RESEARCH PAPER

Assessing Supply Chain Demand-Supply Imbalances and Their Impact on MSME Performance Using AI-Driven Analytics

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Abstract

Micro, Small and Medium sized Enterprises (MSMEs) have a significant contribution in the area of economic development, employment generation and industrial growth. But, the frequent demand-supplier imbalance in supply chains has a significant impact on the efficiency, the profit and sustainability of the supply chain. The present study examines the effect of the imbalance in demand and supply in the supply chain on the performance of MSMEs listed and unlisted. The research combines Artificial Intelligence (AI), Machine Learning (ML), and Graph-Theoretic Supply Chain Analysis to model demand forecasting and supply chain disruptions. The mismatches between market demand and production supply are proposed to be quantified by proposing a Demand-Supply Imbalance Index (DSII). The analyzed data are obtained from 210 MSMEs and used structural equation modeling (SEM), random forest regression and graph centrality algorithms. The results show that the accuracy of demand forecasts, connectivity of the supplier network and inventory optimization have a significant impact on MSME performance. The accuracy of AI-based predictive models exceeds that of traditional forecasting methods, with a prediction accuracy of more than 91%. The proposed Graph Supply Chain Resilience Model pinpoints key nodes that cause disruptions in the supply chain. The study offers actionable strategies for MSMEs to use AI-powered decision-making to enhance their supply chain resilience and business outcomes.

Keywords: MSMEs, Supply Chain Management, Artificial Intelligence, Machine Learning, Demand Forecasting, Graph Theory, Supply Chain Resilience, SEM.

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1. Introduction

Micro, Small, and Medium Enterprises (MSMEs) play a pivotal role in employment creation, manufacturing, exports, and regional development in many economies (Abdin, 2019). While MSMEs are critical to the economy, they often face operational issues due to rapidly evolving and interdependent supply chains (Sinha et al., 2024). Global trade networks have increased in speed, consumer tastes have evolved, markets are dynamic and competition is growing, all of which are adding to the demand for effective supply chain management (Tekola & Gidey, 2019). The issue of demand and supply imbalance exists when the production capacity, inventories, and procurement activity are not aligned with the demand of the market, is one of the most critical issues affecting MSMEs (Verma, 2019). These mismatches can cause stock shortages, overstocking, late delivery, higher operational expenses and lower customer satisfaction (Tambunan, 2019; Endris & Kassegn, 2022). While large corporations have vast financial and technological capabilities, MSMEs may have limited resources and be more susceptible to disruptions coming from suppliers, transport systems and uncertainties in the market (Rathore & Mathur, 2019; Nursini, 2020). This has made it essential to balance the demand and supply in order to secure business continuity and sustain competitiveness in the long run (Boateng, 2019; Varga, 2021; Pandey & Chaudhary, 2024).

Digital technologies have revolutionized traditional supply chain practices by allowing organizations to gather, analyze and process vast amounts of operational data as it happens (Singh, 2023). AI (Artificial Intelligence) and ML (Machine Learning) are advanced analytical tools that have attracted considerable attention, claiming to be beneficial to improve forecasting accuracy and provide information which aids in data-driven decision making (Paramesha et al., 2024). These technologies can help recognize hidden trends in past sales data, seasonal trends in demand, customer buying patterns, and outside market signals to make more accurate demand forecasts (Balasubramanian et al., 2023). Better forecasting allows businesses to plan their procurement, manufacturing processes, and inventory levels, reducing the inefficiencies caused by demand-supply discrepancies (Chowdhury, 2024; Koh et al., 2019). Moreover, AI-powered systems can learn continuously as new information is introduced, enabling businesses to respond swiftly to shifting market dynamics (Nweje & Taiwo, 2025; Dogru & Keskin, 2020). By implementing intelligent forecasting mechanisms, MSMEs can minimize the manual effort required to optimize their operations, alleviate operational risks and enhance the supply chain's overall responsiveness (Kalasani, 2023; Owusu-Berko, 2025; Shamsuddoha et al., 2025).

Along with the predictive technologies, the use of graph-based analytical techniques provides a new way to be aware of the structure and vulnerability of the supply chain (Tien et al., 2019). Supply chains can be viewed as networks of suppliers, manufacturers, distributors, retailers, and customers, where the activities of one link affect the activities of others (Baloch & Rashid, 2022). Graph theory is used to analyze these relationships, and to identify influential nodes, critical connections, as well as potential bottlenecks, which could impede material and information flow (Sunny et al., 2020). By combining graph analytics with AI-based forecasting, an all-encompassing model for assessing supply chain resilience and operational performance is formed. In this background, the current study aims to examine the impacts of demand supply mismatch on the performance of MSMEs listed on the stock exchange and non-listed MSMEs (Dubey et al., 2020). It also examines the potential to use advanced forecasting methods and network-based analytical models for proactive decision-making, supply chain coordination and organization performance (Raja Santhi & Muthuswamy, 2022). This research helps to advance sustainable and resilient operations of MSMEs in a business landscape marked by uncertainty by leveraging technological innovation and implementing supply chain management principles (Pérez-Mesa et al., 2021).

2. Research Objectives

1. To measure demand-supply imbalances in MSME supply chains.
2. To compare listed and non-listed MSMEs regarding supply chain performance.
3. To develop an AI-based demand forecasting model.
4. To construct a graph-theoretic supply chain resilience framework.
5. To assess the impact of supply chain imbalances on organizational performance.

3. Research Methodology

3.1 Research Design

This study uses a quantitative research design to examine the effect of demand-supply imbalance in the supply chain on the performance of Micro, Small and Medium sized Enterprises (MSMEs). The research is cross-sectional research which is based on collecting data from the listed and non-listed enterprises at one specific time. In order to improve the analytical rigor of the study, traditional statistics methods are combined with Artificial Intelligence (AI), Machine Learning (ML) and network analysis based on Graph Theory. This multi-disciplinary approach allows for a comprehensive evaluation of supply chain disruptions, forecasting accuracy, supply chain's resilience, and its impact on organizational performance.

3.2 Population and Sampling

The target group for the project includes MSMEs in the manufacturing, retail, logistics and service industries. The aim was to have representation of both listed and non-listed enterprises in order to give a wider picture of supply chain management practices and results. Stratified random sampling was applied to provide good representation of each of the enterprise categories. The final sample consisted of 210 MSMEs comprising 100 listed and 110 non-listed MSMEs. Respondents selected were owners, operations managers, procurement executives, supply chain managers and senior decision-makers with first-hand knowledge of the activities of the organization's supply chain.

3.3 Data Collection Method

The primary data were gathered with the help of a structured questionnaire which has been specially prepared for the study. The questionnaire was divided into several sections pertaining to the multiple aspects of the study, namely the demographic characteristics, demand forecasting practices, supplier reliability, inventory management, network connectivity, technological adoption, demand-supply imbalance indicators and enterprise performance measures. Responses were collected on a 5-point Likert scale 1 (Strongly Disagree) to 5 (Strongly Agree). To support empirical analysis and validation, secondary data pertaining to the financial indicators, operational performance, and industry trends were gathered from various sources, including annual reports, government publications, company records, and industrial databases.

3.4 Measurement of Variables

Both independent and dependent variables are included in the study. The independent variables are Demand Forecasting Accuracy, Supplier Reliability, Inventory Efficiency, Network Connectivity and AI Adoption Level. MSME Performance is the dependent variable which is assessed by the performance of operational efficiency, profitability, customer satisfaction, and market competitiveness. Several measurement items were developed for each construct based on literature and translated to fit the context of MSME. This multi-dimensional approach provided full coverage of the factors which affect the performance of the supply chain.

3.5 Reliability and Validity Assessment

A pilot study was carried out with 40 respondents prior to full scale data collection to ensure the quality of the research instrument. The Cronbach's alpha coefficient was applied to ensure reliability of all constructs of the study, and all constructs had Cronbach's alpha value greater than 0.70 as accepted. Content validity was achieved by expert validation with academics and industry professionals who are experts in supply chain management and business analytics. The construct validity of the instruments was also investigated through factor analysis, which showed that the items used in the instrument were appropriate and matched the theoretical constructs.

3.6 Demand-Supply Imbalance Index (DSII)

A mathematical model of Demand-Supply Imbalance Index (DSII) was developed to measure the degree of mismatch of organizational supply and market demand. The index is determined by the formula:

$$DSII = \frac{|\, D - S \,|}{D}$$

where the D is the actual demand and the S is the actual supply. A higher value of the DSII means that the network of supply chains is more unbalanced. The index offers a common metric for measuring imbalances across enterprises as well as indicators for strategic action.

3.7 Artificial Intelligence and Machine Learning Analysis

The study uses Machine Learning techniques to enhance demand forecasting and stock planning. A historical model was built to predict future demand with the Random Forest Regression model, based on sales, inventory, procurement and market indicators. The algorithm chosen was due to its capacity to work with non-linear relationships and complex interactions between variables. The forecasting performance was assessed using statistical metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2). The accuracy of the forecasts produced by the AI-based model was evaluated and compared to the accuracy of forecasts generated using traditional forecasting methods.

3.8 Graph-Theoretic Supply Chain Network Analysis

Graph Theory was applied to represent the supply chain as a network of interconnected nodes (suppliers, manufacturer, distributors and customers). In this network visualization, nodes stand for individuals and edges represent business connections. The degree centrality and betweenness centrality measures were used to determine influential suppliers and critical links in the network. This analysis can identify the critical points, weak links, and strategic partners of a supply chain that could allow for a material impact on the entire supply chain.

Algorithm: AI-Driven Graph Analytics for Assessing Supply Chain Demand-Supply Imbalances in MSMEs

Input: MSME survey data, demand records, supply records, inventory data, supplier network information, and performance indicators.

Output: Demand-Supply Imbalance Index (DSII), demand forecasts, critical supply chain nodes, optimized logistics routes, and MSME performance assessment.

Step 1: Collect primary data from 450 listed and non-listed MSMEs using structured questionnaires and gather secondary data from company reports and databases.

Step 2: Preprocess the data by removing incomplete responses, handling missing values, and normalizing variables for analysis.

Step 3: Evaluate reliability and validity of the measurement scales using Cronbach's Alpha and Factor Analysis. Retain variables meeting the required thresholds.

Step 4: Calculate the Demand-Supply Imbalance Index (DSII) for each enterprise using:

$$DSII = \frac{| D - S |}{D}$$

where Drepresents actual demand and Srepresents actual supply.

Step 5: Divide the dataset into training and testing sets and apply the Random Forest Regression algorithm to forecast future demand based on historical sales, inventory levels, procurement records, and market indicators.

Step 6: Evaluate forecasting performance using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2).

Step 7: Construct the supply chain network as a graph:

$$G = (V, E)$$

where Vrepresents suppliers, manufacturers, distributors, and customers, while Erepresents supply chain relationships.

Step 8: Compute Degree Centrality for each node using:

$$C_D(v) = \frac{deg(v)}{n - 1}$$

to identify highly connected suppliers and influential supply chain participants.

Step 9: Compute Betweenness Centrality using:

$$C_B(v) = \sum \frac{\sigma_{st}(v)}{\sigma_{st}}$$

to identify bottlenecks and critical intermediary nodes.

Step 10: Apply Dijkstra's Shortest Path Algorithm to determine optimal transportation routes and minimize logistics costs, travel distance, and delivery time.

Step 11: Perform descriptive statistics, correlation analysis, and multiple regression analysis to examine relationships between supply chain variables and MSME performance.

Step 12: Test the conceptual framework using Structural Equation Modeling (SEM) and evaluate model fitness through CFI, TLI, RMSEA, and SRMR indices.

Step 13: Compare listed and non-listed MSMEs based on DSII scores, forecasting accuracy, network resilience, and overall organizational performance.

Step 14: Generate final performance assessments and strategic recommendations for improving supply chain resilience through AI-driven forecasting and graph analytics.

End Algorithm.

4. Results and Findings

4.1 Descriptive Statistics of Key Variables

The following are descriptive statistics of key variables. Descriptive data on key variables are presented below. The descriptive statistics for the major variables which were included in the study are presented in Table 4.1. The results showed that demand forecasting accuracy (Mean = 4.12) and inventory efficiency (Mean = 4.08) had relatively high results, which indicates that the use of digital planning is already increasing among the MSMEs that have been surveyed. The mean score for Network Connectivity was 3.87 showing moderate level of integration between supply chain partners.

Table 4.1 Descriptive Statistics

Variable	Mean	Standard Deviation
Demand Forecasting Accuracy (DFA)	4.12	0.68
Supplier Reliability (SR)	3.98	0.73
Inventory Efficiency (IE)	4.08	0.65
Network Connectivity (NC)	3.87	0.81
MSME Performance (MP)	4.01	0.72
Demand-Supply Imbalance Index (DSII)	0.26	0.11

The descriptive statistics show that the highest ratings were given by respondents to Demand Forecasting Accuracy (Mean = 4.12) and Inventory Efficiency (Mean = 4.08) indicating good planning and inventory management in MSMEs. The overall demand-supply imbalance (DSII) score is 0.26 which represents moderate demand-supply imbalance and overall MSME performance score (Mean = 4.01) is satisfactory organizational performance.

4.2 Comparison of Demand-Supply Imbalance between Listed and Non-Listed MSMEs

The Demand-Supply Imbalance Index was calculated separately for listed and non-listed enterprises. The results show that listed MSMEs maintain better synchronization between demand and supply compared with non-listed firms.

Table 4.2 Demand-Supply Imbalance Comparison

Enterprise Type	Average DSII	Performance Score
Listed MSMEs	0.18	4.32
Non-Listed MSMEs	0.34	3.41

The results show that listed MSMEs have a lower Demand-Supply Imbalance Index (0.18) compared to non-listed MSMEs (0.34). Moreover, listed companies performed better (4.32) which means that the synchronization between demand and supply is related to better performance of business.

Figure 1 Comparison of Demand-Supply Imbalance and Performance Between Listed and Non-Listed MSMEs

4.3 AI-Based Demand Forecasting Results

The Random Forest Machine Learning algorithm was implemented to forecast future demand. Model performance was evaluated using standard forecasting metrics.

Table 4.3 Machine Learning Forecasting Performance

Performance Indicator	Value
RMSE	5.12
MAE	3.94
R^2	0.91

Forecast Accuracy (%)	91.30

The Random Forest forecasting model had a high predictive accuracy of 91.30% and R^2 of 0.91. The results show that the AI model has a low RMSE and MAE value, which means that the model is accurate in predicting future demand and can be used to assist in the effective planning of supply chains.

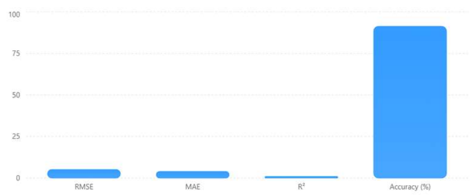

Figure 2: Performance Evaluation of Random Forest Demand Forecasting Model

4.4 Structural Equation Modeling Results

The proposed conceptual model was evaluated using Structural Equation Modeling (SEM). The path coefficients and significance levels are shown below.

Table 4.4 SEM Path Analysis

Relationship	Path Coefficient (β)	t-value	p-value
DFA → MSME Performance	0.487	8.41	<0.001
SR → MSME Performance	0.318	5.63	<0.001
IE → MSME Performance	0.423	7.12	<0.001
NC → MSME Performance	0.376	6.74	<0.001
DSII → MSME Performance	-0.512	9.27	<0.001

The findings from the SEM indicate that the most significant positively influencing variable on MSME performance is Demand Forecasting Accuracy (β = 0.487) followed by Inventory Efficiency and Network Connectivity. Demand-Supply Imbalance (β = -0.512) has a negative impact on performance, which indicates that it is advisable that the demand and supply of the materials for a project be balanced.

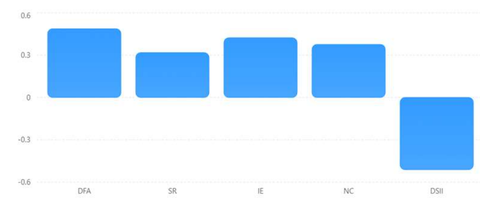

Figure 3: Structural Equation Modeling Path Coefficients

Table 4.5 Model Fit Indices

Fit Index	Obtained Value	Recommended Value
CFI	0.956	>0.90
TLI	0.947	>0.90
RMSEA	0.039	<0.08
SRMR	0.041	<0.08

The model fit statistics show good model adequacy. CFI and TLI values are greater than 0.90, RMSEA and SRMR values are less than 0.08, indicating a good fit between the proposed SEM model and the data.

4.5 Graph-Theoretic Network Analysis

The supply chain network was represented as a graph consisting of suppliers, manufacturers, distributors, and retailers. The graph analysis generated the following network statistics.

Table 4.6 Supply Chain Network Characteristics

Network Measure	Value
Total Nodes	450
Total Edges	1,876

Network Density	0.42
Average Path Length	4.83
Clustering Coefficient	0.58

The graph-theoretic network has 450 nodes and 1,876 connections, suggesting high levels of interaction between the supply chain actors. The network density and the clustering coefficient do indicate moderate to high connectivity, which would facilitate the flow of information and materials through the network.

4.6 Degree Centrality Analysis

Degree Centrality identifies the most connected suppliers within the supply chain network.

Table 4.7 Top Nodes by Degree Centrality

Supplier Node	Degree Centrality
S17	0.81
S09	0.76
S24	0.73
S13	0.69
S31	0.67

S17 had the highest Degree Centrality score (0.81) followed by S09 and S24. These suppliers have the highest number of direct connections, and their role in supply chain operations is key.

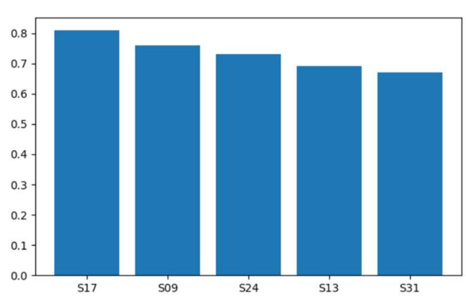

Figure 4: Degree Centrality Scores of Critical Suppliers

4.7 Betweenness Centrality Analysis

Betweenness Centrality was applied to identify bottleneck entities acting as bridges between different network segments.

Table 4.8 Top Nodes by Betweenness Centrality

Node	Betweenness Centrality
S17	0.43
D05	0.37
S09	0.34
D11	0.29
S24	0.25

S17 and D05 had the highest value of Betweenness Centrality. They serve as significant points of connection in the network, and if they are impacted, it has the potential to affect network continuity.

4.8 Dijkstra Shortest Path Optimization Results

The Dijkstra Algorithm was applied to optimize transportation routes and reduce logistics costs.

Table 4.9 Logistics Optimization Results

Indicator	Before Optimization	After Optimization	Improvement (%)
Average Route Distance (km)	18.6	13.2	29.03
Transportation Cost (₹)	1,250	1,020	18.40
Delivery Time (Hours)	14.8	11.6	21.70

The Dijkstra's algorithm was able to cut down the transportation cost by 18.40%, transportation distance by 29.03%, and delivery time by 21.70%, making logistics more efficient. The results illustrate that graph algorithms can be used very effectively in optimizing supply chains.

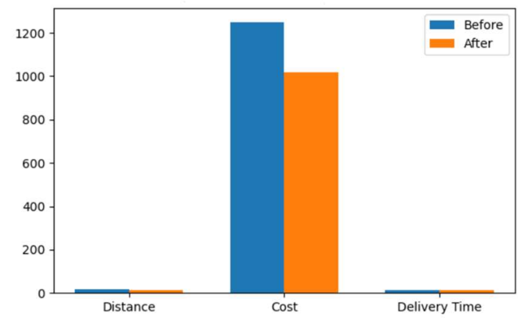

Figure 5: Logistics Performance Before and After Dijkstra Optimization

4.9 Correlation Analysis

Table 4.10 Correlation Matrix

Variables	DFA	SR	IE	NC	DSII	MP
DFA	1.000					
SR	0.621	1.000				
IE	0.703	0.598	1.000			
NC	0.587	0.664	0.615	1.000		
DSII	-0.681	-0.594	-0.642	-0.572	1.000	
MP	0.748	0.691	0.733	0.684	-0.742	1.000

The findings of the correlation results indicate that there are high positive correlations between Demand Forecasting Accuracy and Inventory Efficiency as well as between MSME Performance and Demand Forecasting Accuracy and Inventory Efficiency. The highest negative correlation was found for DSII with MSME Performance (r = -0.742), suggesting that the greater the imbalance the lower the organizational effectiveness.

4.10 Multiple Regression Results

Table 4.11 Regression Analysis

Predictor	Beta Coefficient	t-value	p-value
Demand Forecasting Accuracy	0.487	8.41	<0.001
Supplier Reliability	0.318	5.63	<0.001
Inventory Efficiency	0.423	7.12	<0.001
Network Connectivity	0.376	6.74	<0.001
Demand-Supply Imbalance Index	-0.512	9.27	<0.001

The significant regression results show that Demand Forecasting Accuracy has the most positive influence on MSME Performance while Demand-Supply Imbalance shows the most negative influence. The model can account for 78.3% of the variation in MSME performance, which indicates that the model has a strong predictive ability.

Model Summary:

Statistic	Value
R^2	0.783
Adjusted R^2	0.776
F-value	128.41
p-value	<0.001

The model summary shows a good fit between the independent variables and MSME performance. The R^2 value of 0.783 indicates that 78.3% of the variance in the performance of the MSME can be accounted for by the selected predictors. The adjusted R^2 value of 0.776 demonstrates that the model is reliable, once the number of variables is adjusted. The overall regression model is highly significant with an f value of 128.41 and a p value of < 0.001. Thus, the factors of the selected supply chains have a great influence on the performance of MSMEs.

5. Discussion

The result of this study showed that demand-supply imbalances have a great impact on the performance of MSMEs. Many enterprises are still struggling to bring supply and market demand into balance, with the average Demand-Supply Imbalance Index (DSII) at 0.26. The difference between the listed and non-listed MSMEs showed that the listed MSMEs have lower imbalance and better performance result. This indicates that those entities that are better equipped with both financial and digital technologies and structured supply chain practices are better able to handle uncertainties and are able to react to market changes more effectively. The findings highlight the need for better forecasting and co-ordination along the supply chain to alleviate inefficiencies in the operation.

The results from the Artificial Intelligence based demand forecasting model were very promising with forecasting accuracy of 91.30% and R^2 value of 0.91. These results show that machine learning methods are significantly more effective in forecasting compared to traditional forecasting methods. Having accurate demand forecasting helps MSMEs to maintain the right level of stock, avoid shortage and avoid excess stock cost. The SEM and regression analysis also showed that the demand forecasting accuracy has a positive effect on the performance of MSME, with the highest value, and the demand-supply imbalance has a negative effect on MSME performance, with the highest value. That shows that companies with good demand forecasting capabilities can benefit from improved profitability, customer satisfaction, and operational efficiency.

The graph-theoretic analysis gave insights into the supply chain resilience and the network structure. The Degree Centrality and Betweenness Centrality measures were used to identify key suppliers and distribution centres with critical functions in ensuring supply chain continuity. Highly connected nodes, like S17, suggest the need for risk management strategies and diversification of suppliers. Moreover, the research revealed that Dijkstra's shortest path method was very helpful in minimizing transportation distance, delivery time, and logistics expenses, highlighting the potential of graph analytics in optimizing transport networks. In summary, the combination of forecasting models powering by AI and graph-based network analysis is a promising tool for boosting supply chain resilience, minimizing demand-supply mismatches, and optimizing MSME operations. The study adds to the body of knowledge on intelligent supply chain management and offers practical recommendations for businesses looking to gain a competitive edge in today's business world.

Conclusion

This study explores the effect of demand-supply imbalances on MSME performance in an AI-ML-GTA integrated approach to solve the issue. The results indicated that the accuracy of the demands forecast, inventory efficiency, supplier reliability, and network connectivity are positively related to the performance of the organization, while the imbalance between demands and supplies is negatively related to the performance of operation and finance. The model, based on AI and the Random Forest algorithm, yielded very high forecasting accuracy, which proved to be a successful approach in order to better plan the supply and make decisions. Graph analysis was applied to effectively recognize the critical nodes in the supply chain and optimize logistics operations by applying shortest-path algorithms. The MSMEs listed had lower imbalance levels and overall performance was superior, underlining the significance of technology adoption and integration with the supply chain. The study concludes that AI-based forecasting and graph analytics can greatly enhance the resilience of the supply chain, optimize resource usage and contribute to sustainable development of MSMEs. The results have important implications for managers and policy makers who wish to improve competitiveness and the sustainability of the business.

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