform and discovered that the long short-term memory network (LSTM) strategy had the greatest accuracy of default rate prediction in comparison to conventional models. (Nasseri et al., 2020) investigated the use of a hybrid model incorporating particle swarm optimization (PSO) and artificial neural networks (ANN) for preparing portfolios, demonstrating the applicability of stochastic dominance criteria, ANN, and PSO in developing country capital markets.

In contrast, several studies have proposed and optimised hybrid algorithms that combine machine learning models and optimisation techniques to enhance the performance of ANNs in financial forecasting(Tripathi et al., 2023). for instance, (Ansari et al., 2020), present a hybrid approach, MOA-PSO, which combines Magnetic Optimization Algorithm (MOA) and Particle Swarm Optimization (PSO), to enhance the performance of Artificial Neural Networks (ANN) in bankruptcy prediction. Their suggested approach yields promising results with more precise and quicker predictions. (Dhenuvakonda et al., 2020) emphasise the importance of forecasting and evaluating stock market data, as well as the dominance of deep learning models such as LSTM in this sector. Their research indicates that neural networks, especially LSTM, outperform conventional linear models in forecasting stock values, and that RMS prop is the most effective optimization technique.

These studies highlight the promise of machine learning in finance, as well as the need to continuously explore and optimise its applications. Only a few studies exist in the literature that has employed GEP in finance. For instance, (H. H. Chen et al., 2014) utilised GEP for forecasting mutual fund performance, whereas (Cheng et al., 2018) used GEP for the financial distress of the firms utilizing time-series data.

3. Research Methodology

The fundamental Research framework of the current research is depicted in Figure. I, which consists of the outlined 5 core processes: (i) data gathering; (ii) normalising of data; (iii)

Building various models using datasets to predict capital structure efficiency; (iv) Model evaluation; and (v) conducting sensitivity analysis.

3.1 Stage I Data Gathering and Processing

We gathered a sample of 578 micro, small, and medium-sized (MSMEs) green firm enterprises in India from 2012 to 2021. Based on the government of India's categorisation of Micro, Small, and Medium enterprises, the sample was divided into three subgroups: 2960 observations for small, 2260 for medium, and 590 micro firms. For this study, we collected information from Agriculture, Renewable Energy, Electric Mobility, Recycling and Waste Management, Organic and Sustainable Food Production, and Solar firms. We used data from Prowess, a detailed database by CMIE focusing on Indian companies. Past studies have also emphasised its importance in providing comprehensive financial and non-financial information about Indian companies (Chadha et al., 2023; Seth et al., 2020; Tripathi et al., 2024).

All the variables are expressed in terms of ratios. The variable explanation along with literature support is given in Table II. Furthermore, prior to constructing the model to capture capital structure efficiency, we implemented a data normalization process to mitigate the risks of overfitting and reduce errors. This normalization procedure entailed transforming all input data into a range of values between 0 and 1, ensuring consistency and comparability across the dataset. according to equation 1.

$$N = \frac{(Y - Y_{min})}{(Y_{max} - Y_{min})} \tag{1}$$

Here, 'N' reflects the normalised input parameter value, 'Ymax' denotes highest numerical value among the given inputs for that specific factor, whereas 'Ymin' signifies minimal score among all the inputs for that peculiar factor.

To normalize data, we calculate 'N' by subtracting 'Ymin' from 'Y' and dividing the result by the difference between 'Ymax' and 'Ymin'.

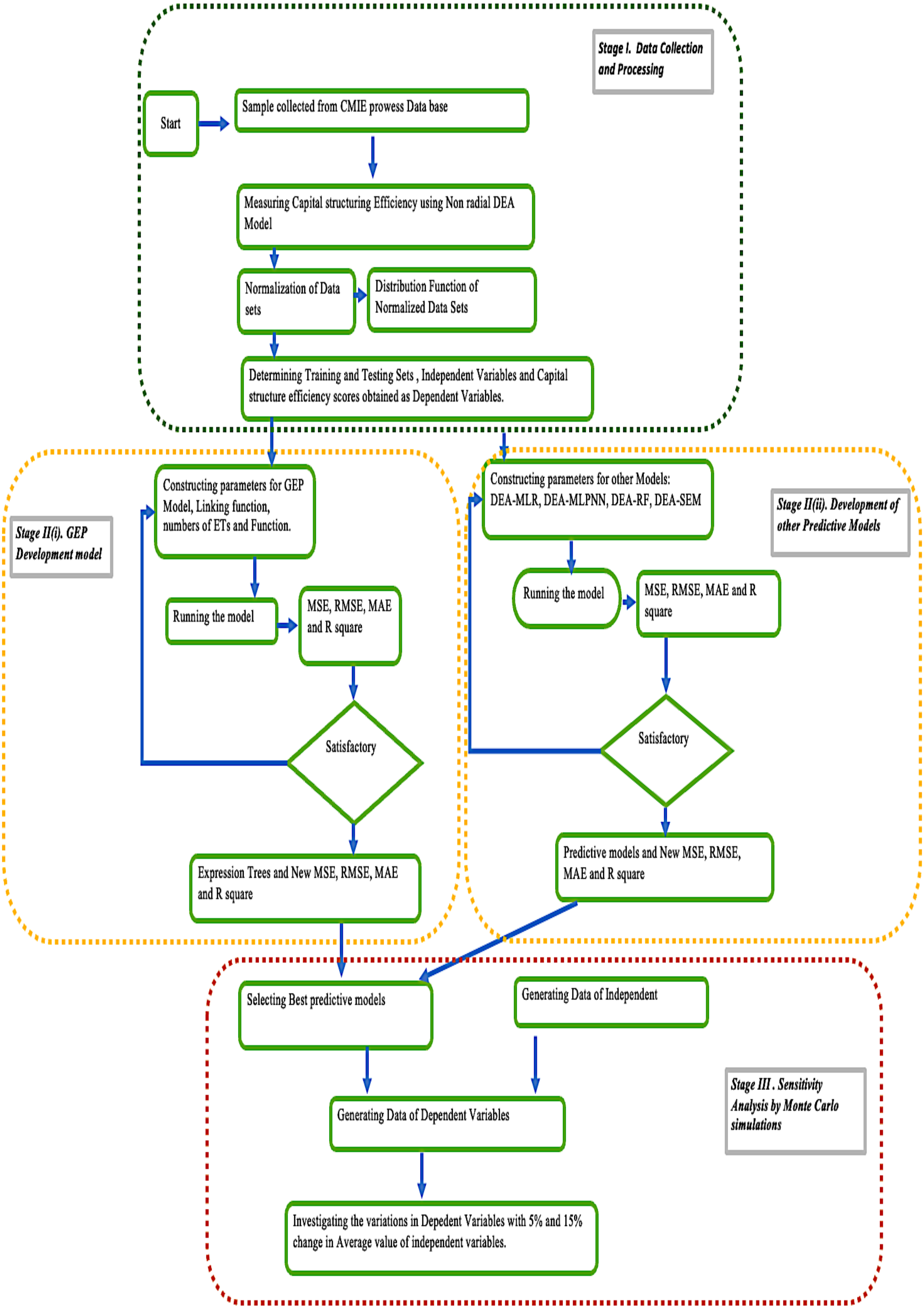


Figure I Research Framework

Table I Basic Definition About the MSMEs.

Type of Firm	Revenue	Plant & Machinery
Micro	≤5 crore	≤1 crore
Small	≥5 crore and ≤ fifty crore	≥1 crore and ≤ 10 crores
Medium	≥50 crore and ≤ 250 crore	≥10 crore and ≤ 50 crores

Note: All currency in INR

Table II Variable Parameters

Variable	Abbreviation	Definition	Source
Debt service coverage Ratio	DSCR	The ratio among Net operating revenue and Debt service which include both principal as well interest.	(Firouzi & Meshkani, 2021)
Interest coverage Ratio	ICR	The ratio of earnings before interest and tax and interest.	(Gul & Cho, 2019)
Equity Multiplier	EQTM	Average Total assets divided by Average shareholders' Equity.	(Viswanatha Reddy, 2013)
Return on assets	ROA	The ratio of Net Income and Total assets	(Vieira, 2017)
Net income	NI	Total income less the Direct and indirect cost	(Ardalan, 2017)
Capital structure efficiency	CSE	Capital structure efficiency score obtained from Employing DEA	Authors own calculation
Firm size	FS	Log of Total assets	(Naser et al., 2013)
Firm Age	FA	Log Age of the firm since its inception in Years	(Tripathi & Chadha, 2023)
Profitability	PROF	The ratio of Profit after tax and Net sales	(Habib & Kayani, 2022)
Return on Equity	ROE	The ratio of Net Income and Shareholders' equity	(Dai & Piccotti, 2020)
Debt EBITDA Ratio	DBEBITDA	The ratio of long term debt and EBITDA	(Brown et al., 2021)

Productivity	PROD	The ratio of Wages paid to employees and Net Revenue.	(Chadha & Seth, 2021)
Debt Asset ratio	DBAsstR	The long term external debt divided by Total asset of the firm.	(Ullah et al., 2020)
Tangibility	TANG	The ratio of Fixed asset and Total asset.	(Panda & Nanda, 2020)
Operating Cash flow	OCF	The ratio of Operating Cash flow and current Liabilities	(Harris & Roark, 2019)

3.2 Data Envelopment Model

Data Envelopment Analysis is a widely used non-parametric technique for assessing firm efficiency, especially suitable for diverse inputs and outputs. However, DEA has limitations, such as not accounting for accumulated efficiency over multiple periods (Seth et al., 2024). To address this, our study employs the Multiple Aggregated Efficiency (MAE) method, which evaluates a firm's efficiency over time by combining input and output data from various periods. This approach considers temporal changes, providing a more accurate assessment of efficiency and insights into the causes of fluctuations, such as market conditions and management practices. Using the panel data approach, MAE integrates information from multiple periods to derive efficiency scores, allowing for trend analysis, efficiency comparisons, and evaluating external factors' impact.

The research utilises the MAE model (Antunes et al., 2022) for calculating Multi-period aggregative efficiency. The linear model is stated below. Table (III) provides the set of inputs and outputs for the model and its characteristics.

$$E_c = \max MQ - \frac{1}{mQ}\sum_{q=1}^{Q}\sum_{i=1}^{m}\frac{s'^{q-}_{i}}{x^{q}_{ip}}$$

$$s.t. \sum_{j=1}^{n} \lambda'^{t}_{j} x^{q}_{ij} + s'^{q-}_{i} = Mx^{q}_{ip}, \qquad \forall_i , \forall_q$$

$$\sum_{j=1}^{n} \lambda'^{q}_{j} y^{q}_{rj} + s'^{q+}_{r} = My^{q}_{rp}, \qquad \forall_r , \forall_q$$

$$MQ + \frac{1}{sQ}\sum_{q=1}^{Q}\sum_{r=1}^{s}\frac{s'^{q+}_{r}}{y^{q}_{rp}} = 1$$

$$\lambda'^{q}_{j} \geq 0, \qquad \forall_j , \forall_q$$

$$s'^{q-}_{i} \geq 0 , \qquad \forall_i , \forall_q$$

$\boldsymbol{s_r^{\prime q+}} \geq \mathbf{0}$, $\forall_r$, $\forall_q$ *where* $M = \frac{1}{T+\frac{1}{sQ}\sum_{q=1}^{Q}\sum_{r=1}^{s}\frac{s_r^{q+}}{y_{rp}^{q}}}$, $\lambda_j^{\prime q} = M\lambda_j^{q}$, $s_i^{\prime q-} = Ms_i^{q-}$ *and* $s_r^{\prime q+} = Ms_r^{q+}$. In this case, the MAE of DMUp is= $MQ - \frac{1}{mQ}\sum_{q=1}^{Q}\sum_{i=1}^{m}\frac{s_i^{\prime q-*}}{x_{ip}^{q}}$ and the efficiency of DMUp at time period q, q = 1, 2,3,4 ……,Q, equals to $\boldsymbol{E_p^{q*}} = \frac{M-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^{\prime q-*}}{x_{ip}^{t}}}{M+\frac{1}{s}\sum_{r=1}^{s}\frac{s_r^{\prime q+*}}{y_{rp}^{q}}}$

3.3 Stage II (Part one): GEP Model

Gene Expression Programming (GEP) is a computational method inspired by biological evolution, specifically genetic processes. Developed by Candida Ferreira in the year 2002, GEP is a type of genetic programming that evolves computer programs to solve complex problems. GEP represents potential solutions as linear sequences of symbols, forming chromosomes, then translated into hierarchical structures called expression trees. These trees, representing the structure of evolved computer programs, are optimised using genetic operators like mutation and crossover over multiple generations. GEP finds applications in various fields, including symbolic regression, classification, optimisation, and machine learning.

In the context of capital structure efficiency, GEP can express the relationship between various independent variables and capital structure efficiency by evolving computer programs that capture the complex dynamics influencing a company's financial structure. It automatically generates and refines features, identifying the most relevant factors and interactions within financial data. We employed the GEP model to predict Capital structure efficiency(CSE) as a function of various endogenous variables listed in Table II. Python was used to fabricate the Gene Expression Programming model. The data is divided into a 60:40 ratio where 60% were part of the training model, and 40% were for testing purposes.

In GEP, data selection and reproduction are accomplished using a roulette wheel mechanism to identify the optimal algorithm for forecasting the objective parameter.

3.4 Stage two (Part II): Model Performance Evaluation

To assess the efficiency of the constructed model in evaluating capital structure efficiency, we used five distinct statistical measures: Root Mean Square Error (RMSE), Mean Square Error (MSE), coefficient of determination (R^2), Relative Absolute Error (RAE), and Mean Root Relative Error (MRRE). These metrics quantify different aspects of the model's accuracy and fitness.

RMSE, derived from Equations. (2) represents the average magnitude of the residuals or errors in a regression model. It measures the overall deviation of the model's predictions from the actual values. Similarly, MSE (Equations. (3)) calculates the average of the squared dissimilarities between predicted and actual values. MSE assesses the overall error or disparity between the model's predictions and the actual values. Smaller MSE values signify the model's superior performance [42].

R^2, expressed in Equations. (4) signifies the amount of variation in the dependent variable that can be accounted for by the independent variables. R^2 ranges from 0 to 1, where 0 signifies that the model fails to explain any of the variance in the dependent variable, and 1 signifies that the model explains all of the variance.

Additionally, two other metrics, Relative Absolute Error (RAE) and Mean Root Relative Error (MRRE), are defined in Equations. (5) and (6) correspondingly. RAE quantifies average absolute deviation between the predicted and actual values, normalized by the average of the actual values, while MRRE calculates the mean root relative error. These metrics provide additional insights into the accuracy and relative performance of the model.

$$RMSE = \sqrt{\frac{1}{r}\sum_{i=1}^{r}\left(E_p - E_r\right)} \tag{2}$$

$$MSE = \frac{1}{r}\sum_{i=1}^{r}\left(E_p - E_r\right) \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{r}\left(E_p - E_r\right)^2}{\sum_{i=1}^{r}\left(E_p - \bar{E}_r\right)^2} \tag{4}$$

$$RAE = \frac{\sum\left|\left(E_p - E_r\right)\right|}{\sum\left|\left(E_p - \frac{1}{r}\sum E_r\right)\right|} \tag{5}$$

$$MRRE = \sqrt{\frac{\frac{1}{r}\sum_{i=1}^{r}\left(E_p - \hat{E}_p\right)^2}{\sum_{i=1}^{r}\left(\hat{E}_p\right)^2}} \tag{6}$$

3.5 Stage two (Part II): Comparison of Models

After obtaining the results of the Gene Expression Programming (GEP) for predicting Capital structure efficiency, a thorough comparative analysis is conducted against other machine learning-based techniques such as Multiple Linear Regression (MLR), Neural Networks (NN), Random Forests (RF) and Structural equational modelling (SEM).

This is of utmost significance, as the precision and effectiveness of different Machine Learning-based techniques must be assessed. Multiple Linear Regression (MLR) modelling presumes a linear correlation between the dependent variable(CSE) and independent variables. In contrast, the Multilayer Perceptron Neural Network (MLP-NN) comprises nine autonomous input neurons connected to the target variable (CSE).

In structural equation modelling (SEM), we examine connections between latent constructs and observed variables. By estimating the parameters of the structural model using statistical techniques like maximum likelihood estimation, we find the best-fit model that minimises the discrepancy between observed and model-implied covariance matrices. Once the parameters are estimated, we use the structural model to forecast the value of an objective parameter associated with endogenous variables. NN methods consider the non-linear nature of the correlations, thereby avoiding the production of unique equations. In the Random Forest (RF), the complete dataset is regarded as the foundation structure and divided into subcategories. Simultaneously, we employ multiple linear regression to forecast dependent parameters.

3.6 Stage three: Monte Carlo simulation

Monte Carlo Simulation is utilised to perform a sensitivity analysis of the optimal forecasting model, which is selected based on statistical metrics. It is important to emphasise that normalised data were employed for the Monte Carlo Simulation, as the models were created using normalised values. The suitability of each probability distribution is assessed using the Anderson-Darling test, specifically considering the probability value.

During MCS, five hundred randomized values were generated for all independent variables, following the parameters of their respective distribution functions. Subsequently, the model-generated equation was utilised to determine the corresponding CSE values for each set. The sensitivity of CSE was then examined by introducing ±15% variations in a single parameter while maintaining the other eight parameters constant.

Table III Descriptive statistics of variables

Variable	Firm type	Obs.	Mean	Std. Dev.	Min	Max
Inputs						
DSCR	Micro	590	1.08	1.56	0.78	3.22
	Small	2960	1.18	2.37	0.70	4.36
	Medium	2230	0.44	1.44	0.16	4.56
ICR	Micro	590	1.33	0.15	0.09	3.47
	Small	2960	1.05	1.14	0.28	3.78
	Medium	2230	2.17	0.85	0.37	4.98
EQTM	Micro	590	1.62	0.15	0.24	4.91
	Small	2960	3.74	0.57	0.78	4.88
	Medium	2230	1.49	0.24	0.19	3.55
Outputs						
ROA	Micro	590	0.1603	0.872	-2.57	16.37
	Small	2960	0.1067	0.523	-10.14	13.67
	Medium	2230	0.1293	0.278	-0.99	5.55
NI	Micro	590	0.59	59.63	0.05	4.79
	Small	2960	28.91	49.29	6.19	48.92
	Medium	2230	87.14	60.48	53.11	239.28
Endogenous variables						
CSE	Micro	590	0.73	2.46	0.01	1
	Small	2960	0.62	3.41	0.02	1
	Medium	2230	0.55	1.38	0.06	1
FS	Micro	590	1.39	1.62	-2.14	5.6
	Small	2960	3.12	1.20	-4.36	5.7
	Medium	2230	4.13	1.42	-3.39	6.5
FA	Micro	590	1.21	0.58	3.1	6.2
	Small	2960	2.28	0.69	0.8	5.9
	Medium	2230	2.68	0.73	0.76	6
PROF	Micro	590	0.07	2.45	-8.48	13.41
	Small	2960	0.12	1.43	-8.6	34.91
	Medium	2230	0.14	6.28	-2.03	24.39
ROE	Micro	590	0.08	7.58	-8.38	5.23
	Small	2960	0.19	1.37	-2.21	2.97
	Medium	2230	0.12	2.62	-0.89	4.97
DBEBITDA	Micro	590	0.28	2.89	0.01	16.26
	Small	2960	0.33	5.81	0.09	38.48
	Medium	2230	0.24	9.62	0.06	23.92

DBAsstR	Micro	590	0.59	2.71	0.07	15.6
	Small	2960	0.29	3.18	0.04	24.8
	Medium	2230	0.43	5.39	0.09	62.4
TANG	Micro	590	0.14	1.28	0.07	1.38
	Small	2960	0.18	2.26	0.03	2.32
	Medium	2230	0.17	1.37	0.08	8.32
OCF	Micro	590	0.13	1.92	-0.82	9.8
	Small	2960	0.19	2.64	-3.58	6.7
	Medium	2230	0.12	2.26	-0.96	7.08
PROD	Micro	590	0.12	1.16	0.14	4.2
	Small	2960	0.17	4.18	0.02	2.6
	Medium	2230	0.15	3.09	0.06	1.4

4. Data Analysis and Discussion

4.1 *Efficiency Measurement and statistical metrics*

In the first phase of our study, we evaluate efficiency based on selected inputs (DSCR, ICR, and EQTM) and outputs (NI and ROA) using Multi-time period Aggregative Efficiency (MAE).

The selection of inputs and outputs in our DEA model is based on both theoretical considerations and empirical evidence. These input and output variables collectively capture different aspects of a firm's capital structure and its financial risk profile. Inputs such as Debt Service Coverage Ratio (DSCR), Interest Coverage Ratio (ICR), Equity Multiplier (EQTM), and Operating Cash Flow (OCF) are chosen for their relevance in assessing financial health and operational performance. DSCR reflects the firm's ability to service its debt from operating revenue (Firouzi & Meshkani, 2021), ICR measures the firm's ability to cover interest expenses, indicating financial health (Gul & Cho, 2019), EQTM represents the leverage level, showing how much of the firm's assets are financed by equity (Viswanatha Reddy, 2013), and OCF indicates liquidity and the ability to sustain operations (Harris & Roark, 2019). Outputs include Return on Assets (ROA), Return on Equity (ROE), and Profitability (PROF), which are critical for assessing the efficiency of capital structures. ROA reflects efficiency in utilizing assets to generate profit (Vieira, 2017), ROE indicates profitability from shareholders' equity (Dai & Piccotti, 2020), and PROF measures operational efficiency as profit after tax to net sales (Habib & Kayani, 2022). These variables provide a comprehensive picture of financial performance and efficiency, capturing essential aspects of financial health, leverage, and operational efficiency, which are crucial for assessing capital structure efficiency.

We express all inputs in ratio form, while NI is presented as a numerical value.

Our choice of the MAE technique is advantageous as it considers the entire dataset period when calculating efficiency, distinguishing it from the basic DEA framework.

4.2 Predictive equations of Capital structure efficiency

In order to construct a GEP model, several variables were adjusted to optimize the determination coefficient while minimizing mean square error and root mean square error. The expected outcomes and their empirical measurements were compared using Multiple Linear Regression (MLR). After multiple iterations with different variables, a GEP framework was developed with a head size of 8 and 4 genes connected through a summation function. This framework included constants and endogenous variables.

Figures II, III, and IV represent gene expression tree models for predicting Capital Structure Efficiency (CSE). These models are designed to forecast CSE based on various factors and are tailored for three different datasets representing small, medium, and micro firms. The Gene Expression Programming (GEP) models for predicting Capital Structure Efficiency (CSE) in micro, small, and medium firms employ a series of sub-expressions that integrate various financial indicators.

For micro firms, **Sub.ET(i)** captures the non-linear relationship between Operating Cash Flow (OCF) and Firm Size (FS) using a hyperbolic tangent function. **Sub.ET(II)** combines OCF, Productivity (PROD), Debt to EBITDA ratio (DBEBITDA), and Debt to Asset Ratio (DBASSTR) through a linear combination with specific weights, reflecting each variable's importance. **Sub.ET(iii)** further incorporates debt-to-asset ratio (DBAsstR) with profitability (PROF), Return on Equity (ROE), and Fixed Assets (FA), emphasizing the interplay between debt, profitability, and asset utilisation. **Sub.ET(iv)** uses a double arc tangent transformation on Debt to EBITDA ratio (DBIBITDA) and tangibility (TANG) to stabilize predictions by reducing outlier influence.

For small firms, **Sub.ET(i)** applies a similar non-linear transformation to the product of Firm Size (FS) and Return on Equity (ROE). **Sub.ET(ii)** includes a linear combination of profitability (PROF), Debt to Asset Ratio (DBAsstR), and Operating Cash Flow (OCF), each weighted to reflect their contributions. **Sub.ET(iii)** integrates the Debt to EBITDA ratio (DBEBITDA) with productivity (PROD), while also considering ROE and FA, to capture the combined effects of leverage, productivity, and asset management. **Sub.ET(iv)** employs a double arc tangent transformation on tangibility (TANG) adjusted by firm size, further stabilising the model.

For medium firms, **Sub.ET(i)** normalizes Firm Size (FS) using the hyperbolic tangent and arc tangent functions. **Sub.ET(ii)** combines Debt to EBITDA ratio (DBEBITDA), Debt to Asset Ratio (DBAsstR), and Return on Equity (ROE) in a linear formula, emphasising key leverage and profitability ratios. **Sub.ET(iii)** merges Operating Cash Flow (OCF) with productivity (PROD), while also including profitability (PROF) and fixed assets (FA), highlighting their collective influence on efficiency. **Sub.ET(iv)** uses an arc tangent transformation on tangibility (TANG) multiplied by a constant, capturing the effect of tangible assets in a stabilized manner.

For CSE prediction of Micro firms

$$Sub.ET(i) = Tanh(Arctan(OCF \times FS)) \tag{7}$$

$$Sub.ET(II) = 0.1637 \times OCF + 0.1183 \times PROD + 0.1072 \times DBEBITDA + 0.0847 \times DBASSTR \tag{8}$$

$$\mathrm{Sub.ET(iii)} = (\mathrm{DBAsstR} \times \mathrm{PROF}) + (0.1273 \times \mathrm{ROE}) + (0.0851 \times \mathrm{FA}) \tag{9}$$

$$\mathrm{Sub.ET(iv)} = \mathrm{Arctan(Arctan(DBIBITDA\ (TANG} - 0.0417))) \tag{10}$$

For CSE prediction of Small firms

$$Sub.ET(i) = Tanh(Arctan(FS \times ROE) \tag{11}$$

$$\mathrm{Sub.ET(ii)} = (0.1637 \times \mathrm{PROF}) + (0.1183 \times \mathrm{DBAsstR}) + (0.1072 \times \mathrm{OCF}) \tag{12}$$

$$\mathrm{Sub.ET(iii)} = (\mathrm{DBEBITDA} \times \mathrm{PROD}) + ((0.3148 \times \mathrm{ROE}) - (0.0216 \times \mathrm{FA}) \tag{13}$$

$$\mathrm{Sub.ET(iv)} = \mathrm{Arctan(Arctan(TANG} \times (\mathrm{FS} - 0.0512))) \tag{14}$$

For CSE prediction of Medium firms

$$Sub.ET(i) = Tanh(Arctan(FS)) \quad (15)$$

$$Sub.ET(ii) = (0.2364 \times DBEBITDA) + (0.1273 \times DBAsstR) + (0.0851 \times ROE) \quad (16)$$

$$\mathrm{Sub.ET(iii)} = (\mathrm{OCF} \times \mathrm{PROD}) + (0.1273 \times \mathrm{PROF} + 0.0851 \times \mathrm{FA}) \quad (17)$$

$$\mathrm{Sub.ET(iv)} = \mathrm{Arctan}(\mathrm{TANG} \times -0.0826) \quad (18)$$

Figure II Gene Expression Tree for CSEmicro

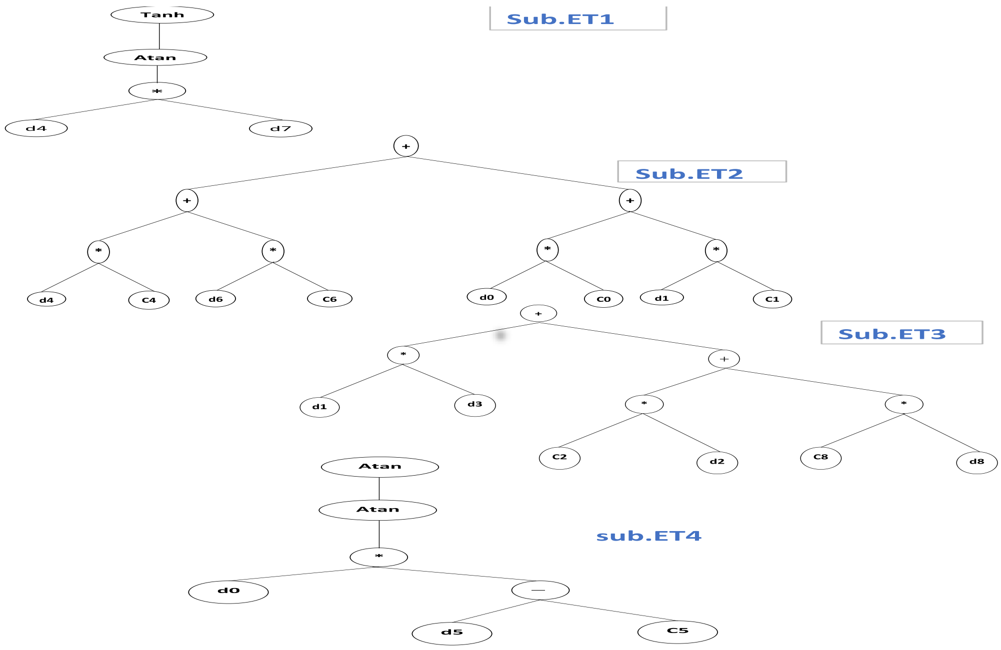


Figure III Gene expression Tree for CSEsmall

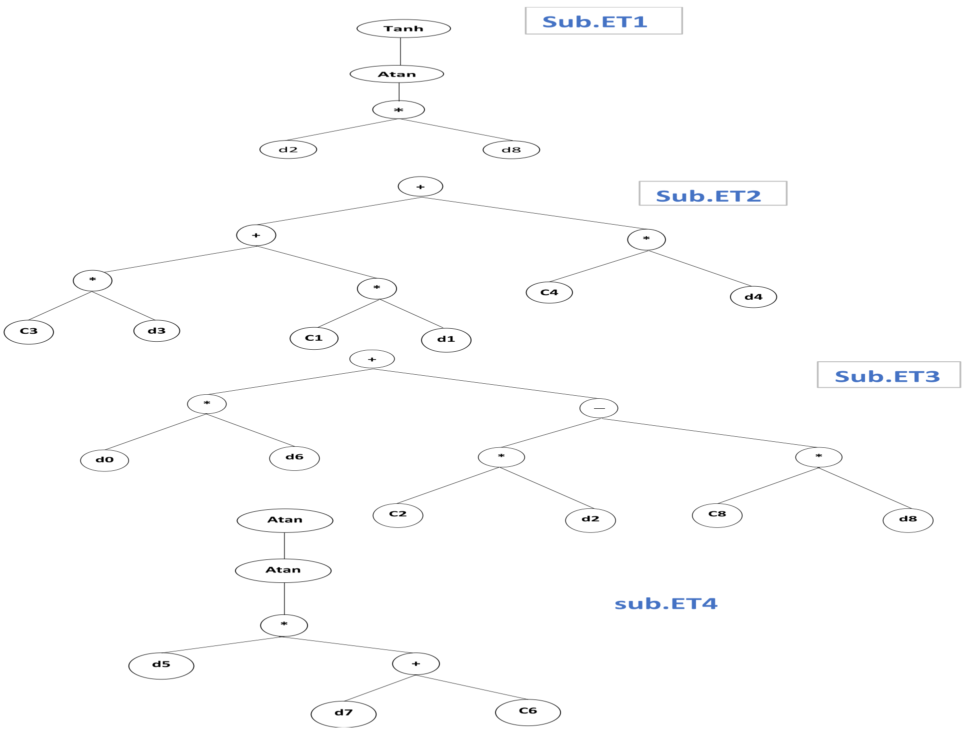
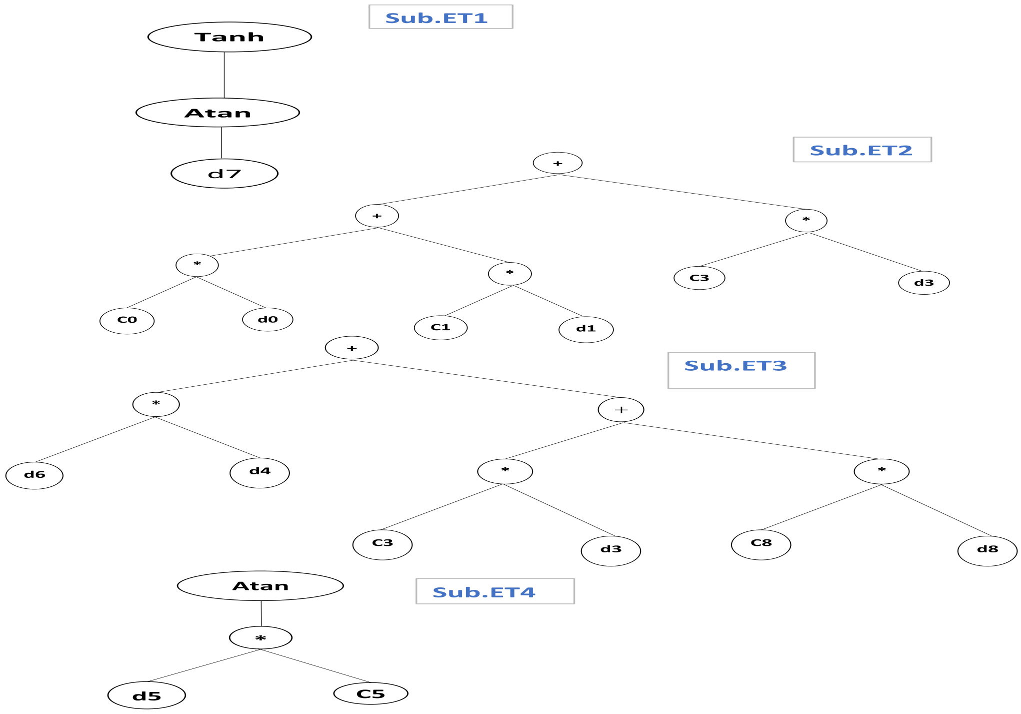


Figure IV Gene expression Tree for CSEmedium



4.3 Comparative analysis

Tables IV, V, and VI present the precision and statistical measurements of various models forecasting CSE across Micro, Small, and Medium firms.

For the CSEMicro Prediction Model, the DEA-GEP model demonstrates strong performance during the training stage with a high R^2 of 0.781, indicating a good fit. However, during validation, the DEA-MLR model outperforms others with the lowest MSE of 0.004 and a reasonable R^2 of 0.765, suggesting it is more accurate in predicting new data. The DEA-MLPNN model also performs well, with a slightly higher MSE but still a respectable R^2. Despite DEA-GEP's high R^2 during validation (0.814), its higher MSE and RMSE compared to DEA-MLR suggest it may not generalise as well. The DEA-SEM model consistently underperforms, showing the highest MSE and lowest R^2, indicating it is less effective for this prediction task.

Table IV Performance parameters for CSEMicro Prediction Model.

Target Variable	model	Stage	MSE	RMSE	MAE	R^2
CSE_{micro}	DEA-GEP	Training	0.006	0.072	0.041	0.781
		Validation	0.009	0.094	0.069	0.814
	DEA-MLR	Validation	0.004	0.078	0.067	0.765
	DEA-MLPNN	Validation	0.007	0.082	0.053	0.728
	DEA-RF	Validation	0.009	0.092	0.061	0.682
	DEA-SEM	Validation	0.011	0.117	0.073	0.584

Table V Performance parameters for CSESmall Prediction Model.

Target Variable	model	Stage	MSE	RMSE	MAE	R^2
CSE_{small}	DEA-GEP	Training	0.008	0.072	0.053	0.793
		Validation	0.007	0.062	0.079	0.842
	DEA-MLPNN	Validation	0.006	0.046	0.038	0.778
	DEA-MLR	Validation	0.008	0.057	0.052	0.749
	DEA-RF	Validation	0.008	0.069	0.058	0.704
	DEA-SEM	Validation	0.009	0.076	0.069	0.541

Table VI Performance parameters for CSEMedium Prediction Model.

Target Variable	model	Stage	MSE	RMSE	MAE	R^2
$CSES_{medium}$	DEA-GEP	Training	0.009	0.068	0.065	0.812
		Validation	0.009	0.059	0.056	0.867
	DEA-RF	Validation	0.074	0.067	0.062	0.731
	DEA-MLPNN	Validation	0.079	0.071	0.058	0.692
	DEA-MLR	Validation	0.008	0.073	0.061	0.658
	DEA-SEM	Validation	0.087	0.078	0.066	0.567

In the CSESmall Prediction Model, DEA-MLPNN achieves the lowest validation MSE of 0.006 and an R^2 of 0.778, making it the best-performing model in terms of accuracy. However, DEA-GEP shows the highest R^2 of 0.842 during validation, indicating the best fit to the validation data, even though its MAE is higher than that of DEA-MLPNN. DEA-MLR and DEA-RF provide moderate performance, with MSE values slightly higher than DEA-MLPNN and DEA-GEP. Again, DEA-SEM shows the poorest performance with the highest MSE and lowest R^2, suggesting it is the least reliable model for predicting CSESmall. This distinction can be attributed to lower errors and improved accuracy in measuring CSE for Small firms, thus making DEA-RF and DEA-MLPNN more effective predictive models than DEA-SEM. Additionally, when predicting CSE for small firms, DEA-MLPNN and DEA-MLR perform slightly better than DEA-RF, exhibiting minor variations in their accuracy. The comparable performances of DEA-MLPNN and DEA-MLR indicate that the forward as well as reverse propagation techniques of MLPNN establish a partially linear correlation among the desired variable and independent input factors.

For the CSEMedium Prediction Model, DEA-GEP is the standout performer with a validation MSE of 0.009 and a high R^2 of 0.867, indicating excellent accuracy and fit. DEA-RF, although having a higher MSE than DEA-GEP, still shows a relatively good R^2 of 0.731, suggesting it is a reasonable alternative. DEA-MLPNN and DEA-MLR have higher MSE and lower R^2 values compared to DEA-GEP, indicating they are less accurate and provide a poorer fit. As with the other models, DEA-SEM has the worst performance, with the highest MSE and lowest R^2, reinforcing its inadequacy for this prediction task. Equations (19), (20), and (21) illustrate the linear correlation between CSEmicro, CSEsmall, CSEmedium, and various independent factors, respectively.

$$CSEmicro = 0.432 \times DBEBITDA + 0.2312 \times DBAsstR + 0.1638 \times ROE + 0.1271 \times PROF + 0.0926 \times OCF + 0.0627 \times TANG + 0.0491 \times PROD + 0.0252 \times FS + 0.0227 \times FA \tag{19}$$

$$CSEsmall = 0.361 \times DBEBITDA + 0.194 \times PROF + 0.152 \times OCF + 0.137 \times DBAsstR + 0.052 \times ROE + 0.0312 \times TANG + 0.0426 \times PROD + 0.0309 \times FS + 0.0234 \times FA \quad (20)$$

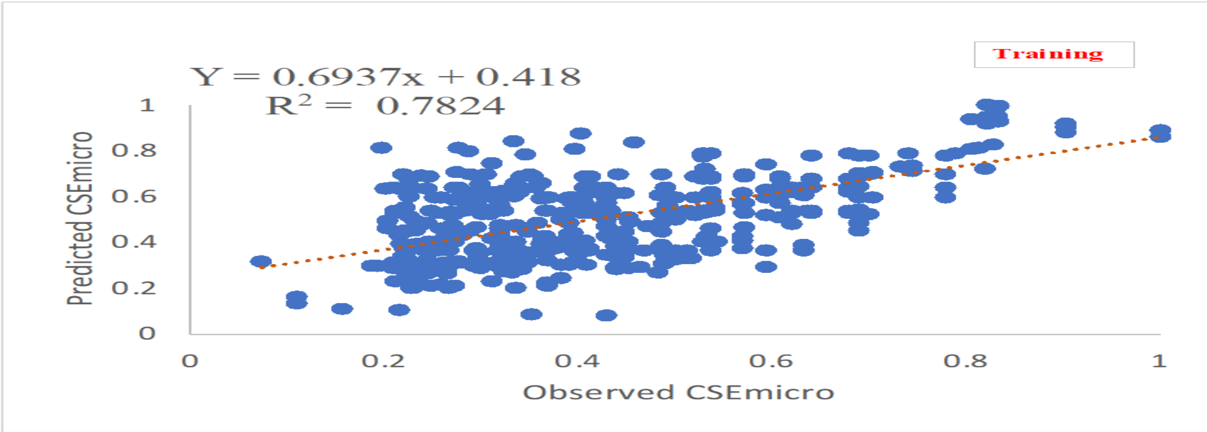
$$CSEmedium = 0.243 \times DBAsstR + 0.184 \times ROE + 0.173 \times DBEBITDA + 0.148 \times PROF + 0.136 \times OCF + 0.0713 \times TANG + 0.0501 \times PROD + 0.0375 \times FS + 0.0348 \times FA \quad (21)$$

As evidenced by Equations (19), (20), and (21), For green micro MSMEs, the most significant factors affecting capital structure efficiency are Debt-to-EBITDA (DBEBITDA), Debt-to-Asset Ratio (DBAsstR), and Return on Equity (ROE). The high weight of DBEBITDA, at 43.2%, indicates a critical reliance on the ability to generate earnings relative to debt levels, ensuring sufficient earnings to cover debt obligations. The significant weight of DBAsstR (23.12%) highlights the importance of balancing asset financing to avoid over-leverage, while ROE (16.38%) reflects the necessity of using shareholders' equity efficiently to generate profits. The high weight of DBEBITDA highlights the importance of generating sufficient earnings to manage debt levels, reflecting the necessity for micro firms to maintain high operational efficiency. Efficient use of resources ensures that micro firms can avoid financial distress caused by excessive debt(Habib & Kayani, 2022). Additionally, Efficient resource allocation helps attract and retain investment, which is crucial for the long-term sustainability of micro firms(Daskalakis et al., 2013).

Meanwhile, in small firms, capital structure efficiency is most influenced by Debt-to-equity (DBEBITDA), profitability (PROF), and operating cash flow (OCF). With DBEBITDA at 36.1%, small MSMEs emphasize maintaining strong earnings to manage debt levels. Profitability, at 19.4%, is crucial for sustaining operations and financing growth, reflecting the need for robust profit margins. OCF, accounting for 15.2%, underscores the importance of cash flow management in meeting short-term obligations and reinvesting in the business. Efficiency in generating profits and managing cash flows ensures that small firms can meet their short-term obligations and reinvest in the business, reducing financial risk and attract investment by demonstrating robust financial health (Mohamed Zabri et al., 2021).

In green medium MSMEs, the key factors influencing capital structure efficiency are the Debt-to-Asset Ratio (DBAsstR), Return on Equity (ROE), and Debt-to-EBITDA (DBEBITDA). The DBAsstR, at 24.3%, is critical for managing the proportion of assets financed by debt, preventing over-leverage and ensuring financial stability. ROE, with a weight of 18.4%, highlights the need for efficient use of equity to generate profits, maintaining investor confidence and supporting growth. DBEBITDA, at 17.3%, remains important for managing debt relative to earnings, ensuring that the enterprise can sustain its debt levels through its operational earnings. Their relative stability and access to diverse financing options reduce their sensitivity to any single financial metric, resulting in a more uniform impact across different variables(Beck & Demirguc-Kunt, 2006). By effectively managing their assets and equity, they can optimise the use of these resources to generate higher returns. This resource-based approach ensures medium firms can leverage their internal and external resources to achieve financial stability and long-term growth.

Figure V Scatterplot of Observed CSEmicro versus Predicted CSEmicro



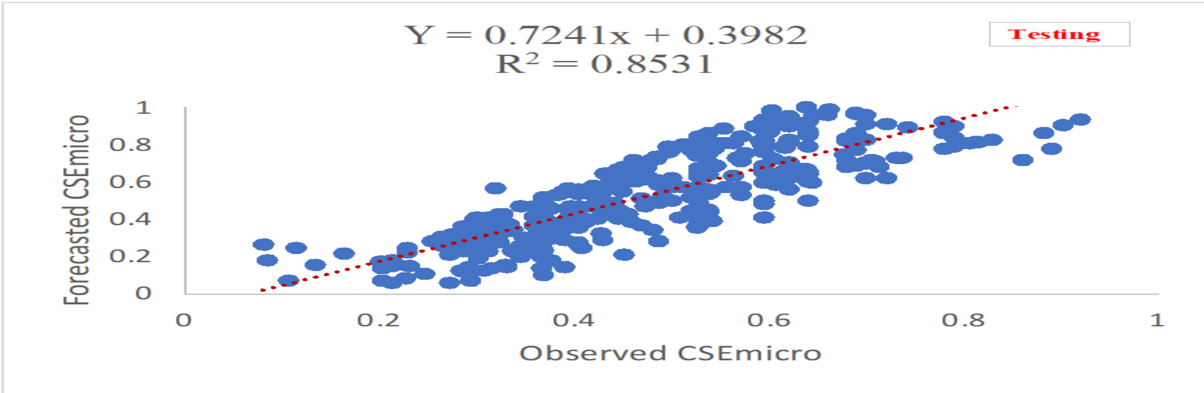
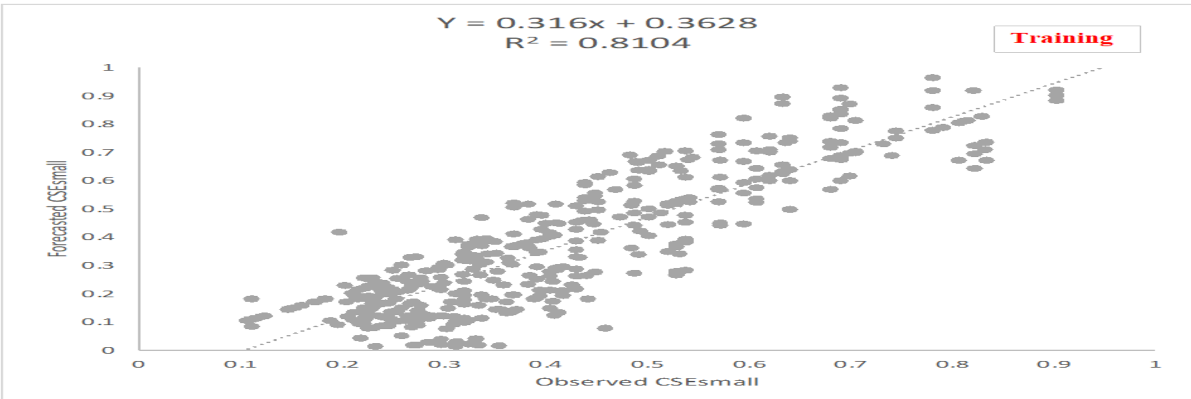


Figure VI Scatterplot of observed CSEsmall versus predicted CSEsmall



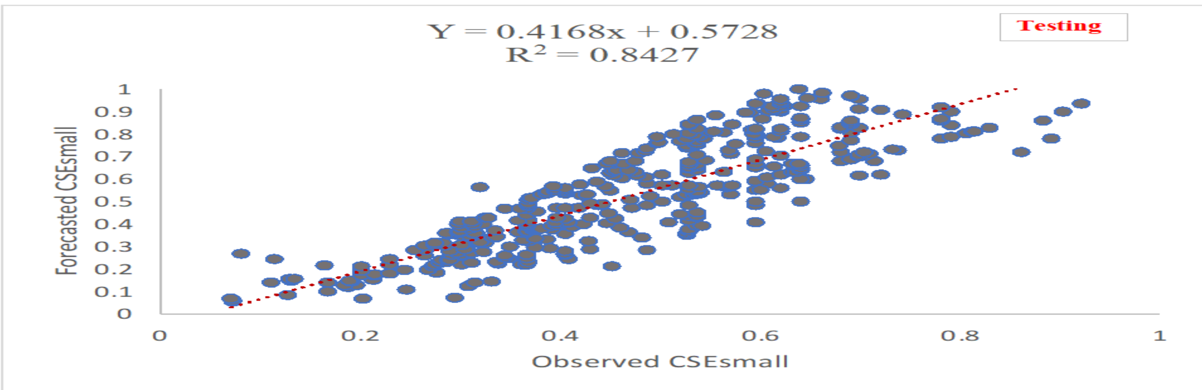


Figure VII Scatterplot of observed CSEmedium versus predicted CSEmedium

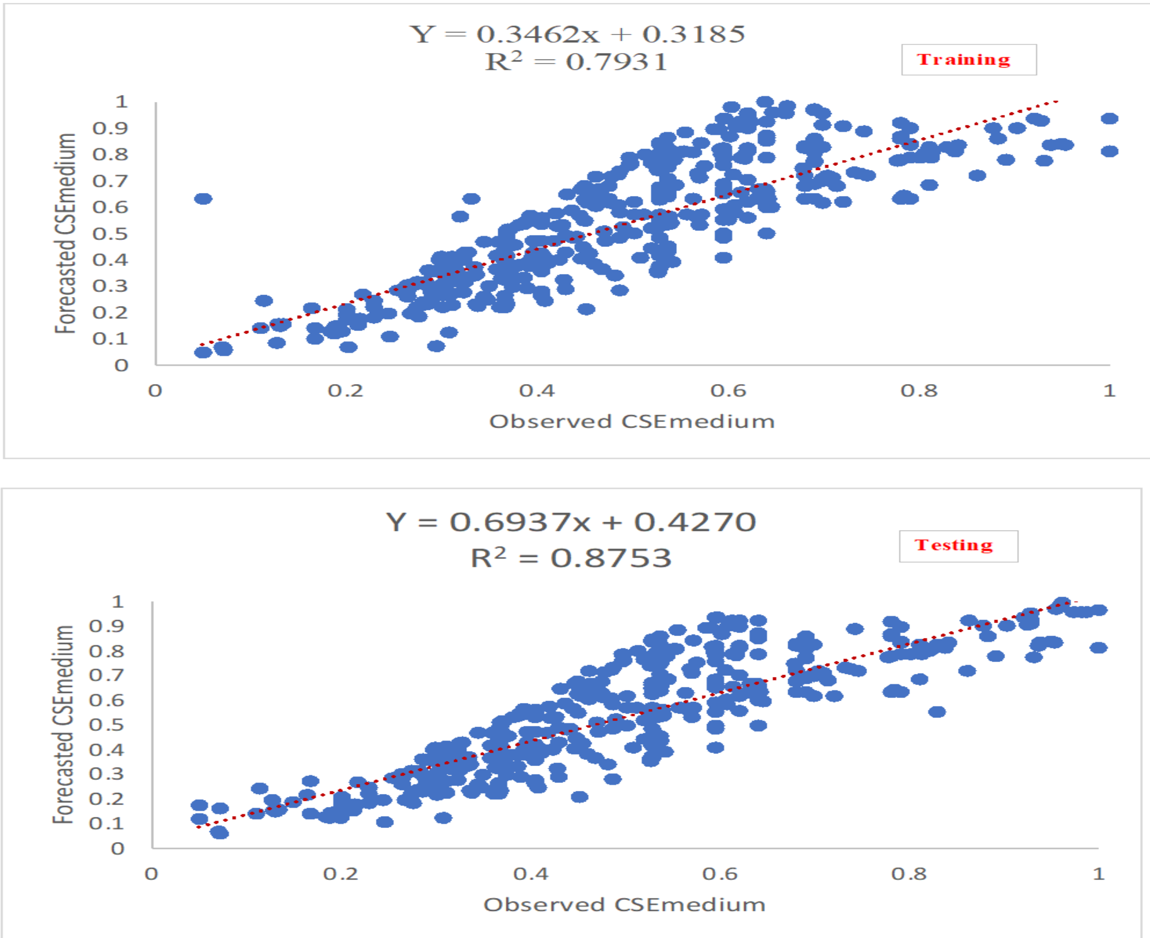


Table VII Results of Monte Carlo simulation at 15% variation in independent variable.

Parameter(1)	Average Value(2)	Variation in average value	CSEmicro(% change compared with(2))	CSEsmall(% change compared with(2))	CSEmedium(% change compared with(2))
DBEBITDA	0.28	+15%	8.83%	7.76%	7.16%
		-15%	-6.74%	-6.92%	-8.24%
ROE	0.13	+15%	7.51%	6.62%	6.97%
		-15%	-6.94%	-6.10%	-6.44%
PROD	2.81	+15%	3.61%	3.17%	3.35%
		-15%	-4.17%	-3.66%	-3.87%
DBAsstR	0.44	+15%	5.28%	8.03%	4.90%
		-15%	-4.73%	-9.37%	-4.39%
PROF	0.11	+15%	6.24%	5.48%	5.79%
		-15%	-6.19%	-5.44%	-5.75%
OCF	0.15	+15%	7.13%	6.62%	6.26%
		-15%	-6.38%	-5.92%	-5.60%

4.4 Sensitivity analysis

The results of a Monte Carlo simulation reveal that a 15% variation in independent variables significantly impacts Capital Structure Efficiency (CSE) across green firms of different sizes (micro, small, medium). For DBEBITDA, a 15% increase leads to an improvement in CSE for all firm sizes, with micro firms seeing an 8.83% increase, small firms a 7.76% increase, and medium firms a 7.16% increase. Conversely, a 15% decrease in DBEBITDA results in a decline in CSE, with micro firms experiencing a -6.74% decrease, small firms a -6.92% decrease, and medium firms an -8.24% decrease, indicating significant sensitivity to changes in the Debt to EBITDA ratio. Examining ROE, a 15% increase leads to a rise in CSE across all firm sizes (micro: 7.51%, small: 6.62%, medium: 6.97%), while a 15% decrease results in a corresponding decline (micro: -6.94%, small: -6.10%, medium: -6.44%), suggesting that Return on Equity positively influences CSE with a similar impact across different firm sizes.

For PROD, a 15% increase improves CSE moderately across all firm sizes (micro: 3.61%, small: 3.17%, medium: 3.35%), and a 15% decrease in productivity leads to a decrease in CSE (micro: -4.17%, small: -3.66%, medium: -3.87%), indicating a relatively moderate effect on CSE compared to other variables. The impact of DBAsstR varies, with a 15% increase resulting in mixed outcomes: a 5.28% increase for micro firms, an 8.03% increase for small firms, and a 4.90% increase for medium firms. A 15% decrease shows a -4.73% decline for micro firms, a -9.37% decline for small firms, and a -4.39% decline for medium firms, highlighting a particularly strong impact on small firms in negative scenarios. For PROF, a 15% increase in profitability enhances CSE for all firm sizes (micro: 6.24%, small: 5.48%, medium: 5.79%), while a 15% decrease reduces CSE (micro: -6.19%, small: -5.44%, medium: -5.75%), demonstrating that profitability improvements consistently positively affect CSE.

Lastly, for OCF, a 15% increase in Operating Cash Flow leads to a significant rise in CSE (micro: 7.13%, small: 6.62%, medium: 6.26%), while a 15% decrease results in a decline (micro: -6.38%, small: -5.92%, medium: -5.60%), highlighting the considerable impact of Operating Cash Flow, particularly for micro firms. The simulation reveals that positive variations in independent variables generally lead to increased CSE, while negative variations result in a decrease. The DBEBITDA and ROE have the most substantial impact on CSE, and PROD has the least. Additionally, the sensitivity of micro firms is particularly affected by variations in DBEBITDA and ROE as they are more reliant on internal funds and sensitive to changes in their debt levels and profitability. High leverage (DBEBITDA) can amplify financial stress in micro green firms, as they have less buffer to absorb economic shocks(Guida & Sabato, 2017). Similarly, ROE reflects their ability to generate profits from shareholders' equity, which is essential for attracting investment and sustaining growth(Aripin & Abdulmumuni, 2020), whereas small firms are affected by DBAsstR, and medium firms exhibit consistent changes across all variables but with slightly lower sensitivity compared to other firm types. The reason is that medium firms typically have more stable cash flows and stronger financial positions, allowing them to absorb variations in financial ratios more effectively(Singh et al., 2022).

4.5 Summary of Findings

The analysis of capital structure efficiency in green MSMEs reveals significant insights into the financial dynamics of these enterprises.

4.6.1 Efficiency Level Firm-wise

The analysis shows that micro-sized green MSMEs exhibit higher capital structure efficiency than medium and small enterprises. The reason is that micro-sized firms often have lower operational costs due to smaller-scale operations. This can lead to more efficient use of capital as they require less financial input to maintain their operations(Khan et al., 2021). Additionally, Micro-sized enterprises can quickly adapt to market changes and are often more flexible in their decision-making processes(Marampa et al., 2020). This agility allows them to efficiently allocate resources and respond to financial challenges or opportunities, maintaining a balanced capital structure. In contrast, medium and small green firms face greater challenges in optimising their capital structures due to various factors. First, these enterprises often have more complex operational structures compared to micro-sized MSMEs, leading to higher fixed and variable costs(Tsuruta, 2017). The increased scale of operations necessitates larger capital requirements, making it difficult to efficiently utilise debt and equity effectively(Grimmer et al., 2017). Additionally, medium and small enterprises typically experience more significant bureaucratic inertia, slowing decision-making processes and reducing the agility required to adapt to changing financial condition(Beck & Demirguc-Kunt, 2006; Ranjan & Gupta, 2016).

4.6.2 Influential Factors firm wise

From the analysis we found that Micro MSMEs prioritize Debt-to-EBITDA (43.2%), Debt-to-Asset Ratio (23.12%), and Return on Equity (16.38%) to ensure earnings cover debt obligations, balance asset financing, and efficiently use equity to attract investment. Small MSMEs emphasize Debt-to-EBITDA (36.1%), Profitability (19.4%), and Operating Cash Flow (15.2%) to manage debt through strong earnings, sustain operations with robust profit margins, and maintain liquidity for reinvestment. Medium MSMEs focus on Debt-to-Asset Ratio (24.3%), Return on Equity (18.4%), and Debt-to-EBITDA (17.3%) to stabilise finances through balanced asset financing, optimize equity for profitability, and manage debt relative to operational earnings. Across all sizes, these factors interact to support sustainable growth by aligning debt management with earnings, asset financing, and investor expectations within the green sector.

4.6.3 Results of the Predictive model comparison.

DEA-GEP consistently shows strong performance across all target variables, particularly excelling with the highest R^2 values, indicating it provides the best fit. DEA-MLPNN is also highly effective, especially for CSESmall, achieving the lowest MSE. DEA-MLR shows promise for CSEMicro predictions but is less effective for CSEMedium. DEA-RF performs moderately well but is generally outperformed by DEA-GEP and DEA-MLPNN. DEA-SEM consistently performs poorly, making it the least reliable model across all target variables. Thus, DEA-GEP stands out as the most robust and accurate model.

5. Conclusions ,limitations and Future Scope.

The research presented into the intricate relationship between capital structure efficiency and sustainability among green Micro, Small, and Medium Enterprises (MSMEs) in India. Through extensive statistical analyses, it was observed that the GEP-derived model delivers more precise outcomes than the alternative model. Additionally, the impact of variations in input parameters on the target variables was evaluated through MCS.

Notably, the findings reveal that micro-sized green MSMEs exhibit higher capital structure efficiency, attributed to their flexibility, lower operational costs, and agility in resource allocation. In contrast, small and medium-sized enterprises face greater challenges due to larger capital requirements, complex operations, and slower decision-making processes. The predictive models developed highlight the importance of these factors in optimizing financial strategies tailored to sustainably drive growth in the green economy.Moreover, the mathematical equations derived from the gene expression programming model disclosed the primary influential factors in estimating CSE for all three categories of companies. Notably, the predominant variables in assessing CSE were found to be leverage ratios. Furthermore, the uncertainty surrounding the CSE values for all three firm types was evaluated using MCS. The findings revealed that DBEBITDA exhibited the highest sensitivity to CSE for green micro, followed by DebtAssets for small, and medium-sized firms. Conversely, the variables FA and FS demonstrated the least responsive nature in the developed model for predicting Capital Structure Efficiency.

Additionally, this study has several limitations that indicate the need for future research. Firstly, the study relied solely on secondary data, which limited the availability of variables that may impact capital structure efficiency (CSE). To address this limitation, future endeavours should aim construct a distinct mathematical framework for forecasting CSE by collecting data through questionnaires, encompassing a comprehensive set of variables.

Secondly, this study focused primarily on the empirical analysis of micro, small, and medium enterprises (MSMEs) in India. Future studies could enhance the understanding of CSE by conducting cross-country analyses of similar firms, thereby verifying the results of the existing model and providing a broader perspective.

The third significant downside of this study stems from its failure to consider contextual factors due to the nature of the adopted technique. Future research should incorporate contextual factors into their analyses to overcome this limitation. This would provide a more comprehensive understanding of how contexts-specific variables influence CSE.

Lastly, the data used in this study only covered ten years. To gain deeper insights into the dynamics of CSE, future research should employ longitudinal data, spanning a more extended period. Longitudinal data would enable researchers to capture temporal changes and trends, resulting a more robust understanding of the factors influencing CSE over time.

6. Implications

6.1 Managerial Implications

Managers of green MSMEs can use these findings to improve their capital structure management and financial strategies. The insights into efficiency levels and influencing factors provide a basis for optimising the balance between debt and equity, aligning financial practices with sustainability goals. For smaller green MSMEs, the study suggests focusing on growth strategies that enhance their financial capabilities and scale. By expanding their operations and improving access to external financing, these firms can achieve greater efficiency and competitiveness. Micro-sized green MSMEs can leverage their advantages in resource and financial management to further optimise their capital structures. They should continue to invest in sustainable technologies and practices that enhance operational efficiency and support long-term financial stability.

Additionally, managers can use the findings to evaluate their relative efficiency levels, identify best practices, and implement strategies to improve their capital structure efficiency. Benchmarking can facilitate knowledge sharing and foster healthy competition within the industry. Moreover, by understanding the factors that influence CSE, Green MSME owners and managers can optimize their financing choices and allocate resources effectively.

6.2 Policy Implications

Policymakers can use the study's findings to design targeted support mechanisms for green MSMEs. Recognising the challenges smaller enterprises face, particularly in accessing financing and achieving efficiency, policymakers can develop programs that provide financial assistance, training, and resources to support these firms. Additionally, Support for green MSMEs in high-efficiency sectors, such as renewable energy and eco-friendly manufacturing, can be tailored to enhance their growth and sustainability. Policies that encourage investment in sustainable technologies and practices will further strengthen the financial efficiency and impact of green MSMEs.

6.3 Theoretical Implications

This study contributes to the theoretical understanding of capital structure management efficiency in green MSMEs. Integrating novel financial theories with sustainability-focused analysis provides a nuanced view of how these enterprises navigate their financial challenges. The findings highlight the need for further research into the unique dynamics of green MSMEs, particularly how their sustainability objectives influence financial decisions and efficiency. Future studies could explore other aspects of financial management in green MSMEs, such as investment strategies and risk management, to provide a more comprehensive understanding of their operations.

The use of DEA and GEP in this study demonstrates the value of combining different analytical approaches to assess and predict financial efficiency. These methods offer robust tools for evaluating the performance of green MSMEs and can be applied in other contexts to analyse financial dynamics and efficiency.

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