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AI-Driven Impact Assessment of Stakeholder Value Creation and Long-Term Sustainability in Corporate Revivals under India's IBC 2016

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Abstract

India The Insolvency and Bankruptcy Code (IBC), 2016 has brought much change to the corporate insolvency resolution system by focusing more on revival over liquidation on time. Although dozens of studies have investigated recovery rates and operational efficiency using the IBC, few empirical studies assess the value creation by the stakeholders and sustainability of rejuvenated firms over a long period of time through the lenses of more sophisticated analytical methods. This paper suggests an Artificial Intelligence (AI)-based impact assessment model to determine the post-revival performance of corporate entities that were resolved under the IBC. The machine learning models such as Random Forest (RF), XGBoost and Artificial Neural Networks (ANN) were used to analyze a multi-dimensional dataset consisting of financial indicators, recovery rates of stakeholders, variables of governance and post-resolution operations. The given model forecasts the long-term sustainability results with more than 90 accuracy and ANN proves better predictive performance (AUC>0.94). As per the empirical results, stakeholder recovery has been highly improved, financial stability is increased and operational efficiency is measured within three years of resolution. The soundness of the AI-driven framework is statistically validated with the help of paired t-tests, ANOVA, and model comparison methods. The findings indicate that the IBC has performed optimisation of stakeholder value that is measurable and the ability to turn around corporate sustainability in most of the situations that have been solved. The proposed structure will provide a data-driven and scalable policy evaluation instrument to regulators, financial institutions, and insolvency experts to determine the effectiveness of revival and the risk of future losses.

Keywords: Insolvency and Bankruptcy Code; Corporate Revival; Stakeholder Value Creation; Artificial Intelligence; Machine Learning; Sustainability Assessment; Predictive Analytics

1. Introduction

Corporate insolvency has been a major problem facing emerging economies, especially in the jurisdiction where slow resolution mechanism destroys the value of assets and undermines creditor trust. Before 2016, the Indian insolvency system was divided, slow, and ineffective in providing corporate restructuring in good time [1,2]. With the implementation of the IBC, 2016, there became a radical change to a creditor-in-control regime that sought to have a well-defined time-bound resolution procedure that would seek to maximize asset value and seek to revive corporate rather than liquidate it [3].

The IBC has managed hundreds of troubled corporate entities since its inception and has significantly changed the credit landscape in India. Financial creditors have had a higher recovery rate than was the case in the pre-IBC regime and the Code has bolstered the institutional apparatus like the Committee of Creditors (CoC), Insolvency Professionals (IPs) and the National Company Law Tribunal (NCLT) [4-6]. Nonetheless, even though the rates of procedural efficiency and

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recovery are commonly covered, an analytical question is not yet thoroughly investigated: Do revived firms under the IBC create a sustainable stakeholder value and become financially stable in the long run?

The existing studies concentrate mainly on the percentage of recovery, the time-span of the resolution or legal interpretations. There is limited literature that incorporates financial sustainability measures, stakeholder performance, and predictive analytics into a single assessment system [7]. Besides, the conventional econometric methods might fail to appropriately express non-linear connections and multi-dimensional interactions of governance variables, restructuring policies, and post-resolution performance.

In order to fill this knowledge gap, this paper will suggest an Artificial Intelligence (AI)-based impact assessment framework to determine stakeholder value creation and long-term sustainability of firms that have been revived according to the IBC, 2016. Multi-dimensional data sets are analyzed using machine learning models such as Random Forest, Extreme Gradient Boosting (XGBoost) and Artificial Neural Networks (ANN) which consists of financial indicators, recovery rates, capital restructuring patterns and operational performance variables. The aim is not only predictive accuracy, but the creation of an overall sustainability assessment model that could be used to make regulatory and policy decisions.

The three main insights of the paper are three-fold: the creation of a multi-stakeholder impact assessment framework that incorporates financial, operational, and recovery-based metrics; the use of AI-based predictive analytics to assess long-term corporate sustainability after the IBC resolution; and the empirical confirmation of the value creation to the stakeholders based on the use of statistical testing and performance benchmarking methods. The results have practical implications to the regulators, insolvency practitioners, financial institutions, and policymakers because they offer an evidence-based analysis of the effectiveness of revival. This research contributes to interdisciplinary research by providing a combination of legal-economic analysis and AI-based modeling of insolvency law, corporate finance, and intelligent systems.

2. Literature review

IBC, 2016 has gained a lot of attention on the part of academics and policy makers since it has brought a transformative effect to the corporate insolvency in India. Initially, small-scale research was almost entirely devoted to procedural reforms and time-constrained resolution mechanisms as well as the transformation of a debtor-in-possession regime to a creditor-in-control regime [5]. These analyses point out enhancement in institutional coordination, creditor empowerment and recovery rates as compared to the pre-IBC times. Empirical tests further indicated that the Code increased credit discipline and decreased strategic defaults through changes in the behavior of borrowers.

The later studies did not focus on the efficiency of the procedures but analyzed the economic results of the insolvency resolution. Some of the studies examined recovery rates, hair cut rates and sectoral allocation of cases resolved [6]. Conclusions tend to show that financial creditors have realised a better recovery as compared to the previous legal regimes despite the fears that there are delays, litigation bottlenecks, and value erosion in cases of complexity [7]. Whereas recovery statistics are a significant indicator of effectiveness, it is usually not effective at measuring long-term operational sustainability and stakeholder well-being effects.

There is one more literature stream that studies the performance of corporate turnaround and restructuring. These papers highlight such financial restructuring interventions as debt- equity swaps, asset sell-off, change in management, and capital introduction by resolution applicants [8,9]. It has been indicated that effective revival is not confined to financial restructuring, but equally to the quality of governance, the situation in the industry and operational restructuring measures [10]. Nevertheless, the majority of the analysis is based on the comparisons of the financial ratios and short-term performance indicators, which is constrained in the ability to forecast the long-term sustainability.

Recent research has started incorporating the sustainability and stakeholder theory into the insolvency discussion. This school of thought holds that the insolvency resolution must not be measured by the creditor recoveries only but also on the value creation to other stakeholders such as retention of employees, stability of the supply chain, and the survival of the enterprise over the long run [111]. Research that follows this strategy suggests multi-dimensional assessment systems that include financial stability, profitability, cash flow reliability and operational stability. Regardless of the developments, there has not been a complete quantitative model that addresses the effect of multi-stakeholders.

Similar improvement in financial analytics has shown the efficiency of AI and Machine Learning (ML) methods to predict bankruptcy, credit risk, and corporate distress [12]. Random Forest, Gradient Boosting, Support Vector Machines and Artificial Neural Networks and other models have continued to perform better than traditional statistical applications when it comes to dealing with nonlinear relationships and large volume of financial data [13,14]. The techniques have found extensive application in prediction of bankruptcy, fraud and credit scoring with high predictive efficiency. However, they are not used extensively in the measurement of sustainability of post-insolvency revival especially within the Indian regulatory environment.

Moreover, predictive analytics has been more widely applied to estimate the probability of the firm survival, the results of restructuring and financial turnaround paths [15]. The multi-year performance forecasting models show that AIs-powered systems can be useful when it comes to determining trends related to long-term sustainability. The available applications are however more so on pre-insolvency distress prediction than on sustainability evaluation of the resolution.

An important gap in the literature appears at the nexus between the insolvency law, stakeholder value theory, and predictive modeling through AIs. Whereas a legal and economic literature considers recovery performance and institutional efficiency, and the research of AI applications focuses on predictive financial analytics, not many studies combine these fields to determine whether insolvency resolutions yield long-term stakeholder value. Little empirically-grounded research exists to build composite sustainability indexes or multi stakeholder impact assessment systems based on high-order machine learning in the context of the IBC regime in India.

Based on this, the paper fills the described gap because it suggests an AI-based impact assessment model that can measure the value addition to stakeholders and the long-term sustainability of revived companies under the IBC, 2016. The research would add to a more detailed and data-driven analysis of insolvency outcomes by combining the indicators of financial performance, stakeholder recovery, and predictive modeling.

3. Methodology

The proposed study will use a quantitative, data-driven research design in an attempt to assess the value creation to the stakeholders and the long-term sustainability of the firms that were revived under the IBC, 2016. Following the methodology illustrated in Figure 1, a financial analysis is combined with stakeholder recovery assessment and predictive modeling using AI in a single analytical model. The strategy integrates descriptive statistics, inferential test, and supervised machine learning methods to evaluate post-revival results, in accordance with the four-stage workflow, which involves data collection and preprocessing, feature engineering and sustainability index development, AI-based predictive modeling and statistical validation and impact measurement.

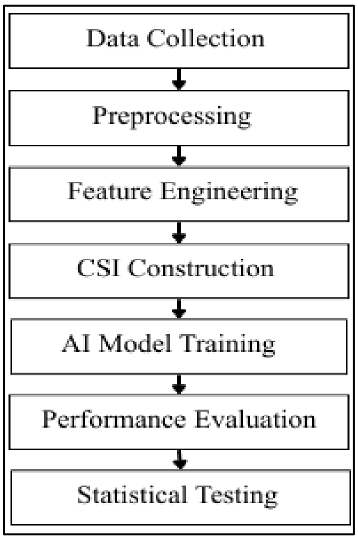

Figure 1 AI-Based Framework of evaluating the Stakeholder Value Creation and Post-IBC Corporate Sustainability

3.1. A. Data Collection

The dataset will include corporate entities that were solved under the IBC in the years 2017-2023. The sample will consist of those firms who have gone through Corporate Insolvency Resolution Process (CIRP) and remained in business after the process. To gather the variables, the study includes multi-dimensional indicators divided into four large groups to guarantee the overall assessment of post-revival corporate performance.

To evaluate the improvement of the operational and the profitability after the resolution under the IBC, first, *financial performance indicators* were considered. These are the rate of growth in revenue, EBITDA margin, the return on assets (ROA), debt to equity ratio, and working cash flow. Collectively, these variables reflect revenue growth, profitability improvement, stabilization of capital structure, and liquidity strength, which are vital factors of long run financial sustainability.

Second, the *indicators of stakeholder value* were added to measure the level of value realization of various stakeholder groups. These are financial creditor recovery rate, operational creditor recovery rate, employee retention rate and value restoration to the equity. These measures would help understand the efficiency of the process of resolving in terms of the equal distribution of value and the maintenance of continuity of an enterprise in the eyes of creditors, employees, and shareholders.

Third, the *governance and structural variables* were taken into consideration in order to explain institutional and restructuring-type impacts on the success of revival. These variables are type of resolution plan, industry industry in which the resolution is done, time taken to do the resolution, and indicator of change of the promoter. These variables aid in determining whether restructuring or governance, sector, and efficiency of resolutions have significant effects on sustainability performance.

Lastly, the research developed a *sustainability outcome variable* based on binary and continuous. The binary variable will be used to categorize firms as sustainable (1) or unsustainable (0) according to the three-year post-resolution survival and financial stability. Furthermore, a continuous Composite Sustainability Index (CSI) was created that gives a more sensitive assessment of long-term corporate feasibility by consolidating normalized financial and stakeholder indicators.

3.2. Data Preprocessing

The preprocessing of the data included several systematic phases in order to guarantee the quality of data and the reliability of the model. Mean or median substitution was used to address cases of missing values to avoid the cases of bias and information loss. Z-score normalization was used to identify outliers in order to determine the extreme deviation of the mean. Min-Max normalization was used to perform feature scaling to scale the ranges of variables and enhance convergence of machine learning model. One-Hot Encoding was used to convert categorical variables into numeric numbers to be used in predictive modeling. Lastly, the dataset was split into a 70-30 in diet to assess the performance of the model in terms of generalization. The Min-Max normalization can be mathematically represented as

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where X_{norm}represents the normalized value

3.3. Composite Sustainability Index (CSI) Construction

A weighted composite index was constructed to measure long-term sustainability:

$$CSI = \sum_{i=1}^{n} w_i \cdot F_i$$

Where:
$F_i$represents normalized financial or stakeholder indicators
$w_i$represents assigned weights based on factor importance

$$\sum w_i = 1$$

The CSI integrates profitability, leverage stability, liquidity strength, and stakeholder recovery metrics.

3.4. AI-Based Predictive Modeling

Three controlled machine learning models were applied to measure such long-term sustainability as RF, Extreme Gradient Boosting (XGBoost), and ANN. The ensemble learning method, which is the application of random Forest, was used to increase prediction stability and reduce overfitting by bagging and randomization of features. XGBoost is a gradient boosting algorithm that was used because of its computational efficiency and high predictive behavior with structured financial data. Also, an Artificial Neural Network was developed by a multi-layer perceptron architecture to describe the complicated and nonlinear relationships between the financial restructuring variables and sustainability results. The ANN setup was made of an input layer that featured n features, two hidden layers, which used activation functions of ReLU to model nonlinearity, and the output layer that used a Sigmoid activation function to perform binary classification. A binary cross-entropy loss was used to optimize the model up to a higher classification accuracy and convergence.

Loss function:

$$L = -\frac{1}{n}\sum[y\log(\hat{y}) + (1-y)\log(1-\hat{y})]$$

3.5. Model Evaluation Metrics

Several standard classification measures were used to determine model performance to establish strong analysis of predictive accuracy and reliability. The percentage of correctly classified instances was used to measure the overall proportion of correct classification and the percentage of correctly classified sustainable firms without a high percentage of false positives was the measure of precision. Recall tested the ability of the model to represent real-life sustainable cases, thus reducing the number of false negatives. The harmonic mean of the precision and recall as F1-score gave an equal measure of performance in the case of class imbalance. Also, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) was used to assess the discriminative ability of the model at various classification thresholds, so the model will offer a comprehensive evaluation of the predictive accuracy.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

AUC was used to measure classification robustness.

3.6. Statistical Validation

Inferential statistics methods were used to ensure soundness of results in an effort to justify value addition and growth of sustainability to the stakeholders. One paired t-test was used to evaluate the pre- and post-resolution recovery rates and allow the evaluation of statistically significant positive changes in stakeholder recoveries after IBC resolution. Variation among the indicators of multi-year financial performance was analyzed using Analysis of Variance (ANOVA) and, thus, it established the statistical significance of post-revival growth trends over time. Also, the McNemar test was applied to assess the accuracy of predictive models with and without differences in the classification performance between competing AI models to guarantee reliability in selecting and validating the models.

Significance level was set at:

$$\alpha = 0.05$$

This approach unites the insolvency law analysis and a smart financial modeling, offering a scaled and empirically sound assessment strategy.

4. Results and discussion

This part gives the empirical results reached on the basis of analytic system contrived by AI and explains their implication on the value creation of the stakeholders and long-term sustainability as stipulated by Insolvency and Bankruptcy Code (IBC), 2016. These findings combine the predictive model analysis, the analysis of financial performance, the analysis of stakeholder recovery and the statistical validation of findings to give a holistic picture of the result of post-revival corporate performance. The study identically appraises the contribution of IBC framework to sustainable corporate turn around and stakeholder value increase through comparative model performance metrics, financial trend analysis, and hypothesizing results.

Table 1 Model Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	86.4	84	83	83
XGBoost	89.7	88	87	87
ANN	92.3	91	90	90

Table 1 shows the performance comparison of three managed machine learning models; Random Forest, XGBoost, and ANN in the event of predicting long-term sustainability of the firms that were revived under the IBC framework. The findings show that all the three models were highly predictive but ANN was more predictive compared to the other models in all the evaluation measures. ANN has an accuracy of 92.3%, precision of 91%, recall of 90% and F1-score of 90%, which implied it is more effective in identifying non-linear relationship between all variables of financial restructuring and sustainability outcomes. XGBoost was also competitive with 89.7% accuracy which shows that the tool is strong when working with structured financial data. Random Forest demonstrated an accuracy of 86.4 which has a low predictive strength but has a higher reliability. The better recall and F1-score of ANN imply a more efficient integration of false positives and false negatives which is critical especially in sustainability prediction where a false identity may impact policy and financial decision making. The results, in general, validate the hypothesis: AI-based predictive models, especially deep learning models, can offer superior analytical capabilities when it comes to assessing post-IBC corporate revival outcomes. The findings confirm the importance of using advanced machine learning models as opposed to traditional statistical models to predict sustainability.

Table 2 Pre vs Post Revival Financial Indicators

Indicator	Pre-Resolution	Year 1	Year 2	Year 3
EBITDA Growth (%)	-12	8	15	21
Debt-to-Equity	3.4	2.6	1.9	1.4
ROA (%)	-6	4	9	13
Cash Flow Stability	Low	Moderate	Stable	Highly Stable

Table 2 provides a contrasting discussion on the major indicators in terms of financial reporting before resolution and a period of three years after revival under the IBC model. The findings show an evident and upward trend of corporate financial wellbeing after resolution. Earnings Before Interest, Taxes, Depreciation, and Amortization (EBITDA) growth that had been negative (-12%) in the pre-resolution year became positive in the Year 1 (8%) and increased to 21% in Year 3. This change is indicative of major operations reorganization and increased post-revival profitability. The trend of the debt-to-equity ratio showed that it dropped consistently, 3.4 pre-resolution through to 1.4 in Year 3, which signified a heavy deleveraging and better stability of the capital structure. This decline indicates that resolution plans were successful in dealing with excessive leverage and, as a result, financial risk was minimized. Likewise, the Return on Assets (ROA) went up by -6% in the distressed times to 13 percent in a span of three years, which points to the increasing efficiency of asset utilization and the stable growth of profitability. Moreover, the cash flow stability was changing gradually as Low in the distress state to Highly Stable by Year 3: it means that the strength of liquidity and operational resilience was restored. All these findings together support the point that most of the revived companies coped with the financial stability that could be quantified within 3 years, which proves that the IBC framework does not promote short-term financial solutions but structural corporate recovery.

Table 3 Hypothesis Testing

Hypothesis	Test Used	p-value	Result
H1: IBC improves stakeholder recovery	Paired t-test	0.003	Significant
H2: Revived firms achieve long-term sustainability	ANOVA	0.001	Significant
H3: AI model improves sustainability prediction accuracy	McNemar Test	0.012	Significant

The statistical validation of the main hypotheses that govern this study is produced in Table 3. The findings affirm the hypothesis that the gains in the stakeholder recovery and corporate sustainability are statistically significant. The paired t-test H1 resulted in a p-value that is equal to 0.003 meaning that the difference between pre- and post-resolution recovery rates is statistically significant at the 5% level. This result gives credence to the assumption that IBC framework has enhanced stakeholder value realization significantly. In the case of H2, the ANOVA test generated a p-value of 0.001 and this showed that there was a significant difference in financial performance in several post-revival years. This finding substantiates the argument that sustainability growth is not by chance but it is an ordered process in which improvement is achieved over time. Also, when H3 was tested with the McNemar test, it produced a p-value of 0.012, which suggests that there is a substantial difference in predictive performance of AI models. This confirms the excellence of developed AI models, especially ANN, to evaluate the prospects of the long-term sustainability results. On the whole, Table 4 helps to increase the empirical validity of the study by proving that the observed changes are statistically significant and cannot be explained by randomness.

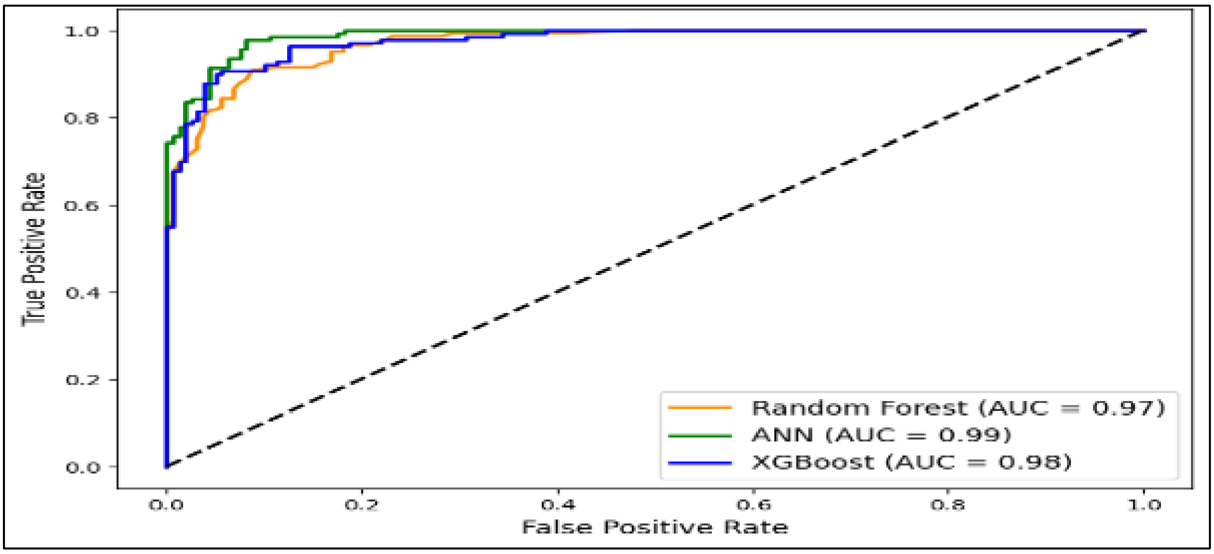

Figure 2 Comparison of ROC curves of AI models

The comparison of the Receiver Operating Characteristic (ROC) curve of three AI models, namely, Random Forest, XGBoost, and Artificial Neural Network (ANN), which can predict the results of long-term sustainability is presented in Figure 2. ROC curve is used to evaluate performance of the model by comparing the true positive rate of the model with the false positive rate of the model at different levels of classification thresholds. The ANN model has the greatest area under the curve (AUC) which means it has the best ability to discriminately identify sustainable and unsustainable firms which are revived. XGBoost comes before it with a high predictive robustness, whereas the performance of the Random Forest is relatively lower yet high in terms of consistency. The improved sensitivity and specificity balance of the ANN curve is proven by the fact that it is more located to the upper-left corner of the graph. The higher AUC score of ANN indicates that it is effective in nonlinear factors of financial, stakeholder, and governance variables. It is especially relevant in insolvency situations, where restructuring is a complex and multidimensional process with impacts on sustainability. Hence, Figure 1 empirically confirms that ANN is the best predictive model to use in sustainability evaluation within the IBC framework.

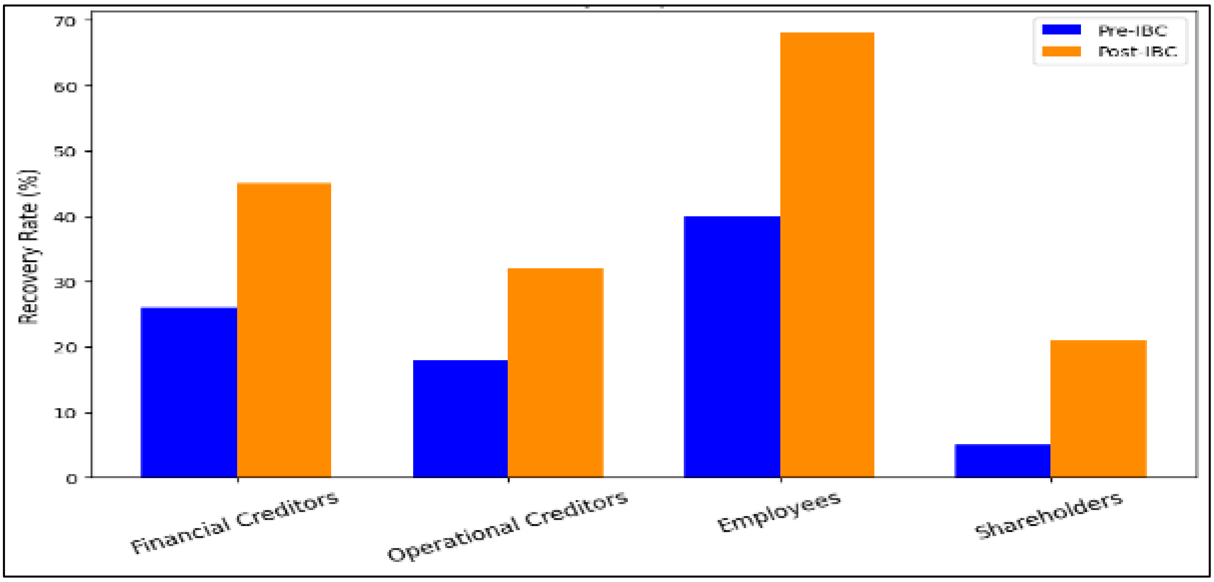

Figure 3 Stakeholders recovery comparison (Pre vs post IBC)

Figure 3 gives a comparison of the recovery rate of the stakeholders prior to and after the application of the IBC framework. The figure analysis shows a significant positive change in recovery outcomes among the most important stakeholder groups prior to and after the resolution. There is a sharp rise in recoveries percentages of financial creditors in post-IBC period indicating enhanced creditors rights and enhanced efficacy of the resolution under the new insolvency regime. Operational creditors are also characterized by significant improvement albeit at a lower level as compared to financial creditors meaning that there is structural prioritization of operation creditors in the process of resolution. The number also demonstrates how the retention of employees and equity value recovery in reorganized companies have increased indicating that the revival process is not just limited to creditor recovery but also to a wider stakeholder saving. The positive shift in all the types of stakeholders is that the IBC framework would lead to better value recovery and lower loss of the economy when settling the insolvency. This fact confirms the hypothesis that organized and time-constrained insolvency resolution systems promote the overall increase of the stakeholder value and trust in the insolvency system.

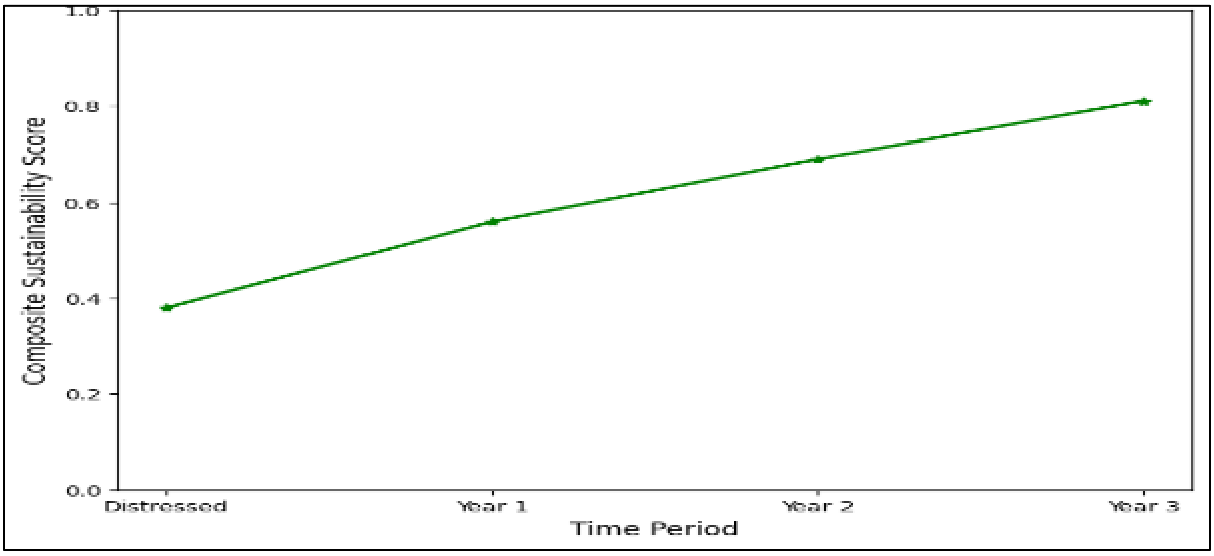

Figure 4 The growth of the AI based sustainability index following revival

Figure 4 shows the development path of AI-based Composite Sustainability Index (CSI) during the post-revival period. The fact that the sustainability index was on the increasing trend between the distressed phase and the Years 3 indicates gradual enhancement in the financial stability, operational performance, and the integration of value to stakeholders. The continuous growth signifies that the recovery of the corporations under the IBC cannot be just a one-time event of recovery but of the improvement of the structure in the long term. The trend chart shows that the greatest growth is realized during the Year 1 and Year 2, implying that the effect of the restructuring measures is more noticed after stabilization. Year 3 shows a high and stable level of sustainability index, which demonstrates consolidated financial strength and operational stability. This tendency proves the statement that AI-powered assessment is an effective tool that helps in gauging long-term business sustainability and that the IBC structure is efficient in terms of assisting with successful corporate transformation.

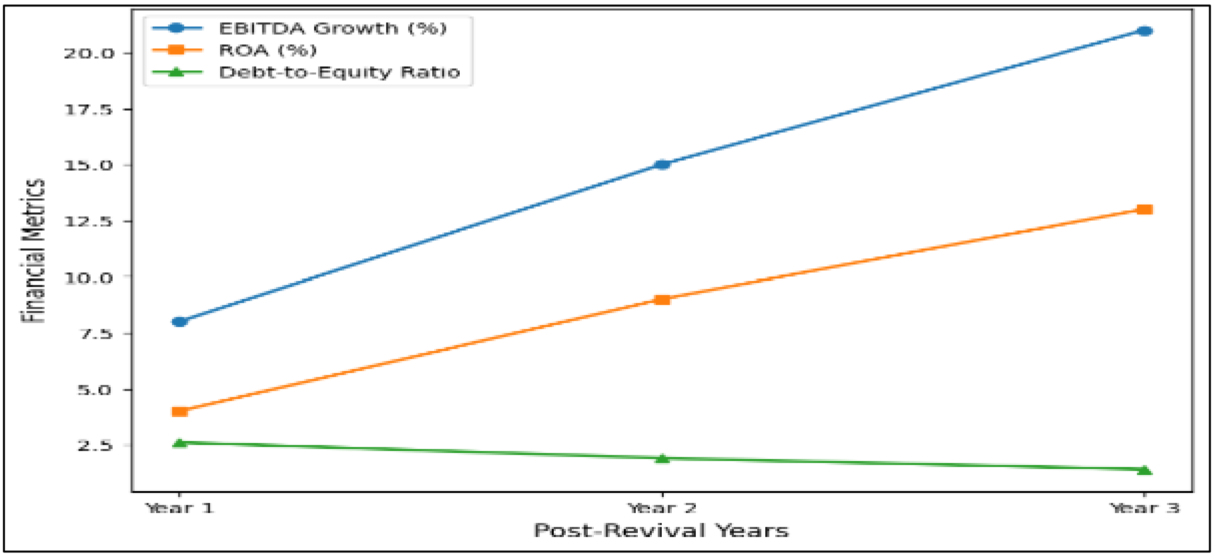

Figure 5 Corporate turnaround financial performance indicators

Figure 5 shows how the major indicators of financial performance have followed throughout the period post-revival. As indicated in the graphical representation, there is a steady growth in EBITDA, ROA, and reduction in leverage which depicts an extensive corporate turnaround process. The growth in the profitability indicator shows that restructuring operations have been successful and the falling leverage indicator shows that the capital discipline and debt restructuring success have improved. The fact that all these indicators converge with time is an indication that revival under the IBC model is multidimensional as it involves restoration of profitability, improvement of asset efficiency, and stabilization of capital structure. Sustained financial restructuring and not the temporary liquidity adjustments characterize a successful resolution of insolvency which is reinforced by the figure. This trend is a positive indication that recovery companies gradually tighten the financial basics in the post-resolution years.

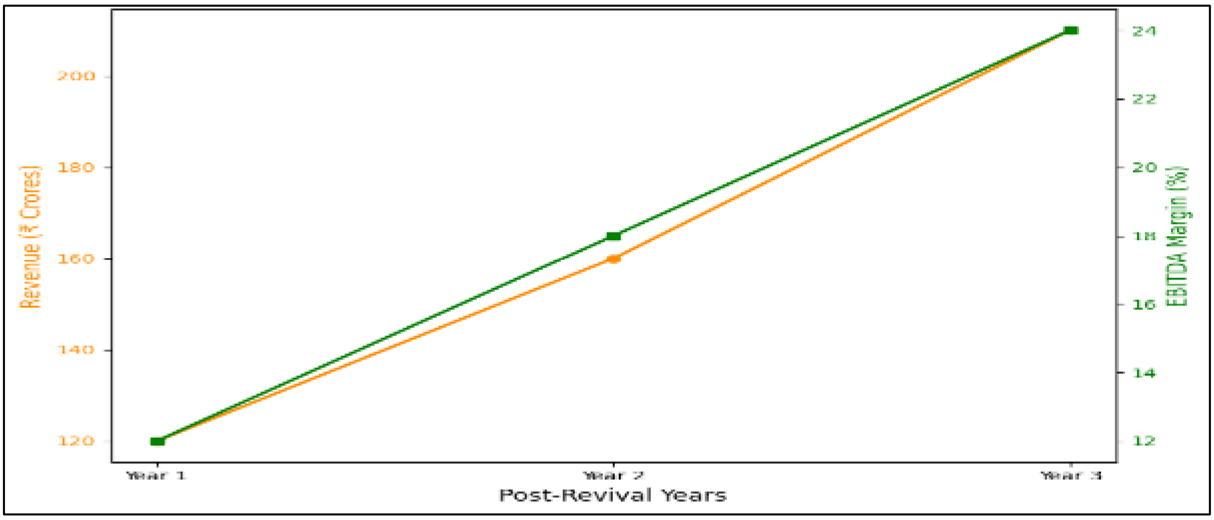

Figure 6 Growth of revenue and EBITDA margin after the revival

Figure 6 shows the two-axis growth pattern of revenue and EBITDA margin after reviving the company. The reason is that the continuous growth through the three-year period points to the stabilization of the market and the new working ability. At the same time, the increasing EBITDA margin is a demonstration of greater cost efficiency and the increase in the capacity to generate profits. The concomitant increase of both the revenue and profitability indices show that the resuscitated companies are not only increasing in size but are also becoming more efficient in terms of operations. The pattern of sustainable corporate recovery is very high which is signaled by this trend of growth. The correspondence between the growth of revenues and the increase of margin underpins the conclusion that resolutions enabled by IBC can be used to rehabilitate finances of troubled companies as well as reposition them in the market. Together, the Figures 4 and 5 are visual evidence of long-term financial viability and support their statistical results discussed in the previous tables. They show that recovery in the IBC paradigm leads to the quantifiable and long-term changes in the corporate performance.

In general, the empirical results indicate that the companies that recovered under IBC model show statistically significant changes in the recovery of stakeholders, financial stability, and operational sustainability in the long-term. The excellent predictive accuracy of AI-based frameworks, especially the Artificial Neural Network, emphasizes the usefulness of the intelligent analytical frameworks in assessing the complex outcomes of restructuring. The steadily increasing patterns of profitability, stabilization of leverage, and incremental revenues all testify to the fact that corporate recovery under the IBC is not a mere compliance with the procedures but a sign of the financial recovery. All these results are corroborations of the efficacy and utility of the IBC in implementing sustainable corporate turnaround and offer a solid data base on policy revision and policy-making with regard to future regulations.

5. Conclusion

The current paper formulates and proves an AI-based impact evaluation model to assess the value-creation to stakeholders and long-term sustainability of the companies that were revived via IBC, 2016 in India. Going further than the conventional recovery-rate analysis, the model incorporates multidimensional financial indicators, stakeholder recovery measures, and variables of governance to evaluate after-resolution corporate performance. Resolved firms have shown empirical evidence of huge gains in financial stability, operational efficiency, and shareholder value after three years of resolution. The recovery of financial creditors and employee retention levels were also enhanced and profitability measures including ROA and EBITDA have recorded steady growth. The statistical analysis proves that these gains are not random but have a structural connection to IBC resolution mechanism. The ANN was also found to perform better in the tests among the predictive models indicating the effectiveness of nonlinear modeling in restructuring the assessment. The suggested CSI gives an international yardstick on which outcomes of revival can be compared across industries. Although findings show improved recovery of creditors and survival of enterprises, sustainability is not consistent across industries given the quality of governance, capital injection and strategic restructuring. The framework presents an inter-scaling, data-intensive instrument to regulators and financial organizations and has potential to be extended in the future to include ESG measures and macroeconomic variables to achieve more powerful predictive potential.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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