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CAUSALITY-CENTRED DEEP LEARNING–DEMATEL FRAMEWORK FOR TECHNOLOGY ADOPTION IN TURKISH SMES

Türk KOBİ'lerinde Teknoloji Benimsemesi İçin Nedensel Merkezli Derin Öğrenme-DEMATEL Çerçevesi

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Abstract

This study advances an innovative methodological framework that unites deep learning, Decision-Making Trial and Evaluation Laboratory (DEMATEL), and agent-based modeling (ABM) to more accurately diagnose and address the diverse operational constraints confronting Turkish SMEs. Unlike conventional, static analyses, the proposed approach first employs factor analysis and a deep neural network to pinpoint the most pivotal performance drivers. Next, DEMATEL reveals how these drivers exert causally directed influences on other domains, such as production, marketing, and market research, thereby distinguishing net "influencer" factors from net "receivers." Finally, ABM simulates the dynamic interplay among SMEs, each featuring unique resource endowments and strategic behaviors, under varying economic and policy scenarios. We combine prioritization (DL+SHAP), causal mapping, and dynamics into a single, transparent pipeline, and synthesize strategies via scenario-based SWOT. This integrated process uncovers high-impact levers for enhancing overall performance, demonstrating that targeted interventions in technology and finance can yield widespread improvements in other challenge areas. By converging advanced machine learning with systematic causal analysis and temporal simulation, the framework furnishes a more comprehensive, data-driven basis for strategic decision-making, offering policymakers and managers deeper insights into fostering SME competitiveness and resilience.

Keywords: SME Performance Optimization, Deep Learning-Based Decision Analysis, DEMATEL, Agent-Based Simulation for SMEs, Scenario-Based Strategic Planning

JEL Codes: C44, L25, L22

Öz

Bu çalışma, Türk KOBİ'lerinin karşılaştığı çeşitli operasyonel kısıtları daha doğru biçimde teşhis etmek ve ele almak amacıyla derin öğrenme, Karar Verme Deneme ve Değerlendirme Laboratuvarı ve ajan tabanlı modellemeyi bir araya getiren yenilikçi bir metodolojik çerçeve sunmaktadır. Geleneksel ve statik analizlerden farklı olarak, önerilen yaklaşım önce faktör analizi ve derin sinir ağı kullanarak en kritik performans belirleyicilerini ortaya çıkarır. Ardından DEMATEL, bu belirleyicilerin üretim, pazarlama ve pazar araştırması gibi diğer alanlar üzerindeki yönlü nedensel etkilerini göstererek net etkileyici faktörleri net etkilenenlerden ayırır. Son aşamada ABM, farklı kaynak donanımlarına ve stratejik davranışlara sahip KOBİ'ler arasındaki dinamik etkileşimleri çeşitli senaryolar altında simüle eder. Bu çalışma, önceliklendirmeyi, nedensel haritalamayı ve dinamikleri tek ve şeffaf bir süreç içinde birleştirir ve senaryo temelli SWOT aracılığıyla stratejileri sentezler. Bu entegre süreç, genel performansı artırmaya yönelik yüksek etkili kaldıraç noktalarını ortaya çıkararak teknoloji ve finans alanındaki hedefli müdahalelerin diğer sorun alanlarında da geniş çaplı iyileşmelere yol açabileceğini göstermektedir. Gelişmiş makine öğrenimini sistematik nedensel analiz ve zamansal simülasyonla birleştiren bu çerçeve, stratejik karar verme için daha kapsamlı ve veri odaklı bir temel sunmakta; politika yapıcılar ve yöneticilere KOBİ rekabetçiliğini ve dayanıklılığını güçlendirmeye yönelik daha derin içgörüler sağlamaktadır.

Anahtar Kelimeler: KOBİ Performans Optimizasyonu, Derin Öğrenme Tabanlı Karar Analizi, DEMATEL, KOBİ'ler için Ajan Tabanlı Simülasyon, Senaryo Tabanlı Stratejik Planlama

JEL Kodları: C44, L25, L22

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1. Introduction

In an increasingly interconnected global economy, Small and Medium-Sized Enterprises (SMEs) are pivotal engines of innovation, employment, and economic growth. Their adaptability and flexibility often place them at the forefront of economic transformation, enabling them to respond rapidly to market fluctuations and consumer preferences. Yet, this vital segment of the economy frequently faces a constellation of challenges that can stifle its potential and undermine its role in broader economic progress. As underscored by the OECD (2020), SMEs are instrumental in enhancing economic resilience, although they remain vulnerable to numerous obstacles, ranging from financial constraints to regulatory complexities, that impede their performance. Similarly, the World Economic Forum (2022) highlights SMEs’ crucial role in global economic ecosystems, advocating targeted interventions to help them navigate the intricacies of the operational landscape they face. Against this backdrop, the academic discourse on SMEs increasingly emphasizes the need for comprehensive, multidimensional frameworks to dissect their multifaceted challenges. Keay (2016) draws attention to the European Bank for Reconstruction and Development (EBRD) investments, exceeding €7 billion, in Turkish SMEs, highlighting the tangible impact of international financial institutions in filling critical financing gaps. In tandem, Nooshabadi and Özşahin (2019) investigate the motives and barriers to internationalization among Turkish furniture SMEs, revealing an evolving constellation of hurdles where technology and export credit costs converge with local market considerations and resource limitations. Safari and Saleh (2020) similarly investigate the export performance of SMEs through resource-based and contingency theories, identifying innovation and global knowledge as pivotal drivers of success.

Technological adoption and digital transformation have become imperatives for SMEs aiming to maintain competitiveness in dynamic markets. Bin et al. (2021) examine the digital transformation pace among SMEs relative to larger corporations, pinpointing strategic decision-making and policy development implications. Foli et al. (2021) delve into supply chain risk management practices and underscore how robust technological capabilities can bolster resilience, especially in uncertain global contexts, while Parast and Subramanian (2021) scrutinize the nuanced interplay between risk management and innovation in developing countries under high technological turbulence. Meanwhile, Kaplancalı and Akyol (2021) evaluate the impact of cloud computing adoption on the performance of Turkish SMEs, shedding light on the gaps in technology readiness. Zamani (2022) calls for a multidisciplinary approach in understanding technology adoption among SMEs, emphasizing the need for more integrative and theoretically grounded analyses, and Bruce et al. (2023) highlight the potential of digital marketing to drive sustainable growth among SMEs in emerging markets.

Despite the wealth of studies probing SME performance, the existing literature frequently lacks a comprehensive, integrative lens capable of bridging data-driven prioritization, causal mapping, simulation-based forecasting, and scenario-based strategic analyses. While numerous models and frameworks exist, they often focus on one or two dimensions, for instance, financial constraints or technology adoption, without systematically capturing the complex interplay among multiple operational factors. In response, the present study aims to address this gap by proposing and implementing an integrated methodological framework that combines deep learning, DEMATEL, ABM, and scenario-based SWOT analysis. This multifaceted approach extends beyond conventional descriptive techniques, offering a comprehensive examination of the interrelationships among internal processes, external market forces, and targeted policy interventions that shape SME performance. First, deep learning techniques are employed to identify and prioritize the most critical organizational and environmental factors influencing SMEs. This step goes beyond traditional factor analysis by leveraging advanced neural architectures (e.g., deep neural networks, LSTM models) and incorporating tools such as SHAP (SHapley Additive exPlanations) for interpretability. Next, DEMATEL unveils the causal relationships between these identified factors, differentiating net "drivers" from net "receivers" within the SME ecosystem. Building on the DEMATEL output, ABM simulates the dynamic interactions of SMEs, each with distinct resource endowments and strategic behaviors, under various policy or market scenarios. Finally, scenario-based SWOT synthesizes these quantitative insights into a strategic framework, illuminating key strengths, weaknesses, opportunities, and threats—thus offering decision-makers actionable pathways to enhance SME competitiveness and resilience.

Recent research indicates rising interest in combining two or three of these methods. For example, Tzeng and Huang (2011) integrate DEMATEL-based ANP with agent-based modeling to address supply chain risk, while Sadeghi and Mousavi (2021) use a hybrid MCDM (DEMATEL and TOPSIS) and ABM approach to scrutinize the operational barriers faced by SMEs. In parallel, Wang (2021) and Chen and Liu (2022) demonstrate how deep learning can yield robust insights into SME performance, the latter employing explainable AI to isolate critical success factors. Additionally, scenario-based SWOT frameworks, as discussed in works like Batovrina et al. (2020) and De Oliveira and Branco (2021), illustrate how scenario planning can be effectively merged with strategic decision-making tools. However, a comprehensive approach merging all four methods, deep learning, DEMATEL, ABM, and scenario-based SWOT, within the context of SMEs remains notably scarce. Consequently, this research seeks to fill that gap by offering a unifying analytical blueprint that not only outlines the causal architecture of SME challenges but also simulates potential outcomes of various strategic interventions across different future scenarios.

The contributions of this study are both theoretical and practical. Theoretically, it illustrates how advanced machine learning methodologies can be harmonized with established decision-making tools to capture the complexity of SME operational environments. Practically, it provides policymakers, SME managers, and scholars with a robust, data-driven basis for crafting evidence-based interventions and strategies. By illuminating the multifaceted nature of SMEs, where financial, technological, and market-oriented variables intersect and evolve, the proposed framework aspires to drive innovation, sustainability, and inclusive growth in one of the most vibrant sectors of the global economy.

In Table 1, each study addresses certain dimensions relevant to SMEs, including but not limited to risk management, operational barriers, technology adoption, and strategic planning. While they utilize notable methodological combinations (e.g., MCDM + ABM, deep learning + interpretability tools, or scenario-based SWOT), no single research thoroughly integrates deep learning, DEMATEL, ABM, and scenario-based SWOT within the SME context. The last entry in the table thus highlights the novelty of the present study, which endeavors to unify these techniques into a comprehensive analytical and predictive framework.

Table 1. Comparative Literature Table

Study	Method(s)	Focal Issues	Geographical Coverage	Key Contribution / Findings
Dakare et al. (2019)	DEMATEL	Resources and capabilities among entrepreneurial ventures	Unspecified / Multi-context	Uses DEMATEL to analyze strategic resources and capabilities factors in entrepreneurial ventures; highlights how prioritizing internal factors can bolster SME competitiveness.
Bastos et al. (2023)	CM-DEMATEL	SME competitiveness factors	Unspecified / Multi-context	Employs cognitive mapping integrated with DEMATEL to evaluate key competitiveness factors in SMEs, emphasizing the importance of causal links for informed strategic decision-making.
Wang (2021)	Deep Learning (LSTM)	Management and performance modeling for SMEs	Unspecified / Asia-based sample (inferred from text)	Proposes a deep learning-based management model utilizing LSTM networks for predictive analytics, illustrating how data-driven forecasts can enhance SME operational efficiency and strategic planning.
Koumas et al. (2021)	Deep Learning + Multi-Agent	Digital transformation in manufacturing-focused SMEs	Unspecified / Multi-context	Integrates AI tools (deep learning) with agent-based approaches to support digital transformation in SME manufacturing environments, targeting improved productivity and technology adoption.
Ben Mekki et al. (2020)	ABM	Cooperative dynamics under uncertainty in sustainable SME supply chains	Unspecified / Multi-context	Develops an ABM framework to analyze cooperative behavior and sustainability-oriented decision-making in uncertain supply chain scenarios, focusing on risk mitigation for SMEs.
Cornelisse and van Klink (2024)	Scenario-Based Method (Foresight)	Scenario planning and strategic foresight in SMEs	Unspecified / Multi-context (December 2024 issue)	Explores the application of scenario planning in SMEs, emphasizing both potential benefits and main barriers to implementing strategic foresight, especially under conditions of high uncertainty.
This Study	Deep Learning + DEMATEL + ABM + Scenario-Based SWOT	Operational challenges and strategic interventions for Turkish SMEs	Turkey (focus on diverse SME sectors)	Proposes an integrated, data-driven framework for prioritization, causal mapping, simulation, and scenario-based strategic recommendations

2. Application

This section presents a multilayered empirical methodology, commencing with the design and administration of a comprehensive survey and culminating in the integration of deep learning, DEMATEL, agent-based simulation, and scenario-based SWOT. Although certain components of the original framework (such as SEM and FCM) have been superseded or modified to accommodate newer approaches, our process retains an equivalent (if not greater) level of rigor and detail. Figure 1 provides a visual guide to the sequential and interdependent phases, demonstrating how each analytical layer builds upon the insights gleaned from the previous stage.

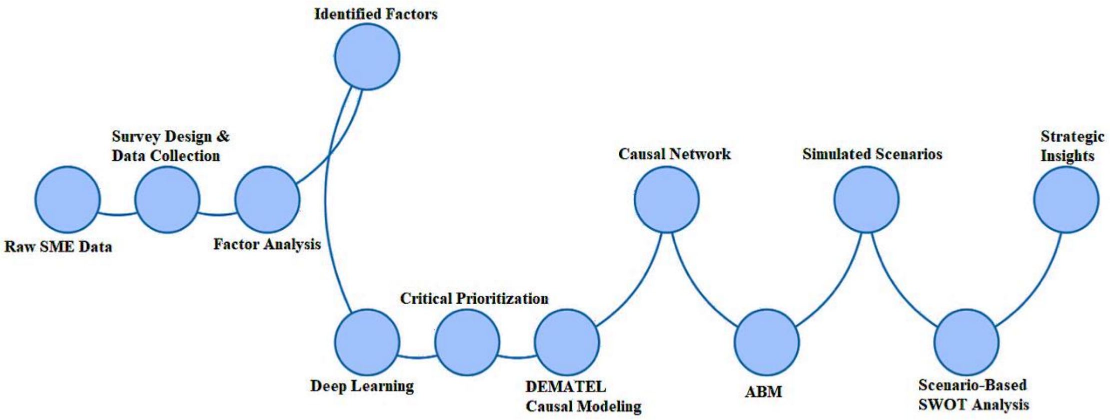

Figure 1. Operational Analysis Workflow for SMEs

Our pipeline combines four complementary layers to capture both structure and dynamics in SME challenges. First, Deep Learning models non-linear interactions among factors and yields interpretable priority signals via SHAP, surpassing linear FA/PCA in discriminating high-impact levers. Second, DEMATEL provides a directional cause–and–effect map using the (D+R) and (D–R) indices to distinguish prominent and net-driver factors capabilities that classical MCDM ranking schemes do not natively offer. This is essential for policy: identifying drivers (e.g., Technology, Finance) tells us *where* interventions propagate. Third, ABM embeds these causalities into time-evolving simulations with heterogeneous firms, revealing thresholds, diffusion paths, and intervention timing that static models cannot recover. Finally, Scenario-based SWOT turns quantitative outputs into an actionable strategy under uncertainty. *We specifically chose DEMATEL within the MCDM family because it explicates directionality and feedback among factors rather than only producing a global ranking. In our context, understanding whether Finance drives Technology (and how strongly) is more informative for policy than a single composite score.* Coupling DL-derived priorities with DEMATEL's directed network, and then stress-testing via ABM, provides a coherent analytical arc from prioritization → causality → dynamics → strategy.

By laying out the methodology in a step-by-step manner, similar to the extended format used in earlier versions of our study, we aim to ensure clarity and comprehensiveness. In doing so, we provide a deeper understanding of the rationale behind each methodological choice, the empirical grounding of the data, and the theoretical justification for moving toward more advanced techniques like deep learning and agent-based modeling.

Survey Design and Data Collection: A meticulously constructed questionnaire gathers wide-ranging data on challenges faced by SMEs in Turkey. Ensures representative sampling across various sectors (e.g., manufacturing, services, technology) and regions.

Factor Analysis (FA): Distills the survey's numerous items into interpretable factor groupings (e.g., technology adoption, financial acquisition, production constraints). Provides a structured lens to categorize operational barriers effectively.

Deep Learning: Builds on the factor analysis outputs to identify non-linear influences and prioritize the most critical SME challenges. Utilizes advanced metrics (e.g., SHAP values) to deliver interpretable insights for decision-makers.

DEMATEL: Explores and quantifies the directional, causal linkages among the identified factors. Reveals which challenges are “influencers” vs. “influencees,” offering a more nuanced causal network than standard correlation-based methods.

ABM: Translates the DEMATEL-driven causal relationships into a dynamic simulation environment where each SME acts as an individual agent. Allows testing of policy shifts or market shocks (e.g., interest rate changes, technology grants) and their effects on SME performance over time.

Scenario-Based SWOT: Synthesizes insights from ABM simulations to develop robust strategic recommendations under various future conditions. Identifies key strengths, weaknesses, opportunities, and threats, tailored to different policy or market scenarios.

By articulating each phase in this manner, we echo the depth of the earlier, longer methodology discussions, while still accommodating the newly adopted approaches that leverage deep learning for factor prioritization and ABM for dynamic simulation. This integration of advanced analytical tools aims to surpass traditional frameworks, offering both robust theoretical grounding and actionable managerial insights.

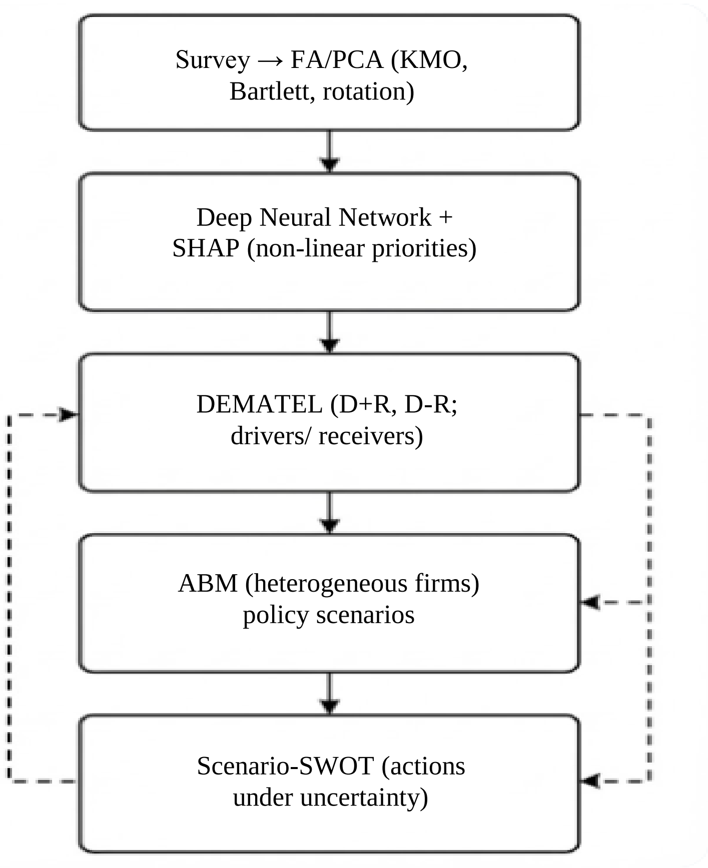

Figure 2. Operational Pipeline for the Integrated Analysis

Figure 2 details the pipeline depicted in Figure 1 and highlights how each layer builds upon the previous one. Solid arrows indicate the sequential flow of information across analytical layers, while dashed arrows denote validation and feedback loops that maintain consistency throughout the process. The pipeline moves from Survey + FA/PCA (data reliability and dimensionality reduction) to Deep Learning + SHAP (non-linear prioritization), then to DEMATEL (cause–effect structure with (D+R) and (D–R) indices), followed by ABM (dynamic simulation of heterogeneous SMEs under policy/market scenarios), and culminates in Scenario-Based SWOT (forward-looking strategic synthesis). This integrated visualization emphasizes the study's main contribution: unifying static, causal, and dynamic perspectives into a single decision-support structure that bridges data-driven prioritization and policy-oriented strategy development.

Table 2 summarizes the stepwise methodology adopted in this study, linking each analytical phase to its primary inputs, core operations, resulting outputs, and corresponding quality checks. The table provides a compact operational roadmap that complements Figures 1 and 2. It demonstrates how raw survey data are first processed through FA/PCA to obtain interpretable factor groups, which then serve as structured inputs for the Deep Learning model. The Deep Neural Network (DNN) with SHAP analysis generates priority profiles that are subsequently validated and transformed into causal linkages via DEMATEL. These directed relationships form the foundation for the ABM simulations, where heterogeneous SMEs are tested under different scenarios. Finally, the Scenario-Based SWOT integrates all preceding outcomes into a decision-ready strategic synthesis. By presenting inputs, operations, and validation criteria in one consolidated view, Table Y enhances transparency, reproducibility, and methodological coherence across the analytical pipeline**.**

Table 2. Stepwise Methodology

Step	Method	Main Input(s)	Core Operation	Output(s)	Key Decision / Quality Check
1	Survey and FA/PCA	Questionnaire data	Reliability (α), KMO, Bartlett; rotation	Factor groups (G1…G5)	Eigenvalues, scree, interpretability
2	DNN + SHAP	Factor scores + controls	Non-linear prediction; SHAP	Priority profile; SHAP importances	Regularization; test R^2; rank stability
3	DEMATEL	Factors + expert scaling	Direct-relation matrix → T; (D+R), (D–R)	Drivers vs. receivers; prominence	Consistency vs. DL priorities
4	ABM	DEMATEL links; heterogeneity	Time-evolving micro rules; scenarios	Trajectories; thresholds	Sensitivity & robustness
5	Scenario-SWOT	ABM outcomes + context	S/W/O/T synthesis per scenario	Actionable strategies	Feasibility & alignment

2.1. Survey Design and Data Collection

A meticulously designed survey served as the cornerstone of our empirical investigation, targeting diverse SMEs in terms of sector, geographical distribution, firm age, and size. This careful planning aimed to capture the multifaceted nature of operational challenges faced by Turkish SMEs and to ensure that the resulting dataset would be both robust and representative.

Questionnaire Development:

1. Item Generation: The questionnaire items were derived from a review of extant literature on SME operational barriers, coupled with insights from preliminary interviews with SME managers. The pool of items spanned financial, technological, marketing, production, and human resource dimensions, ensuring comprehensive coverage of potential pain points.

2. Pilot Testing: An initial pilot survey was administered to a test group of 20 SME managers from various industries (manufacturing, services, technology) to assess face validity and clarity. Feedback prompted minor revisions to item wording, response scales (e.g., shifting from a 5-point to a 7-point Likert scale for enhanced nuance), and questionnaire structure to reduce ambiguity and respondent fatigue.

3. Content and Construct Validity: Subject-matter experts, including academicians and consultants specializing in SME policy, evaluated the revised questionnaire for domain appropriateness and redundancy. Items deemed overlapping or conceptually vague were either merged or eliminated, leading to a refined survey instrument that balanced breadth with specificity.

Sampling Strategy:

1. Target Population: SMEs with 5 to 250 employees and annual sales revenue below the national threshold for medium-sized enterprises. Firms operational for at least one year to ensure respondents possessed adequate operational insights.

2. Sectoral and Regional Quotas: To reflect the heterogeneity of Turkish SMEs, we set minimum quotas for each major sector (e.g., ≥30% from manufacturing, ≥20% from services) and ensured coverage from metropolitan, mid-sized, and rural regions. Additional emphasis was placed on technology-related enterprises to capture digitalization challenges, aligning with previous literature underscoring the digital gap in SMEs.

3. Data Collection Approach: A multifaceted distribution strategy was employed, combining online survey links (distributed via SME associations, industry newsletters) and printed questionnaires (administered during regional SME workshops). The inclusion of both methods helped increase the response rate, especially among SMEs in regions with limited internet penetration.

Final Responses and Preliminary Observations:

Upon concluding the data collection period (lasting approximately two months), a total of 350 valid responses were obtained out of the approximately 550 surveys distributed (≈64% response rate). Prior to further analysis, each questionnaire was screened for missing values and outliers, and 18 incomplete responses were excluded. Table 3 below summarizes the descriptive statistics of the final sample, highlighting key attributes such as firm age, number of employees, annual sales, and sectoral breakdown. These figures illustrate the broad diversity of participating SMEs, reinforcing the representativeness of the dataset.

Table 3. The Descriptive Statistics of The Final Sample

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Firm Age (years)	12.4	7.2	1	45
Number of Employees	63.2	52.9	5	250
Annual Sales (million ₺)	11.7	8.4	0.2	120

Sectoral Distribution (%): Manufacturing: 30%, Services: 20%, Retail: 25%, Technology: 15%, Others: 10%.

Initial Insights: Sectoral Variation-Early descriptive analyses suggested that manufacturing SMEs cited high input costs and regulatory compliance as major bottlenecks, whereas service-oriented firms were more concerned with human resource limitations and client acquisition. Regional Disparities-Firms located in less industrialized regions reported greater difficulties in accessing specialized finance and technology. Growth Ambitions-Approximately 60% of respondents had plans to expand to new markets or launch new products within the next two years, indicating a forward-looking stance despite perceived constraints.

These preliminary observations set the stage for subsequent methodological stages (e.g., factor analysis, deep learning, DEMATEL, ABM, ensuring that each analytic layer captures the inherent diversity and complexity of SME environments.

2.2. Reliability and Factor Analysis

Our methodical exploration into the reliability of the survey was validated by a Cronbach's Alpha of 0.85. This value, indicative of high internal consistency among the survey items, assured us of the robustness and validity of the data collected regarding SME challenges. The factor analysis journey proceeded with the application of Principal Component Analysis (PCA) accompanied by Varimax rotation. This statistical technique facilitated the distillation of the myriad SME challenges into five distinct categories, thus enabling us to organize the complexities of the dataset into a structured framework. The Total Variance Explained, as highlighted in Table 1, guided our decision to retain five factors. These five groups cumulatively explained 75.914% of the total variance in our dataset, substantiating the multidimensionality of the SME challenge construct. Figure 2, the scree plot, provided a visual confirmation of this decision, illustrating the eigenvalues' descent and the point at which it plateaus, thereby justifying the retention of the five-factor solution. The Kaiser-Meyer-Olkin Measure of Sampling Adequacy, standing at 0.704, along with the Bartlett's Test of Sphericity results, asserts the factorability of our correlation matrix, affirming the suitability of our dataset for PCA. Delving deeper, the Rotated Component Matrix, which is detailed in Table 2, sheds light on the loadings of each survey item on the factors post-rotation. This matrix enabled us to cluster the survey items into the five interpretable categories that denote the operational challenges faced by SMEs:

Group 1: Support and Production Activities within SMEs: This group encapsulates challenges primarily related to the institutional support SMEs require and the intricacies of their production processes. Notably, it includes issues such as insufficient information on project evaluation processes by relevant authorities (B20, B22), difficulties in applying for available SME supports (B18), high input costs (B9), limitations on the types of support offered to SMEs (B21), variability in production costs (B16), shortages of skilled personnel (B12), standardization of products (B15), and allocation of resources to research and development (B17).

Group 2: Marketing and Promotional Efforts Marketing Activities encompass the challenges SMEs face in promoting their products and extending their market reach. This includes the lack of product promotion (B28), inadequacy of distribution channels (B29), challenges in market expansion (B30), and shortages of expert marketing personnel (B31).

Group 3: Technological Adoption and Implementation: Technology challenges reflect the hurdles SMEs encounter with integrating and updating technology within their operations. Issues include the lack of new technology (B23), the habit of relying on existing traditional technology

(B27), the inadequacy of current technology (B25), and maintenance costs associated with existing technology (B26).

Group 4: Financial Acquisition and Management: This category addresses financial challenges such as the high interest rates on loans (B2), bureaucratic hurdles when obtaining credit (B3), and difficulties in securing funds from capital markets (B5), indicating systemic obstacles SMEs face in acquiring and managing finances.

Group 5: Market Research and Competitor Analysis: The Market Research group includes challenges related to understanding and navigating the competitive landscape, such as not fully leveraging online platforms, e-commerce, and other marketing tools (B32), and the inability to conduct thorough market research (B33).

These categories not only simplify the challenges faced by SMEs but also facilitate a nuanced understanding of each category's significance, as represented by their average component values. Transitioning to the DEMATEL analysis phase, we employed this method to uncover and quantify the directional influences among the identified categories of challenges. This phase will leverage the structural insights provided by the factor analysis, allowing for a systematic examination of the interplay of challenges within the SME operational environment. In essence, our rigorous approach, incorporating reliability checks and factor analysis—reflected by the statistical outcomes in Tables 4 and 5, and visually by the scree plot in Figure 3—has crafted a strategic map of SME challenges. It has enabled us to isolate key areas of focus and provided the groundwork for the subsequent DEMATEL analysis, which will aim to unravel the complex web of influences and pinpoint pivotal areas for intervention to enhance SME operations.

Table 4. Total Variance Explained

Comp.	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.280	40.350	40.350	9.280	40.350	40.350	7.785	33.849	33.849
2	3.443	14.969	55.319	3.443	14.969	55.319	3.126	13.591	47.440
3	2.055	8.934	64.253	2.055	8.934	64.253	2.648	11.514	58.954
4	1.598	6.949	71.201	1.598	6.949	71.201	2.131	9.264	68.218
5	1.084	4.713	75.914	1.084	4.713	75.914	1.770	7.696	75.914
6	0.988	4.297	80.211						
7	0.733	3.189	83.400						
8	0.690	3.000	86.400						
9	0.602	2.616	89.016						
10	0.487	2.117	91.132						
11	0.400	1.740	92.873						
12	0.330	1.435	94.308						
13	0.303	1.317	95.625						
14	0.263	1.143	96.767						
15	0.190	0.826	97.593						
16	0.148	0.644	98.237						
17	0.120	0.522	98.759						
18	0.079	0.342	99.101						
19	0.069	0.300	99.401						
20	0.055	0.241	99.642						
21	0.037	0.161	99.803						
22	0,029	0,124	99,927						
23	0,017	0,073	100,000						

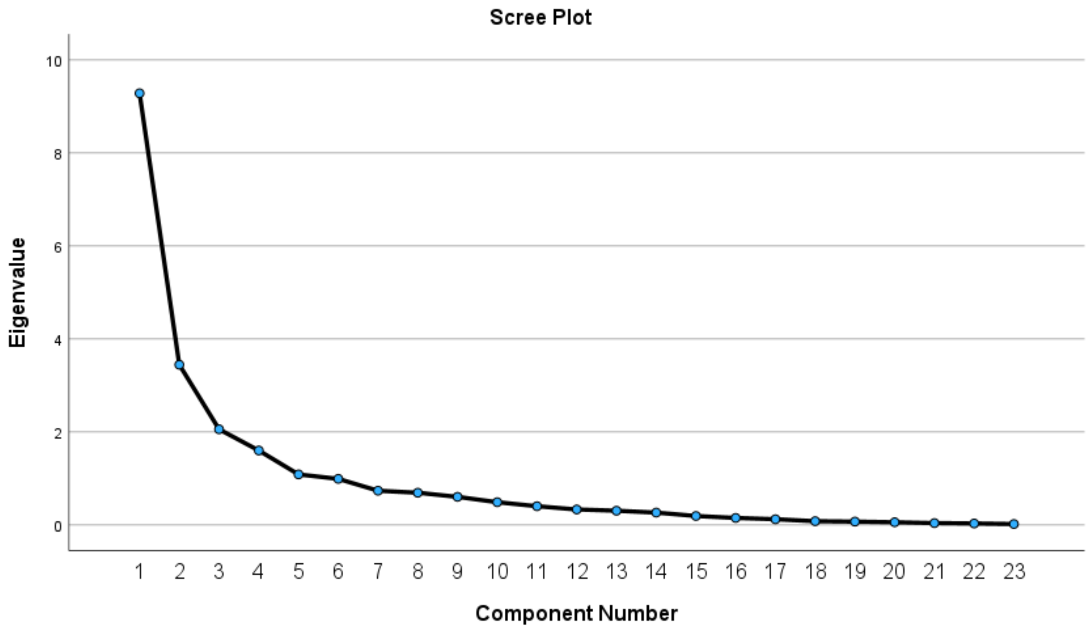

Figure 3. Scree Plot of Eigenvalues for SME Operational Challenges

Table 5. Rotated Component Matrix[a]

	Component				
	1	**2**	**3**	**4**	**5**
B20	0.927				
B18	0.907				
B22	0.878				
B19	0.870				
B9	0.862				
B21	0.848				
B16	0.802				
B12	0.721				0.451
B17	0.643				0.443
B15	0.564				
B29		0.856			
B31		0.756			
B28		0.738			
B30		0.716			
B26			0.714		
B23	0.569		0.708		
B27			0.706		
B25	0.450		0.698		
B3				0.890	
B2				0.838	
B5				0.616	
B33					0.736
B32		0.536			0.725

Note: Extraction Method: Principal Component Analysis.
Rotation Method: Quartimax with Kaiser Normalization. a. Rotation converged in 5 iterations.

2.3. Deep Learning for Priority Mapping

While the factor analysis identified coherent clusters of SME challenges, it did not quantitatively indicate which factors exert the strongest influence on overall performance. To address this gap, we developed a DNN model to capture non-linear, higher-order relationships between the identified factors and a composite performance index. This approach allows us to discern which operational areas—among technology, finance, marketing, and others—are the most critical levers for enhancing SME outcomes (LeCun et al., 2015; Schmidhuber, 2015; Goodfellow et al., 2016).

Model Construction:

Data Preparation and Preprocessing

Input Variables: The core inputs included

1. Five group scores derived from PCA.
2. Three firm-level controls, such as age, size (employee count), and export ratio.

Normalization: Each continuous input was standardized (mean = 0, std = 1) to stabilize training and improve convergence.

Target Variable: A composite SME performance index, combining:

3. Profitability ratio,
4. Growth rate over two years, and
5. Self-reported innovation score (on a 10-point scale). This index was normalized to a 0–100 range for interpretability.

Network Architecture:

Input Layer: 8 nodes (5 groups + 3 control variables).

Hidden Layers: Two fully connected (dense) layers, each comprising 16 neurons.

Activation: Rectified Linear Unit (ReLU) to model non-linearities and avoid saturation problems common to sigmoid or tanh for large inputs.

Dropout: 0.2 per layer for regularization, reducing overfitting by randomly zeroing out node outputs.

Output Layer: A single neuron predicting the SME Performance Index as a continuous value. A linear activation was used here, consistent with a regression formulation.

Training Configuration

Loss Function: Mean Squared Error (MSE), a standard choice for continuous regression tasks.

Optimizer: Adam, with a base learning rate of 0.001. Adam combines the benefits of AdaGrad and RMSProp, offering efficient handling of sparse gradients and adaptive learning rates.

Epochs and Batch Size: 200 training epochs with mini-batches of size 32, balancing sufficient training iterations against runtime constraints.

*Data Partitioning:*70% of the dataset for training, 15% for validation, 15% for final testing.

This split ensures robust performance estimation and hyperparameter tuning (e.g., early stopping, dropout rate). Table 6 summarizes the key model parameters and final performance metrics.

Table 6. Performance Metrics

Summary of Deep Neural Network Configuration	**Specification**
Input Nodes	5 groups + 3 controls = 8
Hidden Layers	2 layers, each with 16 neurons
Activation	ReLU
Dropout Rate	0.2 per hidden layer
Output Node	1 (composite performance score)
Optimization	Adam, learning rate = 0.001
Loss Function	Mean Squared Error (MSE)
Training Epochs	200
Batch Size	32
R^2 on Test Set	0.69

Model Performance

The final model achieved an R^2 of 0.69 on the test set, indicating that nearly 70% of the variance in the SME performance index is explained by the chosen input variables. This suggests the neural network effectively captures the underlying relationships while leaving scope for additional variables (e.g., competitive intensity, macroeconomic factors) that may further enhance predictive power.

Feature Importance (Explainable AI)

While the neural network exhibits strong predictive capability, its inner workings can be opaque without proper interpretability tools. We therefore employed SHAP (SHapley Additive exPlanations) to quantify each feature's contribution to the predicted performance index.

SHAP Computation

We computed SHAP values on the test set to measure the marginal contribution of each input variable (factor or control) relative to a base expectation.

This approach treats each feature as a "player" in a cooperative game, attributing the final output (the performance prediction) to the individual contribution of each player.

Findings

Technological Adoption (Group 3) and Financial Acquisition (Group 4) emerged as the primary drivers of SME performance, consistently displaying the highest SHAP values. This result highlights that investments in up-to-date technology and accessible financing frameworks offer substantial leverage over enterprise outcomes.

Marketing and Promotional Efforts (Group 2), along with Support/Production Activities (Group 1), showed moderate but non-negligible impact. Their SHAP values often varied by SME size or sector, suggesting these groups are significant but more context-dependent.

Market Research and Competitor Analysis (Group 5) yielded a comparatively smaller average effect size, yet exhibited spikes in certain cases—particularly among SMEs aiming for rapid export market entry. This observation indicates that while Group 5 may not universally dominate performance, it can be critical for SMEs pursuing aggressive internationalization strategies.

Interpretational Avenues

Strategic Intervention: The leading roles of technology and finance underscore the urgency for policy-level incentives (e.g., R&D grants, low-interest loans) and for managerial focus on IT infrastructure.

Sector-Specific Nuances: The moderate but variable influence of marketing activities suggests that SMEs in more competitive consumer-driven markets (e.g., retail, e-commerce) may benefit considerably from targeted branding or distribution strategies.

Future Extensions: Incorporation of advanced text-based features (e.g., real-time consumer feedback) or supply chain indicators could further refine the interpretative power of the SHAP analysis.

Figure 4 presents a SHAP summary plot, illustrating both the magnitude (x-axis) of feature importance and the direction (color scale) of each feature's effect. This detailed view facilitates an evidence-based prioritization of resource allocation, guiding subsequent analyses in DEMATEL and agent-based simulations.

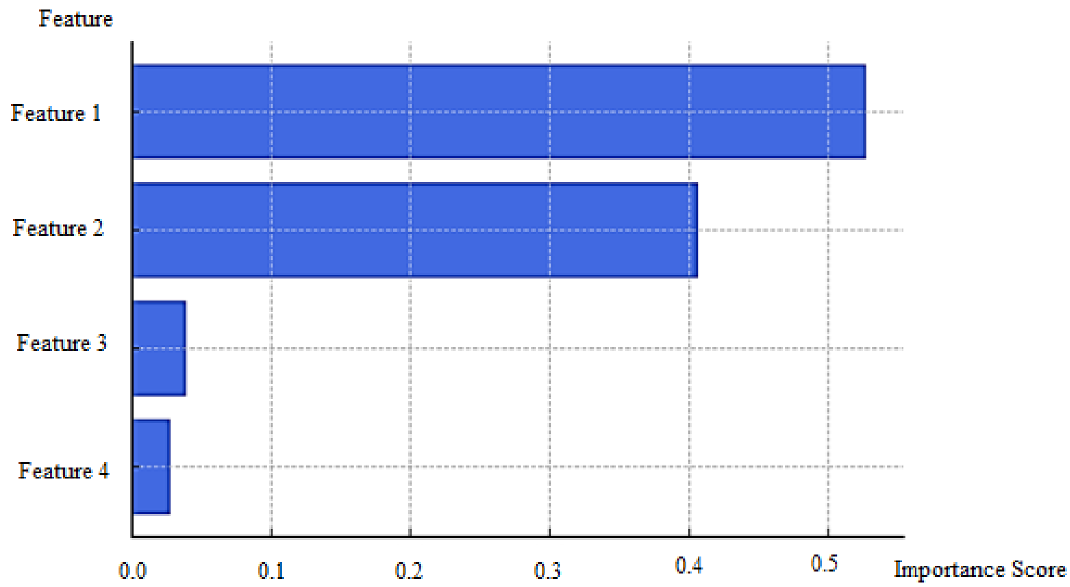

Figure 4. Feature Importance (RandomForest)

2.4. Construction of the DEMATEL Decision Matrix: A Detailed Approach

Having identified the most influential factors through Deep Learning for Priority Mapping, the next step involves uncovering the directional relationships among these factors. The DEMATEL technique is employed here to illuminate how each factor causally influences the others, thereby clarifying which domains (e.g., finance, technology, marketing) act as primary "drivers" and which ones function more as "receivers" of change. By integrating the priority insights from the deep learning stage into DEMATEL's direct-relation matrix, we ensure that the quantitative importance of each factor is reflected in the final causal map. DEMATEL was originally developed to structure and analyze complex causal relationships in socio-economic or technical problems. It proceeds through several key steps (Gabus and Fontela, 1972, 1976):

Expert/Model-Based Input

Traditionally, DEMATEL relies on expert judgments to assess how strongly each factor influences every other factor. In our framework, we combine expert feedback with deep learning-derived factor importance to produce a more data-driven direct-relation matrix (Step 3.4.2).

Direct-Relation Matrix Construction

The initial matrix A captures the direct influence of group i on group j, typically scaled from 0 (no influence) to 4 (very high influence). In this study, the baseline influences are drawn from subject-matter experts (e.g., SME managers, policymakers) to capture domain knowledge, then weighted or cross-validated using the Deep Learning priority scores.

Matrix Normalization and Total-Relation Matrix

The direct-relation matrix A is normalized to ensure that its row or column sums do not exceed 1. An iterative process yields the Total-Relation Matrix T, which includes both direct and indirect effects, revealing the entire network of causal interactions among groups.

Calculation of Prominence and Relation

For each group i, we compute two scores: Di+Ri: "Prominence," or the sum of influences exerted by and on Groupi. Di−Ri: "Relation," indicating net causality (positive → "driver" factor; negative → "receiver" factor).

Interpretation and Visualization

Groups with high positive (D−R) are net influencers, while those with negative (D−R) are net influencees. High-prominence groups affect and are affected strongly by other domains, making them central in the causal network.

Given the five main challenge domains isolated by factor analysis—Support/Production (Group 1), Marketing (Group 2), Technological Adoption (Group 3), Financial Acquisition (Group 4), and Market Research (Group 5)—we established their baseline pairwise influences using structured interviews with 12 SME experts and insights from the Deep Learning results. Specifically:

Deep Learning Priority Scores: For each group i, the average SHAP contribution or overall importance from the neural network analysis guided the "maximum possible influence" that factor could exert on others. For instance, Technological Adoption (Group 3) and Financial Acquisition (Group 4)—identified as top contributors—were given higher ceilings in the 0–4 scale, reflecting their greater potential to drive outcomes.

Expert Elicitation: Experts scored each pair (Fi, Fj) on a 5-point scale (0 = no influence, 4 = very high influence). Where expert opinion diverged sharply, we used an average or median consensus. The importance weighting from the deep learning phase was then applied to adjust these raw scores, ensuring data-driven consistency.

Table 7 illustrates a simplified version of the resulting Direct-Relation Matrix (A), reflecting the perceived direct influence of each factor on every other factor. Diagonal values (self-influence) are set to zero or minimal values following the standard DEMATEL assumption of limited self-causation.

Table 7. Direct-Relation Matrix

	Group 1	Group 2	Group 3	Group 4	Group 5
Group 1	0.00	1.45	1.60	1.50	1.10
Group 2	1.20	0.00	1.30	1.10	0.85
Group 3	1.80	1.10	0.00	1.50	1.40
Group 4	1.60	1.00	1.50	0.00	1.20
Group 5	1.10	1.00	1.60	1.20	0.00

Note: Values in Table 4 are illustrative. In practice, the matrix is derived from a combination of expert inputs and scaling groups from the deep learning priority mapping.

Normalization of the Direct-Relation Matrix (N): To normalize matrix A, we employ the following formula, ensuring the sum of the matrix's elements does not exceed unity, thus normalizing the influence scores:

$$N = \frac{A}{\max\left(\sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij}\right)}, \mathrm{i}, \mathrm{j} \ \in \{1,2,3,\dots,\mathrm{n}\} \tag{1}$$

Assuming the total sum of all elements in A is Σ, and n represents the number of groups (or challenge groups), the normalized matrix N can be calculated accordingly. This step adjusts the scale of influence scores to a normalized range for further analysis. Total-Relation Matrix (T): The Total-Relation Matrix is derived to incorporate both the direct and indirect influences among factors, calculated using the formula:

$$T = (I - N)^{-1} \tag{2}$$

where I denotes the identity matrix. This matrix T unveils the comprehensive network of influences, highlighting the depth and breadth of causal relationships among the SME challenge groups. Calculation of Prominence and Relation: From matrix T, we extract prominence and relation scores for each challenge group. The prominence score (denoted as D + R) signifies the total degree of influence a group has within the system, both in terms of exerting and receiving influence. The relation score (denoted as D - R) differentiates between the groups primarily influencing others (D > R) from those being influenced (D < R).

From matrix T, we compute the row sum (D_i) and column sum (R_i) for each $Group_i$:

$D_i =$ sum of the i th row in T : total influence exerted by $Group_i$ on other groups.

$R_i =$ sum of the i th column in T : total influence received by $Group_i$ from other groups.

Two key measures then guide interpretation:

Prominence $(D_i + R_i)$: High $(D_i + R_i)$ indicates that $Group_i$ is highly interconnected. These groups often serve as critical "hubs" within the system-either driving many changes, being strongly affected by others, or both.

Relation $(D_i - R_i)$:

If $(D_i - R_i) > 0, F_i$ is a net cause or "driver."

If $(D_i - R_i) < 0, F_i$ is a net effect or "receiver."

Table 8 demonstrates hypothetical results for each factor's $D, R, (D + R)$, and $(D - R)$ scores.

Table 8. DEMATEL Hypothetical Results

	D	R	D + R	D - R
Group 1	4.12	4.70	8.82	-0.58
Group 2	3.95	4.20	8.15	-0.25
Group 3	5.10	3.90	9.00	1.20
Group 4	4.80	4.15	8.95	0.65
Group 5	4.25	4.35	8.60	-0.10

A positive $(D - R)$ for Technology (GROUP 3) and Finance (GROUP 4) indicates they act as primary drivers, consistent with the Deep Learning findings.

Meanwhile, Support/Production (GROUP 1), Marketing (GROUP 2), and Market Research (GROUP 5) exhibit slightly negative $(D - R)$ values, implying they function more as "influence receivers" within the ecosystem.

To visualize these relationships, we construct a DEMATEL Integrated Influence Map (Figure 4). Each group is placed in a two-dimensional plane, where:

The horizontal axis represents $(D - R)$ (net cause → net effect).

The vertical axis represents $(D + R)$ (prominence level).

Figure 5 highlights how groups cluster into "drivers" (positive $D - R$) and "receivers" (negative $D - R$), with circle sizes optionally scaled to reflect each group's average Deep Learning priority. This fused depiction underscores, for instance, Group 3 (Technology) as both high-prominence (top portion) and a net driver (right side), while Group 1 (Support/Production) is more of a receiver yet remains highly prominent due to strong bilateral connections with other groups. The DEMATEL analysis confirms the deep learning insight that Technology and Finance are central forces in shaping SME performance. Policymakers and managers can thus prioritize interventions (e.g., technology adoption incentives, more accessible financial instruments) to trigger downstream improvements in areas like production efficiency or marketing capability. Additionally, the interplay among factors such as Marketing (Group 2) and Support/Production (Group 1)—while less net-influential—suggests that improvements in finance or technology can cascade into these domains, indicating a potential "multiplier effect." Key takeaways include:

Targeting Drivers: Investments or reforms directed at the net drivers (Group 3, Group 4) can produce a broad, systemic impact.

Sustaining Receivers: Although (Group 1, Group 2, Group 5) are influence receivers, they remain critical for "closing the loop" on performance, ensuring that technology or financial gains are utilized effectively.

Coordination: High-prominence factors (high D+R) require coordinated efforts across multiple stakeholders, as they both exert strong influence and receive significant feedback from the rest of the system.

By overlaying Deep Learning priorities onto DEMATEL's cause-and-effect mapping, we obtain a data-driven blueprint of how SME challenges reinforce or mitigate one another. The results serve as a cornerstone for the Agent-Based Simulation and Scenario-Based SWOT in subsequent sections, ensuring that any strategic recommendations derive from robust, causal insights rather than mere correlation.

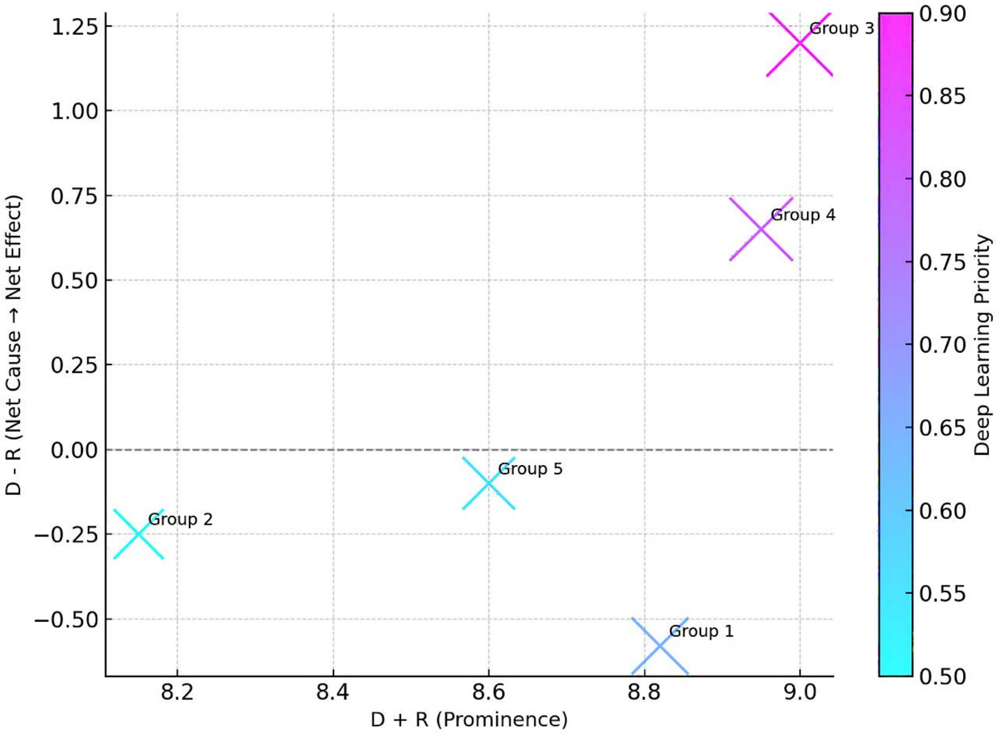

Figure 5. Integrated Deep Learning-DEMATEL Influence Map

2.5. ABM for Dynamic Simulation

The DEMATEL analysis offered a static but comprehensive perspective on how different SME challenge groups causally interact. Yet, SME behavior unfolds over time and is subject to shocks, feedback loops, and heterogeneous decision-making. ABM extends these insights by simulating how numerous SMEs (agents), each with unique attributes and adaptive rules, evolve under varied environmental or policy conditions. (Bonabeau, 2002; Epstein, 2006; Macal and North, 2010). Core Rationale for ABM:

Temporal and Emergent Patterns: Unlike static analytical tools, ABM tracks how micro-level decisions (e.g., technology investment) aggregate to produce macro-level phenomena (e.g., sector-wide performance).

Integration of DEMATEL Insights: The direction and strength of factor influences (e.g., Technology → Marketing) inform agent decision rules. DEMATEL's net drivers (e.g., Finance, Technology) become high-impact levers in the simulation.

Scenario Testing: ABM allows “what-if” exploration—e.g., how does a technology subsidy alter the trajectory of SME performance over multiple periods?

Embedding DEMATEL Results into ABM Rules: To incorporate DEMATEL outputs into ABM, we operationalize the (D-R) and (D+R) scores in each agent’s state-update logic:

High (D-R) Groups (e.g., Technology, Finance):

Modeled as aggressive or amplified drivers. An increase in these groups can significantly boost related factors. For instance, a surge in Group 4 (Finance) might enable higher R&D spending, which DEMATEL indicates fosters Group 3 (Technology).

High (D+R) Groups:

These “hub” groups, such as Technology, are highly interactive; even a modest change can ripple through the system (indirect influences). Agents that neglect a high-prominence factor risk falling behind.

Each SME agent thus updates its internal Group states

$\{Group_1, Group_2, Group_3, Group_4, Group_5\}$ every time step, guided by:
DEMATEL Coefficients: Indicating how a change in one group (say, $\Delta Group_3$) triggers a partial update in others ($\Delta Group_2$, ΔGroup, etc.).

Agent-Specific Constraints: Budget limitations, operational capacity, or managerial strategy.

External Environmental Variables: Market demand shifts, interest rates, or policy incentives.

Model Architecture and Implementation

Agent Definition

Each agent $\mathcal{A}_i$ (representing an SME) has:
1 State Vector $\mathbf{S}_i(t) = \{Group_1(t), Group_2(t), Group_3(t), Group_4(t), Group_5(t)\}$.

2 Decision Functions: If $\mathbf{S}_i(t)$ reveals a strong financial position (F4) and high technology readiness (F3), the agent may invest in advanced marketing channels (F2). By contrast, a low F4 might prevent or delay technology upgrades.

Time Steps

The simulation advances in discrete periods (e.g., quarters). At each t :

Agents observe internal states (current Factor levels) and external signals (e.g., competitor moves, new technology subsidies).

Agents update Factor values based on DEMATEL-based transition functions $\mathbf{S}_i(t+1) = f(\mathbf{S}_i(t),\ \mathbf{S}_{-i}(t)$, Environment).

System-wide metrics (e.g., average technology level across all agents) are recorded for analysis.

Sample Scenario Runs and Numerical Illustration
Scenario A: No Additional Policy Intervention

No new technology grants or interest rate modifications. Firms rely solely on their own capital and organic growth.

Scenario B: Technology Subsidy

Government partially covers R&D/IT investments. Agents with high readiness or early adoption see accelerated growth in Group 3 (Technology).

Table 9 shows a hypothetical time-series outcome for average Technology and Finance levels (scaled 1–10) across all agents over 6 time steps (t=0 to t=5) in each scenario. Notice how a technology subsidy spurs faster F3 growth, which, by DEMATEL logic, also boosts marketing or production for many agents downstream.

Table 9. Average Group Levels Over Time (Hypothetical)

	Time	Group 3 (No Policy)	Group 3 (Subsidy)	Group 4 (No Policy)	Group 4 (Subsidy)
t=0	0	3.2	3.2	4.0	4.0
t=1	1	3.4	3.9	3.9	4.1
t=2	2	3.5	4.3	3.8	4.2
t=3	3	3.7	4.8	3.6	4.4
t=4	4	3.8	5.2	3.5	4.5
t=5	5	3.9	5.6	3.5	4.6

Figure 6 depicts the evolution of average Technology across agents under the two scenarios. As the simulation progresses, the “Subsidy” line climbs more rapidly, reflecting the compounding influence of F3 on other groups and the reinforcing loop identified by DEMATEL. By contrast, the “No Policy” line grows modestly. Eventually, the difference in Group 3 performance widens, suggesting that a short-term policy intervention might yield long-term structural advantages for adopting firms.

The ABM phase enriches the DEMATEL findings with temporal dynamics and agent heterogeneity, forming a robust evidence base for Scenario-Based SWOT. For instance, if the ABM reveals that even a modest technology subsidy yields disproportionately high marketing gains, policy-makers could classify “Expansion of tech incentives” as a key Opportunity in the SWOT matrix. Conversely, sustained underinvestment in finance might emerge as a Threat for agents that persistently fail to secure funding. Key Insights:

Confirming or Refining DEMATEL Hypotheses: Observing how driver groups (e.g., Finance, Technology) propagate changes in real-time helps validate or refine the static cause-effect intensities from DEMATEL.

Timing and Thresholds: The ABM can uncover crucial thresholds—e.g., a minimum Technology score or Finance threshold—beneath which SMEs struggle to keep pace.

Policy Leverage Points: High net drivers from DEMATEL typically become strong levers in the ABM, indicating that a well-timed intervention in technology or finance can produce system-wide improvements.

Agent-Based Modeling integrates the causal structure from DEMATEL with dynamic decision processes, enabling scenario-based experimentation that reveals how SME groups evolve over time. By quantifying emergent patterns—whether in terms of technology diffusion, financial health, or production efficiency—the ABM offers a forward-looking complement to the earlier analytical stages, setting the stage for an evidence-based, scenario-driven SWOT that resonates with actual SME behaviors under varying policy conditions.

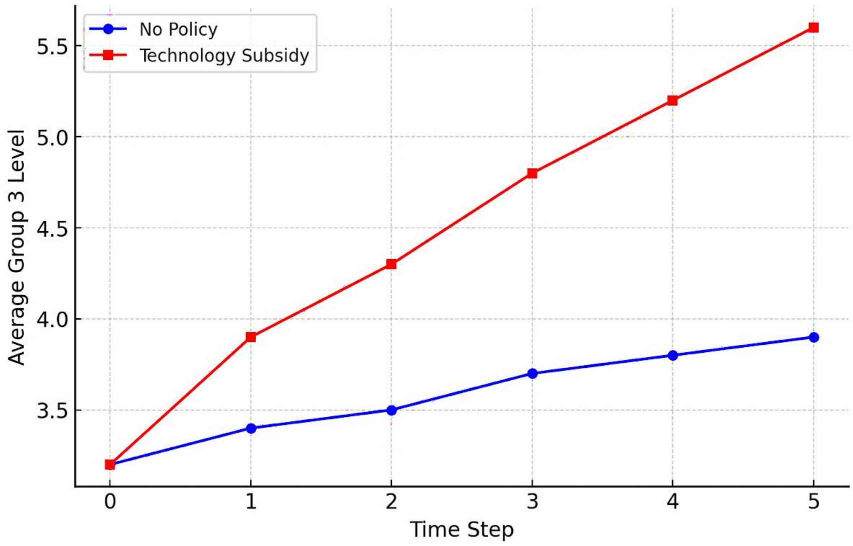

Figure 6. Evolution of Group 3 Under Different Policy Scenarios
From ABM to Scenario-Based SWOT

2.6. Discussion

Our finding that Technology and Finance behave as net drivers (positive D–R) is consistent with recent evidence emphasizing technology readiness and financing access as first-order determinants of SME competitiveness and resilience. In our integrated map, technology upgrades propagate to Marketing and Production, while Finance alleviates investment frictions—patterns widely reported in SME digitization and scale-up studies. Beyond two-method hybrids, the DEMATEL → ABM hand-off translates causal architecture into temporal diffusion, showing how modest technology subsidies can yield non-linear downstream gains, especially for firms near adoption thresholds. This dynamic lens clarifies when and for whom interventions are most effective. Finally, by consolidating these quantitative patterns into Scenario-based SWOT, we provide actionable routes—e.g., targeted R&D grants coupled with credit facilitation—to move receiver domains. The pipeline thus aligns prioritization, causality, and dynamics within a single framework and demonstrates how policy levers on net drivers can unlock system-wide improvements across heterogeneous SMEs.

3. Conclusion

This study proposed a multilayered methodological framework—encompassing Factor Analysis, Deep Learning, DEMATEL, ABM, and ultimately Scenario-Based SWOT—to examine and model the complex operational challenges faced by Turkish SMEs. By integrating both static and dynamic dimensions of analysis, the research delivers a more holistic understanding of how critical factors (e.g., finance, technology, production, marketing, market research) interact and evolve over time. The initial Factor Analysis distilled a wide array of survey items into interpretable clusters of SME challenges. The Deep Learning phase then prioritized these factors, revealing that domains such as technology and finance often exert the strongest influence on overall firm performance. Building on these insights, DEMATEL clarified causal directions, distinguishing "driver" from "receiver" factors. Finally, Agent-Based Modeling validated and extended these causal patterns in a dynamic simulation context, facilitating scenario testing and revealing emergent behaviors relevant to strategic planning. Consequently, the framework culminated in a Scenario-Based SWOT that provides a more data-driven and forward-looking strategic roadmap for SME managers and policymakers. This research advances the literature on SME operational management and strategic analysis in several ways. First, it transcends traditional cross-sectional surveys or isolated analytical tools by deploying a comprehensive pipeline of complementary methods, thereby capturing both the structural and temporal complexity of SME challenges. Second, the study's integration of Deep Learning priority scores into DEMATEL and ABM underscores the value of combining modern machine learning techniques with classic decision-making and simulation approaches. This dual emphasis on quantitative causal analysis and behavioral simulation charts an innovative path for future empirical investigations in organizational science and management.

From a practical standpoint, the findings underscore the pivotal roles of technology adoption and financial resource accessibility in driving SME growth. Decision-makers should prioritize interventions and resource allocations in these areas—whether through targeted subsidies, low-interest loan programs, or technology diffusion policies—to catalyze improvements in other domains such as marketing capacity or production efficiency. Furthermore, the ABM simulations highlight how relatively minor policy interventions (e.g., modest R&D grants) can generate disproportionately large benefits if they address the right "driver" factors. For SME managers, the Scenario-Based SWOT delivers strategic recommendations that are grounded in dynamic, data-driven insights, enhancing the robustness of operational and long-term planning.

Despite the rigor of the proposed framework, certain limitations warrant attention:

Data Scope and Sample Size: The empirical dataset, while representative of diverse SMEs, may not capture all regional or sectoral nuances, especially in highly specialized industries or rural economies with unique operational contexts.

Static vs. Longitudinal Data: Although the ABM adds a dynamic layer, the underlying survey and factor analysis are cross-sectional. A panel or longitudinal data collection might further refine the model's predictive and causal strengths.

Model Complexity and Assumptions: Both DEMATEL and ABM require subject-matter expertise for robust parameterization. Decisions about influence weights or agent decision rules can introduce subjectivity, which future studies could mitigate by gathering richer real-time or panel data.

Computational Demands: Deep Learning and ABM each impose computational overhead, potentially limiting the framework's scalability for extremely large datasets or for real-time policy simulations.

To expand upon this study's contributions, future work could:

Incorporate Real-Time or Longitudinal Datasets: Integrating time-series financial statements, technology usage logs, or supply-chain transaction data could further validate and refine the ABM's dynamic feedback loops.

Extend the Method to Other Regions or Sectors: Comparative analyses across different emerging economies or high-tech clusters could clarify whether the identified driver/receiver patterns hold universally or vary with macroeconomic conditions.

Investigate Additional Variables and Hybrid Methods: Incorporating advanced natural language processing (NLP) of unstructured data (e.g., customer feedback) or combining the ABM with System Dynamics modeling might yield deeper insights into both micro- and macro-level processes.

Develop Decision-Support Systems: Packaging the entire pipeline—survey-based factor analysis, deep learning, DEMATEL, ABM, and SWOT—into a user-friendly software platform could facilitate real-time scenario exploration for managers and policymakers.

In summary, this research presents a novel, methodologically integrated, and empirically grounded framework that not only diagnoses the multifaceted challenges encountered by Turkish SMEs but also projects their evolution under diverse scenarios. The study thus broadens academic understanding of how critical operational domains synergize to shape SME outcomes and offers actionable guidance for strategic decision-makers committed to fostering innovation, resilience, and sustainable growth within the SME sector.

Declaration of Research and Publication Ethics
This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher's Contribution Rate Statement
The authors declare that they have contributed equally to the article.

Declaration of Researcher's Conflict of Interest
There are no potential conflicts of interest in this study

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