Can Smart Manufacturing Benchmark the Complex Landscape of Global Success?

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Can Smart Manufacturing Benchmark the Complex Landscape of Global Success?

Abstract

Purpose: The globalization of markets poses great challenges and thus the manufacturing businesses trying to expand their operations to cater to a global audience have to undergo significant transformations. Therefore, this research aims to identify key challenges and elucidate the critical success factors (CSFs) required for the global growth of manufacturing companies on a worldwide scale.

Design/methodology/approach: A range of Interval Valued Spherical Fuzzy Sets (IVSFs), and flexible methodologies such as the Analytic Hierarchy Process (AHP) and Data Envelopment Analysis (DEA) have been employed to evaluate the issues in detail. It calculates the effectiveness delivered by each Critical Success Factor (CSF), and identifies the factors acting as a barrier to global market penetration.

Findings: This research highlights the transformative potential of smart manufacturing in developing economies, identifying CSFs such as government support, cost optimization, and resilient supply chain management as essential for overcoming obstacles like over-reliance on foreign technologies, regulatory rigidity, and skill gaps. The integration of Interval-Valued Spherical Fuzzy Sets (IVSFS) with AHP and DEA models offers actionable insights to foster localized innovation, reduce foreign dependencies, and promote user-centric designs, aligning with the United Nations Sustainable Development Goals (SDGs).

Originality/value: This study shows that IVSFs, AHP, and DEA can be used together to estimate the global challenges of manufacturing firms in developing markets. The combination of efficient decision-making and these strategies is novel as it provides ways in which businesses in developing countries can deal with their obstacles and improve their competitiveness on the global stage.

Keywords: Local to global; Smart Manufacturing; AHP-DEA; Globalization; Business Strategy; Benchmark.

1. Introduction

Smart manufacturing refers to a new mode of production that is built around new technologies such as the Internet of Things, artificial intelligence, and big data analytics (Mahmoodi et al., 2024). The use of advanced smart technologies automates tasks and increases efficiency while allowing for real-time quality control (Cui et al., 2024). Looking into the realm of digital transformation, SMEs in developing economies are realizing the importance of smart manufacturing in making them competitive on a global scope (Bocken and Geradts, 2020). Smart manufacturing identifies new ways of producing smart products on a global level. In addition to ignoring the sheer size of firms, manufacturing companies properly employ any means available to optimally cut down the expenses of finalizing the product (Baryshnikova et al., 2021). “Flex”, for example, utilizes IIOT in enhancing productivity and automating processes while “Deloitte Consulting” relies on digital twin technology in predictive maintenance and workflow optimization. Workflow optimization and digital twin technology work in tandem in “Deloitte Consulting” due to the need for prediction (Abate et al., 2020). On the other hand, "Boingo Wireless" highlights the significance of strong cybersecurity protocols, which are endorsed by advancing digital security in smart manufacturing and enhancing the confidence of the global market (Alatise and Hancke, 2020).

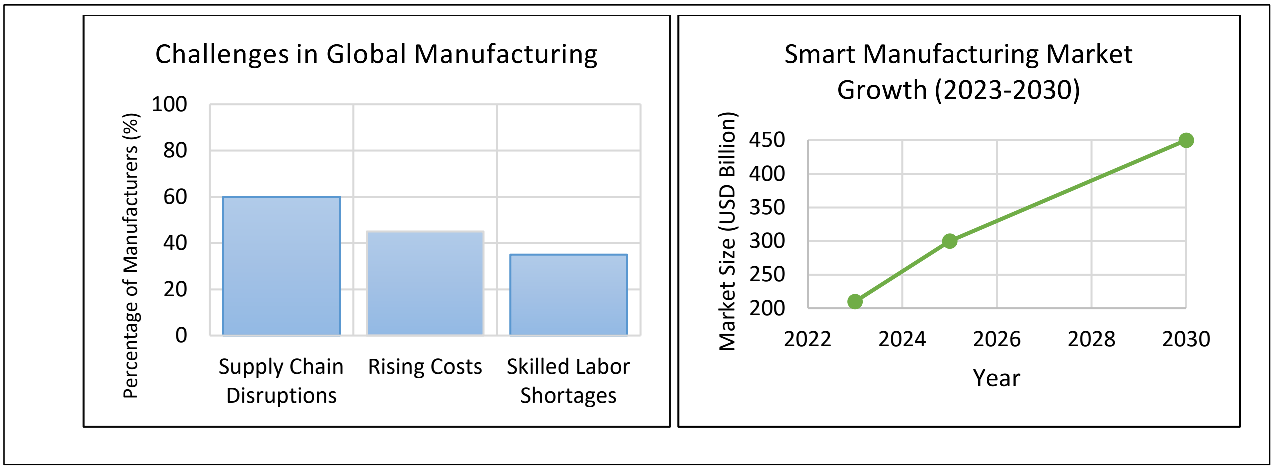

Figure 1. Challenges in Global Manufacturing and Projected Growth of Smart Manufacturing (2023-2030) (Adapted from Hu et al. (2024))

Manufacturers face serious difficulties stemming from issues such as supply chain interruptions (in 60 percent of cases), increasing costs (45 percent), and deficient skilled workers (30 percent) (Hu et al., 2024), as shown in Figure 1. All of these problems emphasize the fact that new strategies like smart manufacturing must be implemented to solve these problems using new technologies such as automation and digital twins (Stefán, 2023). Aside from that, a significant part of Figure 1 focuses on the expected evolution of the smart manufacturing industry, which will increase from 250 billion US dollars in 2023 to more than 450 billion US dollars in 2030. Such a trend suggests a paradigm shift in the global landscape of manufacturing in industries with the further advancement of Industry 4.0 tools and systems that are reliable, effective, and environmentally friendly (Sahoo and Lo, 2022).

The trajectories for reaching competitiveness on a global scale of smart manufacturing coincide with an important milestone which is the complete change from localized invention to global application. These findings make it evident that local innovation is key in putting nations on the map and driving progress around the globe, and thus they can set new markers of manufacturing industrial competitiveness for the world (Wu et al., 2021). The fulfillment of this declaration is reliant on ensuring that a diverse set of barriers are cleared, for example, infrastructure gaps, technical imbalances, and skill gaps among labor (Li and Malerba, 2024). Hence, dealing with such multifaceted problems becomes critical to growing the global footprint of smart manufacturing companies (Zhou et al., 2023).

The existing gaps in research such as globalization strategies which tend to bring in smart manufacturing together still seem to focus on specific areas rather (Qayyum et al., 2024). Anyhow, the overall integration of smart manufacturing firms into the economies of developing nations has still not been extensively researched (Li and Malerba, 2024). This study delves into the smart manufacturing industry's remarkable metamorphosis from local powerhouse to global contender, unearthing the strategic blueprints and innovative practices that pave the path to international success. This manuscript highlights the economic and sustainable benefits for the policymakers of the local manufacturing industry by tackling identified obstacles and incorporating CSFs. Several studies have explored CSFs and challenges in smart manufacturing, focusing on Indian contexts. Shukla and Shankar (2024) highlighted technological readiness and management commitment as crucial for adopting smart manufacturing in Indian SMEs. However, they did not extensively address the critical role of information integration in achieving Industry 4.0 adoption. These studies typically use traditional methodologies like AHP or DEA independently. AHP requires precise pairwise comparisons, making it highly sensitive to inconsistencies and unsuitable for handling vague or ambiguous information (Menekşe and Camgöz Akdağ, 2022). Similarly, DEA, though effective in evaluating efficiency, operates solely with crisp input and output values, limiting its ability to accommodate the variability and imprecision often present in real-world scenarios (Nguyen et al., 2022). This manuscript introduces a novel hybrid approach combining Interval-Valued Spherical Fuzzy Sets (IVSFS), AHP, and DEA, which has never been applied before in this context. The IVSFS-AHP method enhances decision-making under uncertainty, while DEA evaluates relative efficiency, bridging methodological gaps in existing literature. By applying this unique framework, this study provides actionable insights to strengthen India's global manufacturing competitiveness. The explanation of this transformative process can be achieved by addressing the following research questions.

- How does smart manufacturing impact the overall manufacturing sector in developing countries, and what challenges does the manufacturer face in adopting new technologies?
- What are the most influential CSFs for surmounting these obstacles, and how significant is their interrelation?
- How can smart manufacturing pave the way for manufacturers of developing countries to conquer the global stage, despite the obstacles and complexities they face?

The paper seeks to address the aforementioned questions by accomplishing the following research objectives:

- To identify the obstacles that prevent local manufacturers from taking part in the global expansion of smart manufacturing.
- To identify the most effective and dependable CSFs to overcome these obstacles.
- To gauge the efficiency of prospective CSFs to overcome these obstacles.

To meet our research objectives, this manuscript utilizes a hybrid multi-criteria decision-making (MCDM) framework named IVSFs-AHP with DEA. This integrated methodology helps create a hierarchical model organized with the main goal. This procedure can identify and address constraints from start to finish and use performance analysis to rank the CSFs based on their relative efficiencies.

This paper is organized into distinct sections, each addressing a critical aspect of the study. Section 2 presents the literature review, providing an in-depth analysis of the challenges within the smart manufacturing landscape and identifying key research gaps. Section 3 introduces a case study focusing on India's mobile phone manufacturing sector, illustrating the practical relevance of the research. Section 4 describes the research methodology and explains the application of the proposed hybrid framework integrating IVSFs, AHP, and DEA. Section 5 provides a detailed analysis of the results, highlighting significant findings. Section 6 discusses the findings in the context of global manufacturing challenges and opportunities. Section 7 outlines the practical and theoretical implications of the study. Finally, Section 8 concludes the paper, by summarizing the key insights, acknowledging limitations, and suggesting directions for future research.

2. Literature review

Smart manufacturing introduces advanced technologies that enhance productivity, facilitating easier access for businesses in developing countries to global markets (Kasmad, 2022). It establishes a direct link between customer retention and key performance metrics, encompassing financial profitability and corporate valuation (Zimmermann et al., 2021). Recognizing and integrating cultural nuances into product adaptation is a CSFs for companies aiming for global expansion (Chaudhuri et al., 2021). This is exemplified by global giants like McDonald's, which successfully introduced the Mala Grilled Chicken Sandwich in China, tailoring it to local preferences (Ahmad et al., 2020). Such localization efforts involve incorporating indigenous ingredients and flavors to resonate with regional tastes (Shaw et al., 2020). Smart manufacturers must therefore develop a deep understanding of diverse consumer preferences and local regulations to create products that both adhere to global standards and appeal to local sensibilities (Roudometof, 2023).

In light of expanding to international markets, it is essential to consider approaches that suit consumer needs. One effective approach to be able to grow regional markets is through the establishment of local production sites. The significance of localized smart manufacturing technology is not confined to the aforementioned sectors; in other sectors of the world, it also marks further industrial change. In the automobile manufacturing sector, the versatility of smart manufacturing is illustrated by the flexible production techniques of "Auto Global Inc." in response to ever-changing market conditions and the introduction of new technologies (Adhikari and Roy, 2024). This adaptability not only increases efficiency but also helps in reinforcing a strong international presence in the market. Further, AI-powered decision-making enhances manufacturing ability and maintains quality across different geographical locations.

National policies on smart manufacturing vary significantly, reflecting diverse priorities and economic contexts. For instance, in Germany's Industry 4.0 Framework for Industry 4.0, collaboration between the government and industry pushes for the establishment of innovation clusters and includes the integration of IoT and AI technologies into the manufacturing industry (Bhagwan and Evans, 2023). In contrast, As per the '*Made in China 2025*' strategy, it is evident that the country is making great strides in boosting local automation and robotics innovation with a priority on reducing the technology dependence on other nations (Li and Branstetter, 2024). Similarly, the United States "Manufacturing USA program" where investments are made in joint public-private initiatives intended to facilitate transferring technology and providing training to the advanced industry (Shokouhyar et al., 2022). In the case of India, foreign direct investment is being actively encouraged while at the same time, the Make in India campaign is meant to foster the adoption of smart metering among SMEs (Shang and Chiu, 2023). All of the above-mentioned strategies alone show a nation's target policy focus to aspire for innovation, solve existing impediments, and develop the manufacturing sector of a country sustainably.

Building on this, strategic localization by Xiaomi in the Indian mobile phone market shows its ability to adjust the product mix to the preferences of the target audience (Roudometof, 2023). Thus, smart manufacturing methods have enabled some aspects of design and features to be adjusted to different societies quickly while controlling production attention has been directed at efficient sourcing of components and improvement of the processes. Through this strategy, the Xiaomi 3 is reported to have significantly increased its share in the global market (Bucknell Bossen and Kottasz, 2020, Lu and Menezes, 2024). Thus, these works illustrate the important role of smart manufacturing: how global strategic expansion can be combined with local adaptation so that a company can reach leadership positions across several markets. Previous studies on smart manufacturing focus on technological advancements like IoT and AI While several works highlight the transformative potential of Industry 4.0, the practical challenges in resource-constrained settings are frequently overlooked (Narkhede et al., 2024) or emphasize global competitiveness factors such as supply chain integration and compliance (Christopher, 2016). However, they stop short of connecting these domains in a unified framework. My study picks up by bridging this gap, using a combined IVSFs AHP-DEA methodology to rank critical success factors, validating them with sensitivity analysis, and linking smart manufacturing strategies directly to global competitiveness benchmarks.

The literature review reveals that globalization and the manufacturing sector in developing countries have traditionally been examined as distinct entities. However, a combined analysis of these two dimensions reveals the potential for revolutionary change within the smart manufacturing landscape. Consequently, this manuscript seeks to identify and analyze the obstacles impeding the global expansion of industries utilizing smart manufacturing. The subsequent section employs a Systematic Literature Review (SLR) to achieve this objective, which the expert group further validates. SLR, as shown in Figure 2, focuses on understanding the role of smart manufacturing in the transition toward global existence. It involves a comprehensive and methodical analysis of existing literature, with the selection of ninety-three relevant articles. It further specifies inclusion and exclusion criteria for study selection and employs targeted databases and keywords to execute the literature search. The SLR effectively summarizes how smart manufacturing interrelates with success towards global expansion.

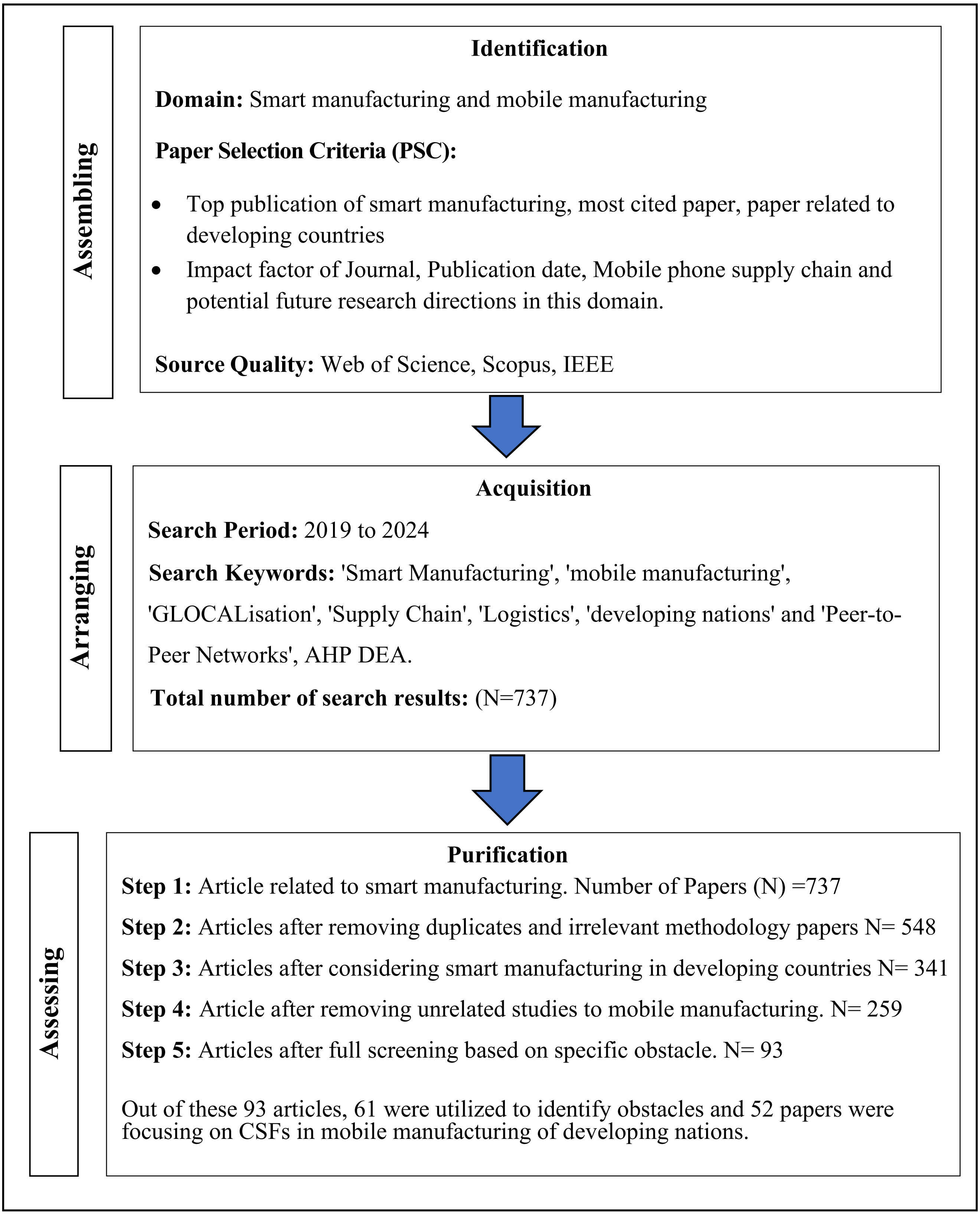

Figure 2: Systematic literature review methodological framework (Created by authors)

This research examines pathways to global success in smart manufacturing, focusing on the challenges faced by developing countries. Initial analysis identified 30 potential obstacles to smart manufacturing implementation. Through expert consultation and literature review, this was refined to 22 obstacles specific to the mobile manufacturing industry. This focus on mobile manufacturing highlights the importance of emerging mobile technologies for enhancing efficiency and competitiveness in the global tech trend.

Table 1: Obstacles for local companies incorporating smart manufacturing technologies

Category	Obstacles of smart manufacturing	References
Technical	Integration of legacy systems with new technologies	(Mahmoodi et al., 2024) (Kim et al., 2023)
	Cybersecurity threats and vulnerabilities	(Mardanya et al., 2022) (Yang et al., 2023)
	Lack of standardization across platforms and devices	(De Matos et al., 2023) (Fathi et al., 2022)
	High costs associated with implementing smart technologies	(Ignatov, 2018) (Buran and Erçek, 2022)
	Data management and analysis complexities	(Fathi et al., 2022) (Mahmoodi et al., 2024)
	Rapid technological obsolescence	(Kou et al., 2021) (Bachir et al., 2019)
	Challenges in IoT device connectivity and management	(Fathi et al., 2022) (Yang et al., 2023)
Organizational	Resistance to change among employees	(Malagihal, 2021) (Lim et al., 2023)
	Lack of clear strategy for digital transformation	(Beikmirza et al., 2023) (Bachir et al., 2019)
	Insufficient collaboration between IT and operations	(Abonyi et al., 2024) (Witt, 2019)
	Difficulty in scaling smart manufacturing solutions	(Ledro et al., 2022) (Abonyi et al., 2024)
	Intellectual property concerns in a collaborative arena	(Kou et al., 2021) (Mahmoodi et al., 2024)
	Alignment of smart manufacturing initiatives with overall business goals	(Beikmirza et al., 2023) (Lim et al., 2023)
Economic	Limited access to financing for technology upgrades	(Kocsis and Xydis, 2019) (Fathi et al., 2022)
	Uncertain return on investment for smart manufacturing initiatives	(Abonyi et al., 2024) (Witt, 2019)
	Economic fluctuations impacting investment decisions	(De Matos et al., 2023) (Bachir et al., 2019)
	Cost of training employees on new technologies	(Goodarzian et al., 2020) (Fathi et al., 2022)
	Competition from companies in countries with lower labor costs	(Lim et al., 2023) (Kou et al., 2021)
	High upfront costs of smart technology adoption	(Mahmoodi et al., 2024) (Malagihal, 2021)
Regulatory	Compliance with evolving industry standards and regulations	(Yang et al., 2023) (Witt, 2019)
	Data privacy laws and regulations affecting data usage	(Kim et al., 2023) (Kou et al., 2021)
	Environmental regulations impacting manufacturing processes	(Fathi et al., 2022) (De Matos et al., 2023)

	Export controls and trade barriers affecting global supply chains	(Abonyi et al., 2024) (Yang et al., 2023)
	Safety standards for workplace and product safety	(Yang et al., 2023) (Bachir et al., 2019)
	Regulatory uncertainty in emerging technology fields	(Mahmoodi et al., 2024) (Witt, 2019)
Labour-related	Skill gaps in the workforce for operating smart technologies	(Buran and Erçek, 2022) (Bachir et al., 2019)
	The aging workforce and challenges in attracting younger talent	(Fathi et al., 2022) (Malagihal, 2021)
	Need for continuous learning and development programs	(Yang et al., 2023) (Bachir et al., 2019)
	Cultural barriers to adopting new work practices	(Lim et al., 2023) (Goodarzian et al., 2020)
	Managing workforce transitions and job displacements due to automation	(Kim et al., 2023) (Fathi et al., 2022)

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2.2. Research Gap

- The interaction of global processes and local context in India and its relation to the smart manufacturing process diffusion in the developing world is still less studied. However previous research has called for greater contextual studies in developing economies without offering much about the scenarios in these nations (Arcidiacono and Schupp, 2024).
- The current body of literature inclines to focus more on the expected advantages of smart manufacturing and to pay little if any, attention to the difficulties encountered by manufacturers in developing countries. Although some of the works underline the potential of Industry 4.0 to change the economics, implications of resource-constrained settings are at times not addressed (Narkhede et al., 2024).
- Some critical success factors have already been established, but further research is needed to ascertain the actual relationships between the CSFs and the contributing factors to the smooth transition to smart manufacturing. For instance, much has been done to categorize CSFs, but little has been done to determine their interrelationships concerning barriers to adoption in developing countries (Malaga and Vinodh, 2021).
- The Indian industrial sector is like a hybrid which is quite recent to the literature on smart manufacturing. While The discourse of smart manufacturing is global, it appears that the Indian context and associated problems are of a special nature, which the existing research does not fully encompass (Kumar et al., 2024).

3. Case Application – India's Mobile Phone Manufacturing Sector

India is a vibrant country with a rapidly changing smart manufacturing industry and an exciting case of mobile manufacturing. In the last 12 years, the mobile industry has grown at a pace of 2000%, which shows that the sector has the potential to act as a model for other industries (Dutta et al., 2024). The mobile manufacturing sector presents the Indian approach toward technology and how most manufacturers face challenges and opportunities created with the shift of smart manufacturing on the global stage. The focus on mobile production is needed in developing countries as it contributes a significant portion of the manufacturing budget. Mobile manufacturing is the best example to consider because it includes a high level of technology and a core understanding of the supply chain across continents. India has 800 million active users of mobile phones, showing the huge market potential (Lim et al., 2023). The mobile manufacturer was previously dependent on assembly-based production which is now pushed by smart manufacturing principles and exemplifying the aspiration of the nation (Makaya et al., 2023). This transformation is surprising because emerging economies have gone from conventional production to directly jumping on advanced technology like the Internet of Things, AI, and digital twins. The mobile industry is not just about production. It is also about the consumer connection with innovation in product variation and process differentiation (Shokouhyar et al., 2022). Now, the Indian manufacturer is incorporating smart technology in its production to become more competitive on a global scale.

The Indian government has launched new incentive packages such as ‘Make in India’, ‘Production Link Scheme’, and ‘SAMARTH Udyog Bharat 4.0’ to promote the setting up of domestic manufacturing bases which will produce components that are utilized in mobile handsets (Shang and Chiu, 2023). With the aforementioned initiatives, it is expected that the extent of value addition by India in the business of manufacturing mobile phones will grow from the current 15% to between 25 and 30% in the next seven years (Mehrotra, 2020). Those efforts combined with the new incentive package that the government is going to roll out, are likely to help India establish itself as a stronghold for mobile pitch manufacturers who want to go global and act local at the same time, which is very important. This smart manufacturing journey is more than just a transformation in technology, it’s a cultural, tactical, and technical evolution that requires major investment into acquiring the right knowledge and expertise on smart manufacturing (Goswami and Daultani, 2022). The case study of India’s mobile assembly industry will highlight the effect smart manufacturing has on emerging economies and the associated policy, market, and innovation changes. It serves as an excellent example for other developing countries seeking to utilize smart manufacturing to achieve economic growth and enhance their global competitiveness.

3.1. Obstacles affecting local-to-global mobile manufacturing sectors

The obstacles to implementing smart manufacturing (as shown in Table 1) apply to a wide range of industries. Therefore, this study focuses specifically on these industry-specific obstacles that mobile manufacturers face when expanding globally through the implementation of smart manufacturing. These factors were identified through extensive SLR and expert consultation.

3.1.1. Technological obstacles

This section details the technological obstacles that affect mobile phone manufacturing on a global scale. The study focuses on the engineering and developmental obstacles to mobile phone manufacturing as shown in Table 2. The study focuses on identifying key technological obstacles using the keywords "technology integration", "innovation constraints", and "digital infrastructure challenges" in academic databases such as Google Scholar and Web of Science.

Table 2: Technological Obstacles

Code	Obstacle	Obstacle Effect	References
T1	Delayed Implementation of Emerging Trends	• The swift adoption of 4G LTE technology by Chinese companies, led to high-quality, cost-effective cell phones. • Indian brands' failure to recognize and adapt to the 4G trend.	(Abate et al., 2020) (Pierson et al., 2016)
T2	Foreign OEMs Undervalued	• Indian companies initially underestimated the market impact of Chinese OEMs. • Failure to prioritize timely establishment of production facilities. • Recognition of strategic misjudgment only after significant market losses.	(Ghosh et al., 2021) (Ignatov, 2018)
T3	Complexity in Carrier Aggregation	• The complex task of adapting to a multitude of band combinations and augmenting handset radiofrequency channels is a necessity stemming from the global diversity in spectrum allocation. • The requirement for operators to integrate up to five carriers, • is a process essential for achieving data transmission rates surpassing 300 Mbps and offering bandwidth capacities over 40MHz.	(Mardanya et al., 2022) (Kou et al., 2021)
T4	Poor Choice of Antenna Architecture	• Shift towards uplink carrier aggregation for broader frequency band coverage, driven by the surge in real-time uploads. • Bandwidth limitations inherent in Time Division Duplex (TDD) systems, China has resorted to intra-band solutions, necessitating the deployment of power amplifiers (PAs) characterized by high linearity.	(Gupta and Mittal, 2023) (Kim et al., 2023) (Rodriguez et al., 2019)
T5	Challenges in Power Output Control	• Envelope Tracking (ET) technology, once a standard for enhancing battery life and LTE network coverage, now presents significant implementation challenges for local and mid-tier phone manufacturers. • Devices equipped with Class 2 power functions require the integration of filters with high linearity and low loss characteristics, which are essential to minimize gearbox losses and ensure effective heat dissipation. • The lack of such advanced technological measures in local mobile phones has led to an increased risk of overheating, necessitating the adoption of stringent quality control protocols.	(Kou et al., 2021) (De Matos et al., 2023)

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3.1.2. Operational obstacles

This section scrutinizes previous research findings in the MPSC. The study identifies operational challenges as critical obstacles (shown in Table 3) using keywords such as 'supply chain efficiency', 'logistics management', and 'production bottlenecks' in databases like “Dimensions” and “Lens.org”.

Table 3: Operational obstacles

Code	Obstacle Name	Obstacle Effect	References
O1	Cost Reduction in CBU vs. Local Manufacturing	• The cost gap between importing Completely Built-up Units (CBUs) and local manufacturing has led to a significant increase in CBU imports in India, often through facilitated agreements. • This trend results in lower costs for imported phones in India compared to international markets, posing a considerable threat to domestic handset manufacturers.	(Bachir et al., 2019) (Rodriguez et al., 2019) (Shokouhyar et al., 2022)
O2	Challenge of the Expanding Capabilities of Mid-Tier Smartphones	• Chinese manufacturers have swiftly captured a significant share of the global mobile phone market with their mid-range smartphones. • Indian domestic manufacturers are limiting their model range due to difficulties in meeting demand. • There is a growing trend towards integrating mid-range smartphone radio frequency front ends, RF Flex, to cut costs while retaining design customization capabilities.	(Li et al., 2018) De Campos et al., 2020)
O3	Pursuit for Higher Gigabit Speeds	• Achieving gigabit speeds in cell phones introduces a new level of complexity in radio frequency (RF), challenging for manufacturers with limited advanced skills. • Modern RFFEs need to provide high linearity and efficiency, along with integrating multiple features. • RF complexity escalates, and manufacturers are increasingly dependent on specialized RFFE vendors for compliant, integrated solutions.	(Gupta and Mittal, 2023) (Abate et al., 2020)
O4	Reliance on Imported Products	• The share of mobile communication hardware in the national import portfolio has risen to 26.4%. • Imports have grown from 64.3% in 2012–13 to 79.4% in 2020–21. • less value creation, due to heavy dependence on imported products.	(Malagihal, 2021) (Nguyen et al., 2022)
O5	The Reverse Logistics Dilemma	• Indian mobile manufacturers face challenges due to the underutilization of reverse logistics (RL), leading to inventory stagnation and resource wastage.	(Beikmirza et al., 2023) (Leramo et al., 2022) (Goswami and Daultani, 2022)

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3.1.3. Government policy and regulations obstacles

This section delves into Government Policy and Regulations Obstacles (shown in Table 4) in the MPSC, identified as critical obstacles in prior research. Utilizing keywords like 'regulatory impact', 'policy constraints, and 'government legislation' in search engines such as "Science.gov" and "ERIC", the study examines how these obstacles affect smart manufacturing efficiency and growth, to provide strategic insights for operating within these regulatory frameworks.

Table 4: Government policy and regulations

Code	Obstacle name	Obstacle effect	References
G1	Drawbacks of Phased Manufacturing Program	• Increase in import taxes on specific mobile parts in India by 2022, including display components and motors. • Government tax initiatives stress the need for a robust local ecosystem for effective policy implementation.	(Robustelli et al., 2019) (Yang et al., 2023)
G2	Undesirable Effects of SEZs	• Despite the development of production facilities under the "Make in India" initiative, duty-free SEZ-to-DTA sales may unfairly advantage SEZ-based companies, distorting the competitive landscape.	(Abate et al., 2020) (Lim et al., 2023) (Fathi et al., 2022)
G3	Misusing Export Privileges	• Export Oriented Units moving products to DTAs without equivalent tariffs are seen as inequitable. • Government support is needed to ensure fairness amidst 'Make in India' local smartphone production	(Malagihal, 2021) (Bortoloti et al., 2022) (Li et al., 2022)
G4	Vendor Impediments	• Advocacy for delaying import taxes on foreign 5G gear, citing superior performance over domestic components. • Without changes, India faces the risk of falling behind in 5G technology compared to developed countries.	(Yang et al., 2023) (Li et al., 2018)
G5	Stagnant Regulatory Framework	• Indian telecom authorities push for reforms to attract foreign investment, lacking equivalent tax incentives for domestic manufacturers. • This imbalance gives foreign companies a competitive edge over local mobile manufacturing firms.	(Bucknell Bossen and Kottasz, 2020)

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3.1.4. Environmental obstacles

This sub-section investigates Environmental Obstacles in the smart manufacturing implementation (shown in Table 5), a critical area highlighted by previous studies. Focusing on keywords such as ' Waste Generation ', 'e-waste management', and 'green manufacturing' in academic databases, the research seeks to understand the environmental challenges impacting the manufacturing sector, aiming to offer solutions for more sustainable and eco-friendly practices.

Table 5: Environmental obstacles

Code	Obstacle Name	Obstacle Effect	References
E1	Obstacles in Segregating Components	• Developing nations' firms struggle with developed countries' environmental laws on phone component recovery. • Inadequate E-waste regulations result in unsafe handling.	(Robustelli et al., 2019) (Lim et al., 2023) (Imran et al., 2023)
E2	Faulty Collection Systems	• Poor e-waste collection practices in some countries. • Negative environmental impact tarnishes mobile manufacturers' image. • Leads to protests and possible bans on companies.	(Kou et al., 2022) (Witt, 2019)
E3	Recycling Plastic Conundrums	• Mobile phone plastics, containing harmful compounds, impede eco-certifications. • Challenges in reuse and waste management for developing country firms.	(Bachir et al., 2019) (Kim et al., 2023)
E4	Neuronal Damage Due to Electronic Waste	• Mobile phones' diverse materials, including hazardous elements, pose neurological risks.	(Buran and Erçek, 2022) (Wu et al., 2021)

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3.1.5. Knowledge and behavioral obstacles

This sub-section unravels the intricate tapestry of Knowledge and Behavioral Obstacles (shown in Table 6) within the MPSC. Guided by a search for nuanced terms like 'knowledge gaps', 'behavioral dynamics', and 'organizational learning' in scholarly databases, this exploration delves into the less-charted cognitive and behavioral terrains that significantly shape the MPSC's landscape.

Table 6: Knowledge and behavioral obstacles

Code	Obstacle Name	Obstacle Effect	References
K1	Chinese Players' Supremacy	• Chinese brands held 57% of the Indian mobile market in early 2021. • Indian firms lag due to limited exposure and weaker promotion strategies.	(Witt, 2019) (Abate et al., 2020) (Luo, 2021)
K2	Scarcity of Specialized Applications	• lack of domestically tailored applications. • Challenges local manufacturers to improve device usability.	(Fathi et al., 2022) (Rajabpour et al., 2022, Shaw et al., 2020)
K3	Cost Troubles	• High mobile device costs in developing economies deter consumers. • Local manufacturers need cost-efficient innovations to stay competitive.	(Bachir et al., 2019) (Bortoloti et al., 2022) (Vijh et al., 2020)

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3.2. Critical Success Factors (CSFs) for Local Manufacturers to Go Global

The CSFs identified in this research are strategically tailored to mitigate the obstacles encountered by the mobile phone sector to adopt smart manufacturing. These CSFs, derived from an exhaustive literature review, serve as pivotal solutions to the specific obstacles highlighted in the study. Some of these previous studies have shown how companies with smart manufacturing practices often experience improved brand reputation, increased market share, and greater global success (Sunny et al., 2020). The author's identification of CSFs was facilitated by a targeted keyword search encompassing terms such as 'Smart Manufacturing', 'Global Distribution', 'Government Initiatives', 'Customer Management', 'mobile manufacturing', and 'Grey Market Problem' in databases like Web of Science, IEEE, and Scopus. The selected academic papers were distinguished by their rigorous methodological approach, explicitly identifying both obstacles and CSFs in smart manufacturing. The alignment of CSFs with the obstacles not only provides a targeted approach to overcoming obstacles but also underscores the practical applicability of this research. By focusing on the twelve most pertinent CSFs (as shown in Table 7), the paper offers a strategic roadmap for mobile manufacturers in emerging economies, guiding them toward achieving global success despite the prevalent obstacles.

Table 7: CSFs for mobile manufacturers utilizing smart manufacturing to go global

Code	CSF Name	CSF Effect	References
CSF 1	Intelligent Manufacturing	• Collaboration among local manufacturers, suppliers, and stakeholders. • Targets optimal design and radiation mitigation • Engages government and financial entities • The automotive industry utilizes intelligent manufacturing for predictive maintenance, where BMW implemented AI-based systems that reduced unplanned downtime by 20% and improved vehicle assembly precision.	(Yang et al., 2023) (Zheng et al., 2018)
CSF 2	Context-aware Computing	• focus on personalized user experiences through perceptive computing. • Data collection enhances global market competitiveness • Aids in production optimization and supply chain efficiency • Siemens Smart Factory uses context-aware computing to dynamically adjust robotic assembly lines based on real-time production bottlenecks, achieving a 15% reduction in cycle time.	(De Matos et al., 2023) (Farahbakhsh et al., 2021)
CSF 3	Stop grey marketing of products	• RFID tag integration combats grey market challenges in manufacturing. • Protects revenues, brand integrity, and intellectual property. • Bolster's global competitiveness of regional mobile manufacturers. • Samsung combats grey marketing using blockchain to track products across global supply chains, reducing counterfeit issues by 30%.	(Rajak et al., 2022) (Finlay et al., 2022)

CSF 4	Multiple Carrier Aggregation	• Local manufacturers are encouraged to adopt this technology for competitive parity. • Aims to enhance resource allocation across multiple carriers. • Ensures minimum quality of service for subscribers based on priority. • Foxconn leverages carrier aggregation to manage seamless communication between IoT devices across multiple production facilities, enabling faster response times and uninterrupted operations.	(Beikmirza et al., 2023) (Kim et al., 2023)
CSF 5	Impartialness in OEM's country of origin	• The manufacturer's location impacts value capture and supplier network design. • Localized R&D gives domestic firms a global supply chain advantage. • Anonymizing manufacturer origin in supplier talks reduces national bias. • Apple ensures impartial sourcing by engaging with multiple OEMs from China, India, and Vietnam, fostering competitive pricing and reducing dependency on a single country.	(Turienzo and Lampón, 2022) (Trejos et al., 2020)
CSF 6	Customer management	• Focus on customer service and online presence. • Customer retention is key to global expansion. • Market share through unique offers • GE's Additive Manufacturing division employs customer feedback data to customize 3D-printed components, reducing order errors by 25% and improving satisfaction.	(Hilton et al., 2020) (Ledro et al., 2022)
CSF 7	Establish a global distribution network	• Global expansion for local mobile companies via strong distribution networks. • Enhances logistics efficiency and customization ease. • Growth exemplifies robust distribution network benefits. • Amazon Robotics uses automated warehouses combined with a global distribution network to enable same-day delivery, setting a benchmark in smart logistics.	(Aguado et al., 2019) (Sunny et al., 2020)
CSF 8	Utilize Strategic Partnerships	• Global companies leverage multi-firm collaborations for growth. • Partnerships enhance distribution, technical strength, and resource access. • Microsoft-Huawei collaboration on Windows Phone is a successful example.	(Musa et al., 2019) (Yan and Huang, 2022)

		• Boeing collaborates with tech companies like NVIDIA to implement AI-driven production lines, resulting in 20% faster assembly times for aircraft.	
CSF 9	Government support	• Emphasis on research and development and human resource deployment Creates an environment conducive to market entry. • Elevating global competitiveness. • Infrastructure improvement, and strategic trade agreements. • Germany's Industry 4.0 initiative provided grants to SMEs for smart manufacturing adoption, increasing digitization rates in manufacturing by 50%.	(Muñoz et al., 2021) (Chen et al., 2021)
CSF 10	Compliance with international standards	• International standards boost customer trust. • Cultural sensitivity enhances global customer relations. Product flexibility and increased brand loyalty in diverse markets. • Siemens complies with ISO 50001 energy standards, enhancing energy efficiency by 15%, which helps secure contracts in environmentally conscious markets.	(Leramo et al., 2022) (Van Der Valk et al., 2020)
CSF 11	Development of Resilient supply chain	• Flexible supply chains adapt to changing technology and user demands. Streamlining logistics is essential for global expansion. • Mobile solutions improve supply chain efficiency and risk reduction. • Enhances global demand and competitiveness. • During COVID-19, Toyota implemented digital twins to model supply chain disruptions, reducing recovery times by 50% and maintaining production schedules.	(Kamble et al., 2020) (Goodarzian et al., 2020)
CSF 12	Focus on Cost optimization	• Effective cost management in unit delivery enhances B2C business growth and profitability. • Prioritizing supply chain efficiency drives cost optimization. • Comprehensive cost analysis boosts efficiency from sourcing to delivery. • Tesla optimizes costs by vertically integrating its supply chain, allowing it to reduce battery costs by 30% while maintaining quality.	(Kocsis and Xydis, 2019) (Best et al., 2020)

*(Created by authors)

4. Research Methodology

This manuscript fills a gap in the literature by presenting the obstacles and CSFs of smart manufacturing in the context of developing countries. The keywords so searched for are discussed in Section 2 about the literature that was triangulated using the SLR approach. In section 3, building on the analysis conducted in the SLR, this study discovered thirty unique obstacles and twelve CSFs in smart manufacturing. The scope of this research narrowed the obstacles to twenty-two distinct ones due to expert interviews, SLR analysis, and brainstorming sessions regarding manufacturing in developing countries. In a similar context, the CSFs and obstacles identified above were used in the final section of this study, where MCDM methods were employed to assess the dominance and interdependence of the mentioned constraints. A spherical fuzzy set is a more innovative approach when compared to fuzzy sets since it allows the attachment of membership value and uncertainty radius to each element of the fuzzy set (Yang et al., 2019). SFS outperforms the other modeling frameworks when it comes to noise interference cum slashing outliers within fuzzy sets. SFS takes the form of a two-dimensional substructure in which each element of the SFS is associated with a radius to dampen the effect that noise has on the degree function of membership (Sarraf and Nejad, 2020). With SFS, the variability for each element is always the same. This may not correctly capture the uncertainty or the variability that existed in the data sets (Buran and Erçek, 2022). IVSF, on the other hand, does not have such restrictions allowing more elements to accommodate a diverse range of interlinked uncertainty (Yilmaz et al., 2022). This extended multi-dimensional view of uncertainty representation allows the more intricate details of uncertainty to be captured therefore enhancing the representation of the uncertain data (Khezrimotlagh et al., 2019).

Interval valued spherical fuzzy sets combined with AHP-DEA have the potential to expand the alternative performance assessment tools. Menekşe and Camgöz Akdağ (2022) synthesized AHP-DEA with the novel spherical fuzzy and computer simulation models to ascertain which manufacturing sector possessed the most robust assembly systems. The simulation models and IVSFs AHP were deployed to provide input data for the DEA. Some manuscripts also see a combination of ratio estimation using IVSFs and AHP, where AHP was utilized in combination with IVSFs for model selection with a view of determining nations' competitiveness Non-Decision Making Units (Buran and Erçek, 2022). Using IVSFs with AHP, researchers equated the performance of nations on a pair-wise basis at diverse levels (Nguyen et al., 2022). IVSF in AHP enabled researchers to assess the ranking of country performance at different levels against each other. Such an analysis provided a basis for other developing countries seeking full efficiency and contributed to measuring performance. IVSFS with AHP-DEA is a new combination resulting from little attempts and very few research scholars' endeavors. As a result, this method has a great opportunity to provide precision solutions and insight concerning complex decision-making issues.

This research presents a novel hybrid framework combining IVSFs-AHP and DEA to address obstacles and critical success factors (CSFs) for local manufacturers' global expansion in the mobile manufacturing sector through smart manufacturing. The IVSFs approach captures uncertainty and improves decision-making reliability, while DEA enables comprehensive efficiency evaluations, surpassing traditional methods DEMATEL and MICMAC. Mangla et al. (2018) used DEMATEL to examine interdependencies in supply chain resilience factors. The study highlighted its ability to uncover cause-effect relationships between factors, which are essential for strategic interventions. However, the method's reliance on precise input values limited its robustness in scenarios with inherent data ambiguity. Dube and Gawande (2016) used MICMAC to identify barriers in sustainable manufacturing, effectively categorizing challenges but struggling to capture dynamic interdependencies due to its deterministic nature. The framework benchmarks performance criteria like cost-efficiency, technological readiness, and resource allocation, aligning micro-level strategies with SDG 9's macro-level goals for sustainable industrialization. By addressing challenges in technology adoption and the interrelation of influential CSFs, this study provides actionable insights for policymakers and manufacturers to enhance global competitiveness and offers a replicable model for other sectors.

Integration of the Methodology

The combination of IVSFs, AHP, and DEA addresses the multidimensional challenges of globalization as follows:

- **Uncertainty Management**: IVSFs ensure robust decision-making in the presence of incomplete or uncertain data.
- **Priority Structuring**: AHP aligns organizational objectives with global manufacturing challenges.
- **Performance Benchmarking**: DEA identifies best practices and measures the effectiveness of CSFs in overcoming market entry barriers.

By aligning these methodologies with the specific challenges of globalization, this study provides a comprehensive decision-making framework that is both innovative and practical for global manufacturing firms.

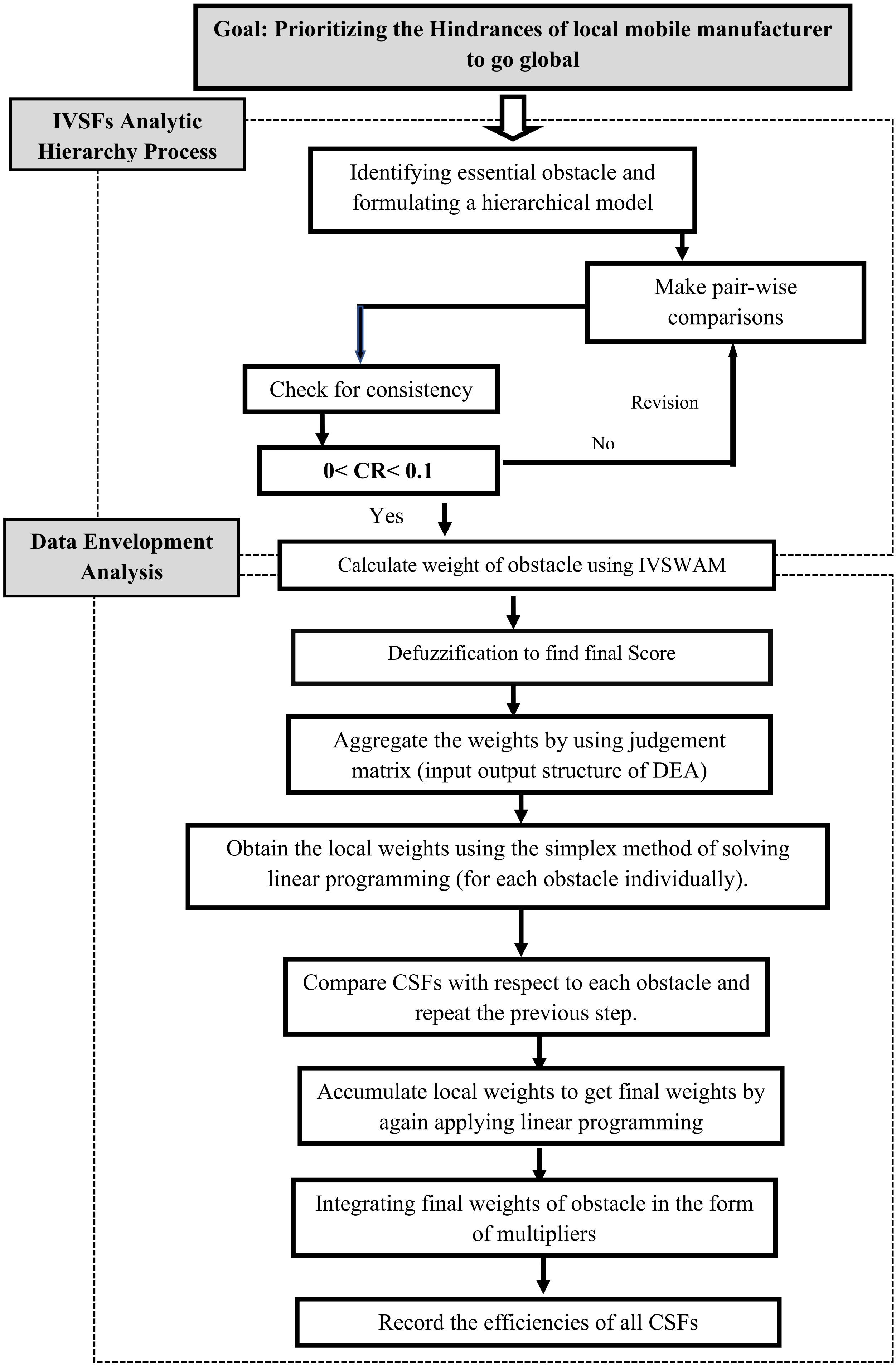

Figure 3: Flowchart of IVSFs AHP-DEA Methodology (Created by authors)

A structured framework to prioritize the problems faced by local mobile industries seeking global growth is shown in Figure 3. The analysis here begins with the application of IVSF-AHP to two aspects: identify key obstacles and devise a ranking model. A series of pairwise comparisons is conducted to fix the relative significance of the potential obstacles and then a consistency check is done where the allowable value of the consistency ratio CR is set at 0.1. The consistency in AHP guarantees the reliability and validity of the pairwise comparisons resulting in more credible and stronger decision-making outcomes. If there are inconsistencies, iterations are made to correct these inconsistencies. Once a degree of consistency is reached, the weights of the obstacles are calculated using the Average Method Weighted Spherical Valued Interval as shown in *(EQ.2),* with the results then defuzzified to obtain final values *(EQ. 3)*. These weights are then integrated into a judgment matrix incorporated in the input-output structure of DEA (*EQ. 4)*. Local weights of each barrier are then calculated using linear programming models. The process also involves analysis of dependencies of critical success factors (CSFs) against each CSF and reevaluation of the process. The local weights are then used to obtain final weights in these models through further applications of linear programming *(EQ 5)*. Lastly, these weights are combined into factors that make it possible to determine the efficiencies of all CSFs *(EQ. 7)*. This rigorous methodology provides a comprehensive and methodologically robust evaluation of the obstacles impeding global expansion and CSFs to cater to those obstacles.

4.1. Application of IVSFs AHP-DEA Method

The following section proposes the steps for the IVSFS AHP-DEA methodology, assimilating the concept of efficiency measurement for the factors and alternatives indexed above. A graphical representation of the steps to apply the proposed methodology is given in Figure 3.

Step 1. Identification of obstacles: This step comprises splitting of problem into elements based on their common specifications. The obstacle and sub-obstacle are thus identified, and a hierarchy has to be created.

Step 2. Construction of the hierarchical structure:

A hierarchical structure consisting of at least three levels is developed in this step (Fig. 2) to select the best alternative based on a score index at Level 1. obstacle $C = (C1, C2, C3 \ldots Cn)$ are shown at Level 2, and there may be several sub-obstacle for each criterion C defined at Level 3. At Level 4, a discrete set of m feasible CSFs X = ($x1, x2, \ldots\ldots xm$) ($m > 2$) is defined.

Step 3. Calculate the consistency of IVSFS judgment matrices based on the linguistic measure of importance given in Table 8.

Step 4. To assess the consistency of each pairwise comparison matrix, convert the linguistic terms to their corresponding score indices based on Table 8 and perform a classical consistency check. If the resulting Cr value is less than 10%, the crisp pairwise comparison matrix is considered consistent, and its corresponding spherical fuzzy pairwise comparison matrix can be used. For example,

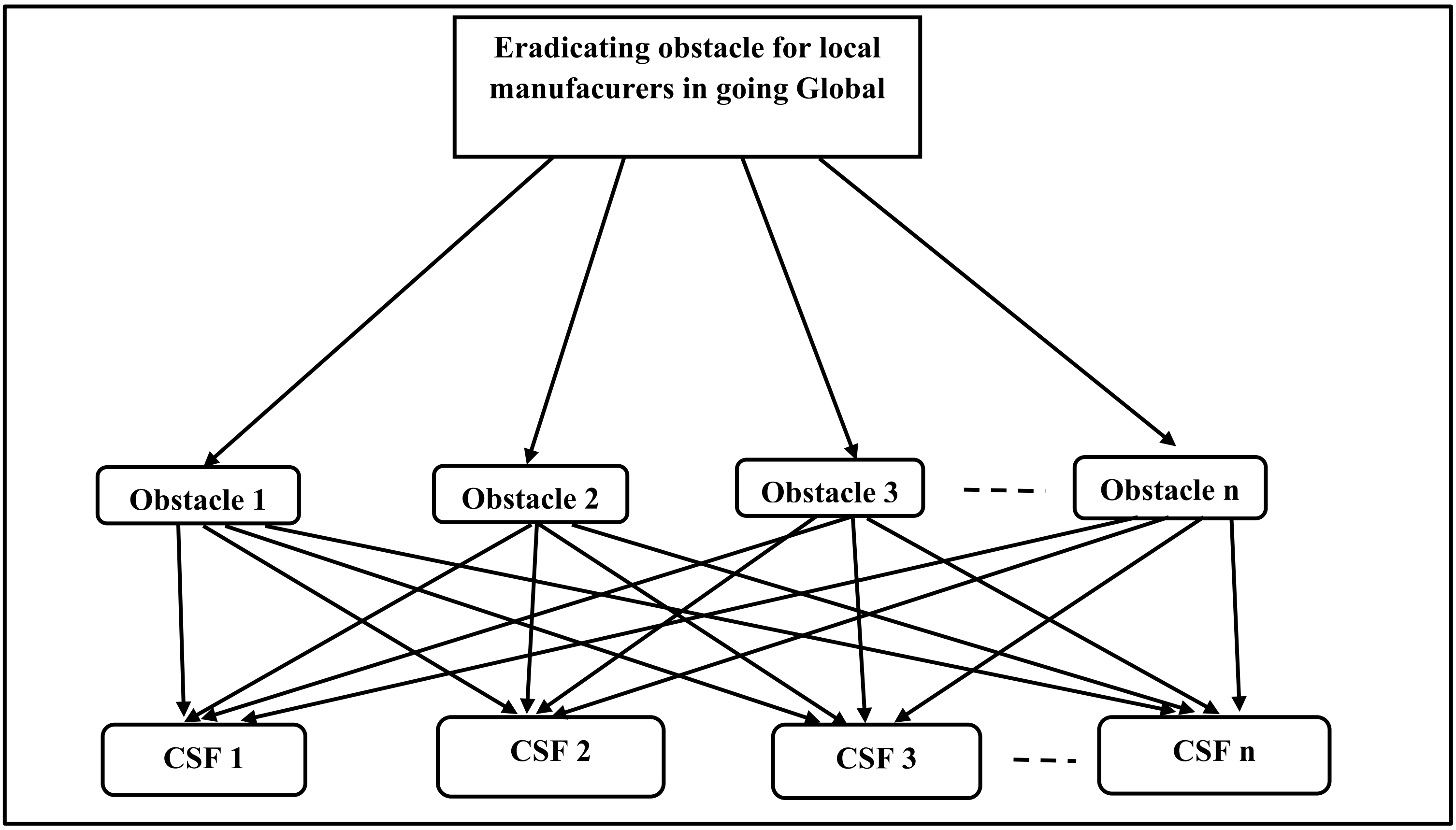

Figure 4: Hierarchical Model for IVSFs AHP-DEA Analysis (Created by authors)

Table 8: Linguistic terms used for pairwise comparisons

Linguistic Preference Scale	**Score Index**	**IVSFs** $\tilde{A}_S = \{u, ([\mu^L_{\tilde{A}_S}(u), \mu^U_{\tilde{A}_S}(u)], [v^L_{\tilde{A}_S}(u), v^U_{\tilde{A}_S}(u)], [\pi^L_{\tilde{A}_S}(u), \pi^U_{\tilde{A}_S}(u)]) \mid u \in U\}$
Absolutely more importance (AMI)	9	([0.85, 0.95], [0.10, 0.15], [0.05, 0.15])
Very high importance (VHI)	7	([0.75, 0.85], [0.15, 0.20], [0.15, 0.20])
High importance (HI)	5	([0.65, 0.75], [0.20, 0.25], [0.20, 0.25])
Slightly more importance (SMI)	3	([0.55, 0.65], [0.25, 0.30], [0.25, 0.30])
Equally importance (EI)	1	([0.50, 0.55], [0.45, 0.55], [0.30, 0.40])
Slightly low importance (SLI)	1/3	([0.25, 0.30], [0.55, 0.65], [0.25, 0.30])
Low importance (LI)	1/5	([0.20, 0.25], [0.65, 0.75], [0.20, 0.25])
Very low importance (VLI)	1/7	([0.15, 0.20], [0.75, 0.85], [0.15, 0.20])
Absolutely low importance (ALI)	1/9	([0.10, 0.15], [0.85, 0.95], [0.05, 0.15])

*(Created by authors)

Step 5. Calculate the interval-valued spherical fuzzy local weights of obstacles and CSFs.

Determine the weight of each alternative using Interval valued Spherical Weighted Arithmetic Mean (IVSWAM) operator given in Eq. (1) concerning each criterion. Where the IVSFs for any linguistic scale are defined by ([a,b], [c,d], [e,f]) (Kutlu Gündoğdu and Kahraman, 2019).

$$\text{Accuracy } (\tilde{\alpha}) = H(\tilde{\alpha}) = \frac{a^2+b^2+c^2+d^2+e^2+f^2}{2} \qquad Eq.(1)$$

The weighted arithmetic mean is used to compute the IVSF weights (Kutlu Gündoğdu and Kahraman, 2019)

$$IVSWAM_w(\tilde{\alpha}_1, \tilde{\alpha}_2 \dots, \tilde{\alpha}_n) = w_1 \cdot \tilde{\alpha}_1 \oplus w_2 \cdot \tilde{\alpha}_2 \oplus \cdots \oplus w_n \cdot \tilde{\alpha}_n$$
$$= \left\{\left[\left(1 - \prod_{j=1}^{n} \left(1 - a_j^2\right)^{w_j}\right)^{1/2}, \left(1 - \prod_{j=1}^{n} \left(1 - b_j^2\right)^{w_j}\right)^{1/2}\right],\right.$$
$$\left[\prod_{j=1}^{n} c_j^{w_j}, \prod_{j=1}^{n} d_j^{w_j}\right], \left[\left(\prod_{j=1}^{n} \left(1 - a_j^2\right)^{w_j} - \prod_{j=1}^{n} \left(1 - a_j^2 - e_j^2\right)^{w_j}\right)^{1/2},\right. \qquad Eq.(2).$$
$$\left.\left.\left(\prod_{j=1}^{n} \left(1 - b_j^2\right)^{w_j} - \prod_{j=1}^{n} \left(1 - b_j^2 - f_j^2\right)^{w_j}\right)^{\frac{1}{2}}\right]\right\}$$

where w = $1/n$.

Step 6. To obtain the final ranking orders for the CSFs, a hierarchical form is established and the interval-valued spherical fuzzy weights at each level are combined to determine the global weights. The computation is carried out from the bottom level (CSFs) to the top level (obstacle), as shown in Figure 4. There are various IVSFS-AHP approaches, and our partially IVSFS-AHP approach uses Equations (3) - (5), while our completely IVSFS-AHP approach employs Equation 7. Equation 3 uses a modified score function to defuzzify the obstacle weights, and we add 1.0 to the previous score function definition to make it more practical for spherical calculations.

$$Score\ (\overline{w}_j^s) = S(\overline{w}_j^s) = \frac{a^2+b^2-c^2-d^2-(e/2)^2-(f/2)^2}{2} + 1 \qquad Eq.(3)$$

Example: Let $\alpha_1 = \langle[0.85, 0.95], [0.1, 0.15], [0.05, 0.15]\rangle$, $\alpha_2 = \langle[0.20, 0.25], [0.65, 0.75], [0.20, 0.25]\rangle$ and $\alpha_3 = \langle[0.55, 0.65], [0.25, 0.30], [0.25, 0.30]\rangle$ be three interval-valued spherical fuzzy numbers. According to $Eq.$ (3) we have $S(\alpha_1) = 0.790$, $S(\alpha_2) = -0.467$ and $S(\alpha_3) = 0.248$. Thus, the alternative α_1 is better than others. This example indicates that the proposed score function is reasonable

Equation (4) normalizes the obstacle weights ($\overline{w}_j^s$)

$$\overline{w}_j^s = \frac{S(\tilde{w}_j^s)}{\sum_{j=1}^{n} S(\tilde{w}_j^s)} \qquad Eq.\ (4)$$

Equation (5) is used for weighting the decision matrix ($\bar{\alpha}_{S_{ij}}$) (Monika and Sangwan, 2022).

$$\bar{\alpha}_{S_{ij}} = \bar{w}_j^s \cdot \bar{\alpha}_{S_i}$$
$$= \left\{ \begin{array}{l} \left[\left(1-\left(1-a_{S_i}^2\right)^{\bar{w}_j^s}\right)^{\frac{1}{2}}, \left(1-\left(1-b_{S_i}^2\right)^{\bar{w}_j^s}\right)^{\frac{1}{2}} \right], \left[\left[c_{S_i}^{\bar{w}_j^s}, d_{S_i}^{\bar{w}_j^s} \right] \right. \\ \left[\left(\left(1-a_{S_i}^2\right)^{\bar{w}_j^s} - \left(1-a_{S_i}^2-e_{S_i}^2\right)^{\bar{w}_j^s} \right)^{\frac{1}{2}}, \left(\left(1-b_{S_i}^2\right)^{\bar{w}_j^s} - \left(1-b_{S_i}^2-f_{S_i}^2\right)^{\bar{w}_j^s} \right)^{\frac{1}{2}} \right] \end{array} \right\} \qquad Eq.(5)$$

To obtain the final spherical fuzzy AHP score for each CSF, the global preference weights ($\bar{F}$) are aggregated using the spherical fuzzy addition operator as specified in Eq. (7).

$$\bar{F} = \sum_{j=1}^{n} \bar{\alpha}_{S_{ij}} = \bar{\alpha}_{S_{i1}} \oplus \bar{\alpha}_{S_{12}} \cdots \oplus \bar{\alpha}_{S_{in}} \forall i \qquad Eq.\ (6)$$

Performance Assessment Using Interval-Valued Spherical (Monika and Sangwan, 2022)

$$\tilde{\alpha}_{S_{11}} \oplus \tilde{\alpha}_{S_{12}} =$$
$$\left\{ \begin{array}{l} \left[\begin{array}{l} \left(\left(a_{\tilde{\alpha}_{11}}\right)^2 + \left(a_{\tilde{\alpha}_{S_{12}}}\right)^2 - \left(a_{\tilde{\alpha}_{S_{11}}}\right)^2 \left(a_{\tilde{\alpha}_{S_{12}}}\right)^2 \right)^{1/2}, \\ \left(\left(b_{\tilde{\alpha}_{S_{11}}}\right)^2 + \left(b_{\tilde{\alpha}_{S_{12}}}\right)^2 - \left(b_{\tilde{\alpha}_{S_{11}}}\right)^2 \left(b_{\tilde{\alpha}_{S_{12}}}\right)^2 \right)^{1/2} \end{array} \right], \left[c_{\tilde{\alpha}_{S_{11}}} c_2, d_{\tilde{\alpha}_{S_{11}}} d_2 \right], \\ \left[\begin{array}{l} \left(\left(1-\left(a_{\tilde{\alpha}_{S_{12}}}\right)^2\right) \left(e_{\tilde{\alpha}_{S_{11}}}\right)^2 + \left(1-\left(a_{\tilde{\alpha}_{S_{11}}}\right)^2\right) \left(e_{\tilde{\alpha}_{S_{12}}}\right)^2 - \left(e_{\tilde{\alpha}_{S_{11}}}\right)^2 \left(e_{\tilde{\alpha}_{S_{12}}}\right)^2 \right)^{1/2}, \\ \left(\left(1-\left(b_{\tilde{\alpha}_{S_{12}}}\right)^2\right) \left(f_{\tilde{\alpha}_{S_{11}}}\right)^2 + \left(1-\left(b_{\tilde{\alpha}_{S_{11}}}\right)^2\right) \left(f_{\tilde{\alpha}_{S_{12}}}\right)^2 - \left(f_{\tilde{\alpha}_{S_{11}}}\right)^2 \left(f_{\tilde{\alpha}_{S_{12}}}\right)^2 \right)^{1/2} \end{array} \right] \end{array} \right\}$$

Eq.(7)

Step 7. Introduction of dummy input: In this, a column of dummy input '1' has to be introduced in the judgment matrix (Arora et al., 2022).

	Output 1	**Output 2**	**……**	**Output N**	**Dummy Input**
CSF 1	1	a_{12}	…….	a_{1N}	1
CSF 2	$1/a_{12}$	1	…….	a_{2N}	1
⋮	⋮	⋮	⋮	⋮	1
CSF N	$1/a_{1N}$	$1/a_{2N}$	…….	$1/a_{NN}$	1

Judgment Matrix

Step 8. Conversion into Linear Programming Problem: The problem is then converted into LPP and solved using the simplex method. Further, the LPP is solved using a basic CRR model (Arora et al., 2022). Where x and y are the elements of the Z function.

Considering the values for B as,

$$B = \begin{bmatrix} y11 & y12 & \dots & \dots & \dots & y1n \\ y21 & y22 & \dots & \dots & \dots & y2n \\ . & & & & & \\ . & & & & & \\ . & & & & & \\ ym1 & \dots & \dots & \dots & \dots & ymn \end{bmatrix}$$

Max $Z = y_{11}x_{11}+y_{12}x_{12}+\dots\dots+y_{1n}x_{1n}$

Subject to: $u_{11}=1$

$y_{11}x_{11}+y_{12}x_{12}+\dots\dots+y_{1n}x_{1n}-u_{11}\leq 0$

$y_{21}x_{11}+y_{22}x_{12}+\dots\dots+y_{2n}x_{1n}-u_{11}\leq 0$

Eq. (8)

$\vdots$

$y_{m1}x_{11}+y_{m2}x_{12}+\dots\dots+y_{mn}x_{1n}-u_{11}\leq 0$

$x_{11},x_{12}, \dots\dots\dots\dots x_{1n}\geq 0$

Now, the local weight of criterion C_1 is obtained.

Perform similar operations to get the local weight of all obstacles.

Step 9: Comparing CSFs *w.r.t* each Obstacle: This step involves comparing the CSFs with each other based on each obstacle. To achieve this, a set of 'n' tables is created, where 'n' represents the number of obstacles and 'm' represents the number of CSFs. Each table represents the comparison of each CSF with every other CSFs for a specific obstacle. The local weight (*Wij*) of CSF *Ai* w.r.t criterion *Cj* is determined for each of these n tables by solving a linear programming problem using the simplex method (Arora et al., 2022).

	A_1	**A_2**	**……**	**A_m**
A_1	a_{11}	a_{12}	……	a_{1m}
⋮	⋮	⋮	⋮	⋮
A_m	a_{m1}	a_{m2}	……	a_{mm}

Comparison of CSFs w.r.t C_j

$$\text{Max } Z = a_{11}z_{11}+a_{12}z_{12}+\ldots\ldots.+a_{1n}z_{1n}$$

$$\text{Subject to: } u_{11}=1$$

$$a_{11}z_{11}+a_{12}z_{12}+\ldots\ldots.+a_{1n}z_{1n}-u_{11}\leq 0$$

$$a_{21}z_{11}+a_{22}z_{12}+\ldots\ldots.+a_{2n}z_{1n}-u_{11}\leq 0 \qquad Eq. (9)$$

$$\vdots$$

$$a_{m1}z_{11}+a_{m2}z_{12}+\ldots\ldots.+a_{mn}z_{1n}-u_{11}\leq 0$$

$$z_{11},z_{12}, \ldots\ldots\ldots\ldots\ldots z_{1n}\geq 0$$

Step 10: Accumulation of local weights to get final weights: After obtaining the local weights of different CSFs based on their performance on different obstacles, a table with m rows (representing the CSFs) and n columns (representing the obstacles) can be created. The values entered in the (Wij) represent the weight of each CSF (i) relative to obstacle j. These weights will be used as outputs to evaluate the CSFs based on the obstacle. Then, the linear programming problem can be solved for each CSF using the simplex method. The resulting values for all the CSFs represent their efficiency.

	C_1	**C_2**	**C_3**	**……**	**C_n**
A_1	W_{11}	W_{12}	W_{13}	……	W_{1n}
A_2	W_{21}	W_{22}	W_{23}	……	W_{2n}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
A_m	W_{m1}	W_{m2}	W_{m3}	……	W_{mn}

Linear programming for CSFs 1 (Arora et al., 2022). Where W and V are the elements of the Z function

$$\text{Max } Z = W_{11}V_{11}+W_{12}V_{12}+\ldots\ldots.+W_{1n}V_{1n}$$

$$\text{Subject to: } u_{11}=1 \qquad Eq.\ 10$$

$$W_{11}V_{11}+W_{12}V_{12}+\ldots\ldots.+W_{1n}V_{1n}-u_{11}\leq 0$$

$$W_{21}V_{11}+W_{22}V_{12}+\ldots\ldots.+W_{2n}V_{1n}-u_{11}\leq 0$$

$$\vdots$$

$W_{m1}V_{11}+W_{m2}V_{12}+\ldots\ldots.+W_{mn}V_{1n}-u_{11}\leq 0$

$V_{11},V_{12}, \ldots, V_{1n}\geq 0$

Step 11. Applying constraints in Step 9: Considering d_1, d_2…….d_n as the obstacle local weights of respective obstacles.

$$\mathrm{V11} = \frac{\mathrm{d1}}{\mathrm{d2}}\,\mathrm{V12}$$

$$\mathrm{V11} = \frac{\mathrm{d1}}{\mathrm{d3}}\,\mathrm{V13}$$

$$\mathrm{V11} = \frac{\mathrm{d1}}{\mathrm{d4}}\,\mathrm{V14}$$

$$\mathrm{V11} = \frac{\mathrm{d1}}{\mathrm{dn}}\,\mathrm{V1n}$$

Step 12. The final value 'Z' for all the cases is calculated: Now the calculation of the efficiency of CSFs is done. By using the normal procedure involved in DEA, the aggregation is carried out and the final weight of the CSFs is then calculated. Further, the CSFs are ranked in descending order of their weights.

5. Result Analysis

This research explores how local companies that use smart manufacturing can survive and even grow in the worldwide market. Utilizing the IVSFs AHP-DEA methodology, this study intricately maps twenty-two hindering factors, each weighed against their influence on market entry and expansion. These impediments are further juxtaposed with CSFs, meticulously selected for their role in company success. The adoption of this multi-methodological approach ensures an unbiased ranking of CSFs and effectively sidesteps the 'rank-reversal' predicament often seen in traditional AHP methods. This paper thus acts as a comprehensive blueprint for market-entry optimization, laying bare both obstacles and accelerators in a local-to-global brand metamorphosis.

Table 9: Weight Classification of Obstacle

Class	Obstacle	Weights
Class I	T2	1
	T3	1
	T5	1
	O1	1
	O4	1
	G1	1
	G2	1
	G4	1
	G5	1
	K3	1
Class II	K2	0.9884

	T4	0.9571
	O2	0.9263
	O5	0.9153
	T1	0.8632
Class III	E3	0.8522
	O3	0.8519
	G3	0.8477
Class IV	K1	0.7500
	E4	0.7500
Class V	E2	0.7143
	E1	0.6143

*(Created by authors)

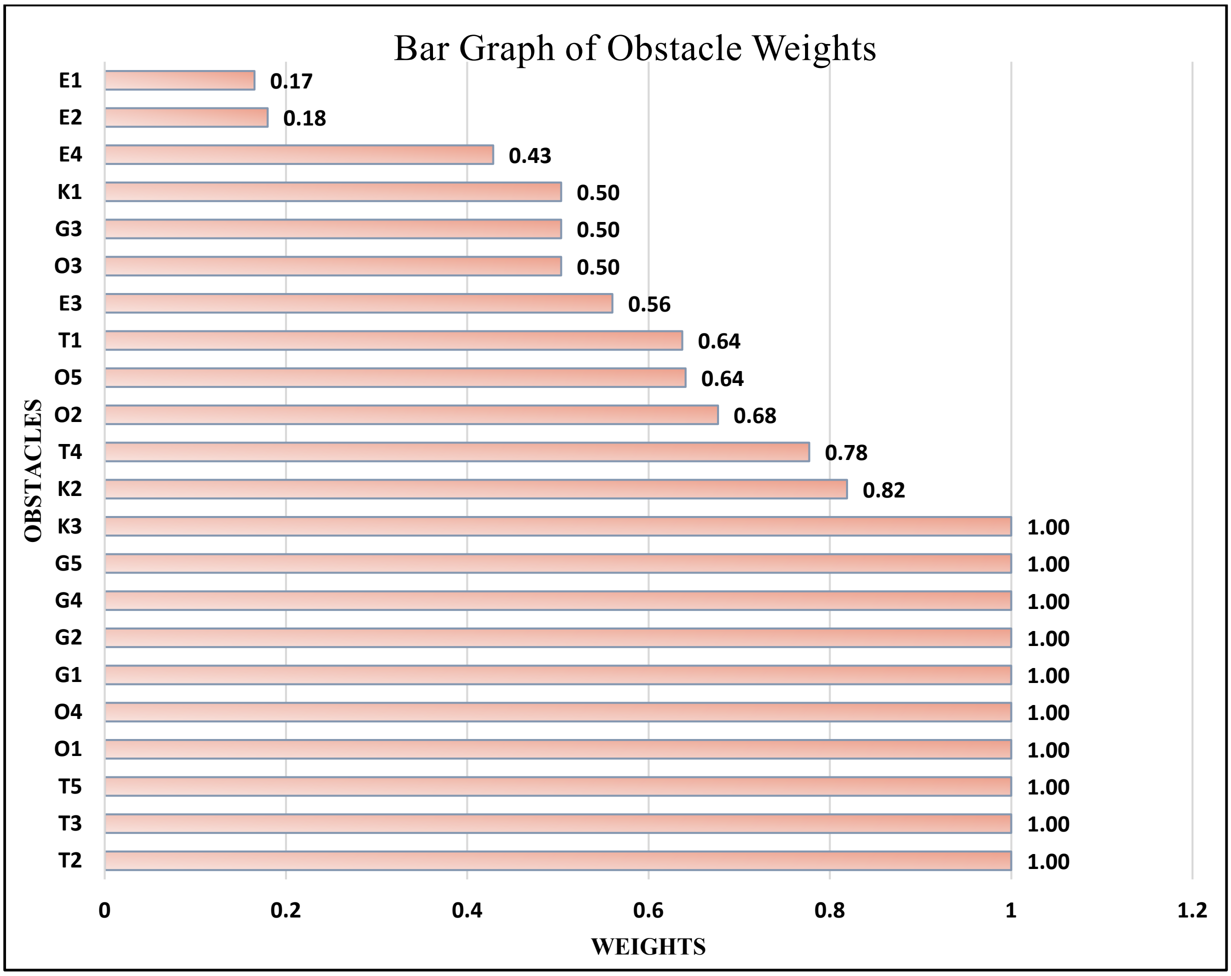

Figure 5: Local obstacle Weightage (Created by authors)

Table 10: CSF Weights per Obstacle (*(Created by authors)

	T1	T2	T3	T4	T5	O1	O2	O3	O4	O5	G1	G2	G3	G4	G5	E1	E2	E3	E4	K1	K2	K3
CSF 1	1.000	0.858	1.000	1.000	1.000	0.622	0.328	1.000	1.000	1.000	1.000	0.429	0.354	0.629	0.528	1.000	1.000	1.000	1.000	1.000	0.895	1.000
CSF 2	1.000	0.644	1.000	0.617	0.328	0.341	1.000	1.000	0.339	0.352	0.600	0.152	0.200	0.534	0.351	0.184	0.189	0.131	0.339	0.516	1.000	1.000
CSF 3	0.176	0.142	1.000	1.000	0.445	1.000	1.000	0.543	1.000	0.367	0.605	1.000	1.000	1.000	0.775	0.155	0.195	0.188	0.302	0.655	1.000	0.763
CSF 4	1.000	0.489	1.000	1.000	1.000	0.351	1.000	1.000	0.429	0.344	0.445	0.149	0.134	0.352	0.348	0.167	0.245	0.138	0.202	0.429	1.000	0.281
CSF 5	0.569	1.000	1.000	1.000	1.000	1.000	0.600	1.000	0.607	0.620	1.000	1.000	1.000	1.000	0.630	0.353	0.504	0.354	0.812	0.600	0.635	0.763
CSF 6	1.000	0.432	0.830	0.628	0.479	0.611	1.000	0.244	1.000	1.000	1.000	1.000	0.793	0.652	0.664	1.000	1.000	1.000	1.000	0.664	0.763	0.443
CSF 7	1.000	1.000	1.000	1.000	0.165	1.000	0.924	1.000	0.778	0.622	1.000	1.000	1.000	1.000	1.000	0.431	1.000	1.000	1.000	1.000	0.387	1.000
CSF 8	1.000	0.620	0.315	0.621	1.000	0.751	1.000	1.000	1.000	0.622	1.000	0.433	0.486	0.775	1.000	1.000	0.338	0.220	0.742	1.000	0.888	0.352
CSF 9	1.000	1.000	0.640	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.778
CSF 10	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.678	0.367	1.000	0.146	0.161	0.352	0.351	1.000	1.000	1.000	1.000	0.715	1.000	0.435
CSF 11	0.731	0.750	0.209	0.458	0.601	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.616	1.000	1.000	1.000	1.000	1.000	1.000	1.000
CSF 12	1.000	1.000	0.335	0.616	0.343	1.000	1.000	0.328	1.000	1.000	1.000	1.000	1.000	0.469	1.000	1.000	1.000	1.000	0.201	1.000	1.000	1.000

Table 11: Crisp Ratings of Obstacle *(Created by authors)

	T1	T2	T3	T4	T5	O1	O2	O3	O4	O5	G1	G2	G3	G4	G5	E1	E2	E3	E4	K1	K2	K3
T1	0.998	4.998	2.996	2.982	0.232	0.143	0.116	2.819	0.111	2.819	1.641	3.525	0.925	1.157	0.143	0.925	1.157	3.525	2.819	2.819	0.099	0.099
T2	0.200	0.999	4.997	2.982	0.139	0.143	7.000	0.925	0.111	2.819	1.641	1.157	2.819	7.000	0.143	2.819	3.525	1.157	5.598	5.598	3.525	0.099
T3	0.333	0.200	0.998	4.942	0.099	0.111	1.157	2.819	0.143	0.113	0.198	1.157	0.186	0.232	0.200	2.819	7.000	0.139	0.925	0.925	1.157	0.077
T4	0.333	0.333	0.200	0.998	0.139	0.111	1.157	2.819	0.143	0.925	0.141	3.525	0.113	0.142	0.200	5.598	3.525	1.157	2.819	0.186	0.139	0.099
T5	2.996	4.998	6.999	4.942	0.142	0.143	1.157	0.113	0.200	5.598	0.329	1.157	0.925	3.525	0.333	5.598	3.525	3.525	5.598	2.819	1.157	0.232
O1	6.995	6.999	9.000	9.000	7.000	0.203	3.525	9.000	0.333	9.000	5.000	7.000	9.000	3.525	0.333	9.000	3.525	7.000	9.000	2.819	7.000	0.232
O2	6.000	0.143	0.333	0.333	0.232	0.200	0.142	0.113	0.200	0.186	0.141	0.099	0.111	0.099	0.143	0.925	1.157	0.232	0.925	0.925	3.525	0.139
O3	0.200	0.333	0.200	0.200	0.142	0.111	0.142	0.113	0.143	2.819	0.329	1.157	0.925	0.142	0.111	0.113	1.157	3.525	0.925	0.925	0.139	0.232
O4	8.995	9.000	6.998	6.964	3.525	1.661	3.525	5.598	0.203	1.572	5.000	7.000	2.819	3.525	0.333	2.819	7.000	3.525	9.000	5.598	7.000	3.525
O5	0.200	0.200	0.994	0.333	0.099	0.111	1.157	0.111	0.250	0.113	0.198	0.139	0.186	0.139	0.111	5.598	1.157	0.142	0.186	0.111	0.232	0.139
G1	0.333	0.333	4.997	6.967	1.157	0.200	7.000	0.925	0.200	2.819	0.201	0.232	2.819	7.000	0.200	0.925	3.525	1.966	0.925	0.186	3.525	0.139
G2	0.200	0.333	0.333	0.200	0.232	0.143	7.000	0.186	0.143	2.819	1.641	0.142	0.925	0.232	0.143	2.819	1.157	0.139	0.186	0.111	0.139	0.099
G3	0.333	0.200	2.994	0.997	0.232	0.111	3.525	0.186	0.200	0.925	0.198	0.232	0.113	0.232	0.200	2.819	3.525	1.157	0.186	0.925	0.232	0.099
G4	0.333	0.143	2.996	0.998	0.139	0.200	7.000	0.113	0.200	2.819	0.141	1.157	0.925	0.142	0.333	0.925	1.157	1.157	2.819	2.819	0.232	0.139
G5	6.994	6.999	4.997	4.942	1.157	1.661	7.000	9.000	1.661	9.000	5.000	7.000	2.819	1.157	0.203	2.819	7.000	7.000	5.598	9.000	7.000	7.000
E1	0.333	0.200	0.200	0.143	0.099	0.111	0.232	0.113	0.200	0.080	0.329	0.139	0.111	0.232	0.200	0.113	0.232	0.142	0.925	0.186	1.157	0.139
E2	0.333	0.200	0.143	0.200	0.139	0.200	0.232	0.186	0.143	0.186	0.198	0.232	0.111	0.232	0.143	0.925	0.142	0.142	0.113	0.186	0.232	0.099
E3	0.200	0.333	4.997	0.333	0.139	0.143	1.157	0.111	0.200	0.113	0.247	3.525	0.186	0.232	0.143	0.113	0.142	0.142	0.925	0.925	0.139	0.139
E4	0.200	0.143	0.333	0.200	0.099	0.111	0.232	0.186	0.111	0.925	0.329	1.157	0.925	0.139	0.143	0.186	0.142	0.232	0.113	0.111	0.139	0.077
K1	0.200	0.143	0.333	2.980	0.139	0.200	0.232	0.186	0.143	2.819	1.641	3.525	0.186	0.139	0.111	0.925	1.157	0.232	2.819	0.113	3.525	0.139
K2	6.998	0.200	0.333	4.942	0.232	0.143	0.139	2.819	0.143	0.925	0.198	3.525	0.925	1.157	0.143	0.186	1.157	3.525	2.819	0.111	0.142	0.232
K3	6.995	6.999	8.999	6.965	1.157	1.661	3.525	0.925	0.200	2.819	5.000	7.000	5.598	3.525	0.143	2.819	7.000	3.525	9.000	2.819	1.157	0.142

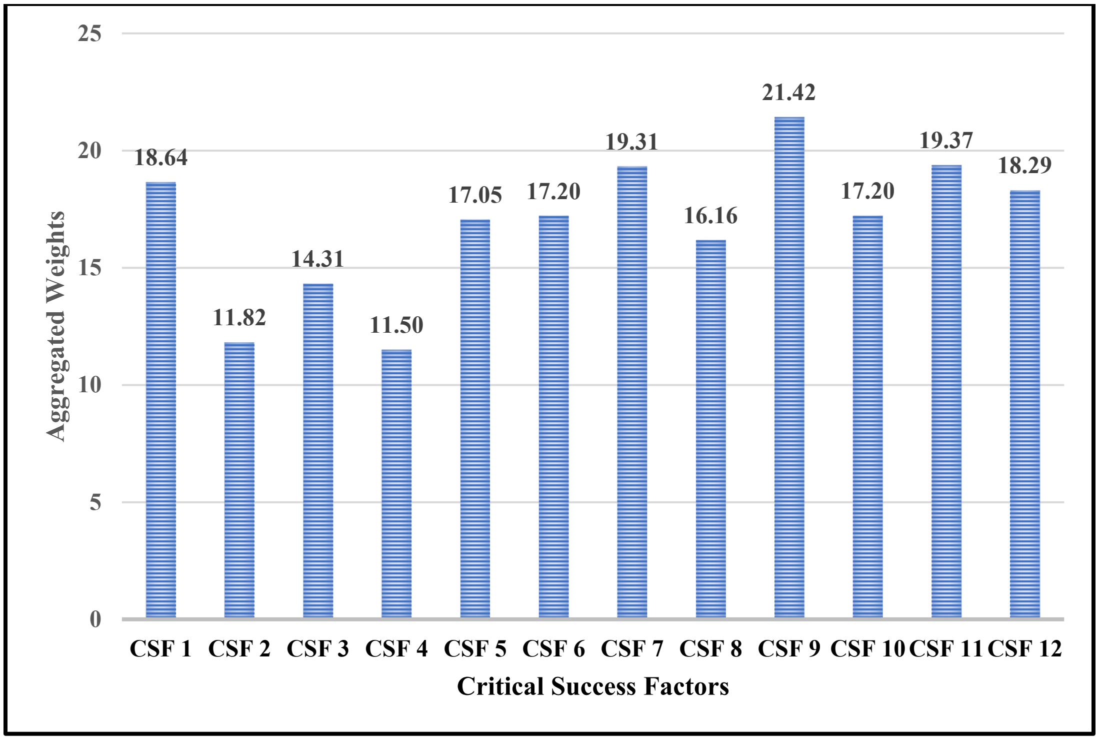

Figure 6: Aggregated Weights per obstacle w.r.t CSF (Created by authors)

Table 9 reveals the weights assigned to various obstacles faced by local mobile manufacturers utilizing smart manufacturing. Based on these weights, we categorized these challenges into five distinct groups, with Group 1 representing the most critical factors hindering their globalization efforts. This pivotal group includes obstacles such as Foreign OEMs Undervalued (T2) and Cost Reduction in CBU vs. Local Manufacturing (O1), among others. T2 underscores the quick adaptation of new technologies by foreign OEMs, putting domestic manufacturers at a disadvantage, especially noted in the 4G market share capture. O1 suggests that domestic handsets fail to meet the quality benchmarks at competitive pricing, making differentiation challenging in global markets. The clustering in Figure 5 identifies subgroups of smart manufacturing decision alternatives based on local weights, guiding targeted strategies.

An additional barrier to smart manufacturing adoption resides in the inertia of regulatory frameworks, designated here as G5 in Group 1. Such regulatory stagnation hinders the rapid integration of emerging technologies into smart manufacturing processes, constraining companies from fully capitalizing on the potential of advanced manufacturing paradigms. Another prominent concern, referred to as K3, is the competitive disadvantage that local firms encounter compared to large-scale businesses. The latter, capitalizing on the economics of scale, enforces a downward force on market pricing, so compressing the profit margins of smaller enterprises and indirectly impacting their product quality. The obstacle from Group 5 has a negligible effect on MPSC.

Table 10 shows that a decision that works well overall for smart manufacturing might not be the best when looking at specific problems. Simply put, a high overall score does not necessarily mean better performance in all areas. Figure 6 enhances the justification presented in Table 10 by providing a comprehensive perspective on the effects of CSFs on results at the system level. The aggregated value of CSFs in the context of smart manufacturing implementation indicates that CSF 9 holds the highest weightage, suggesting its potential to address multiple obstacles within the system.

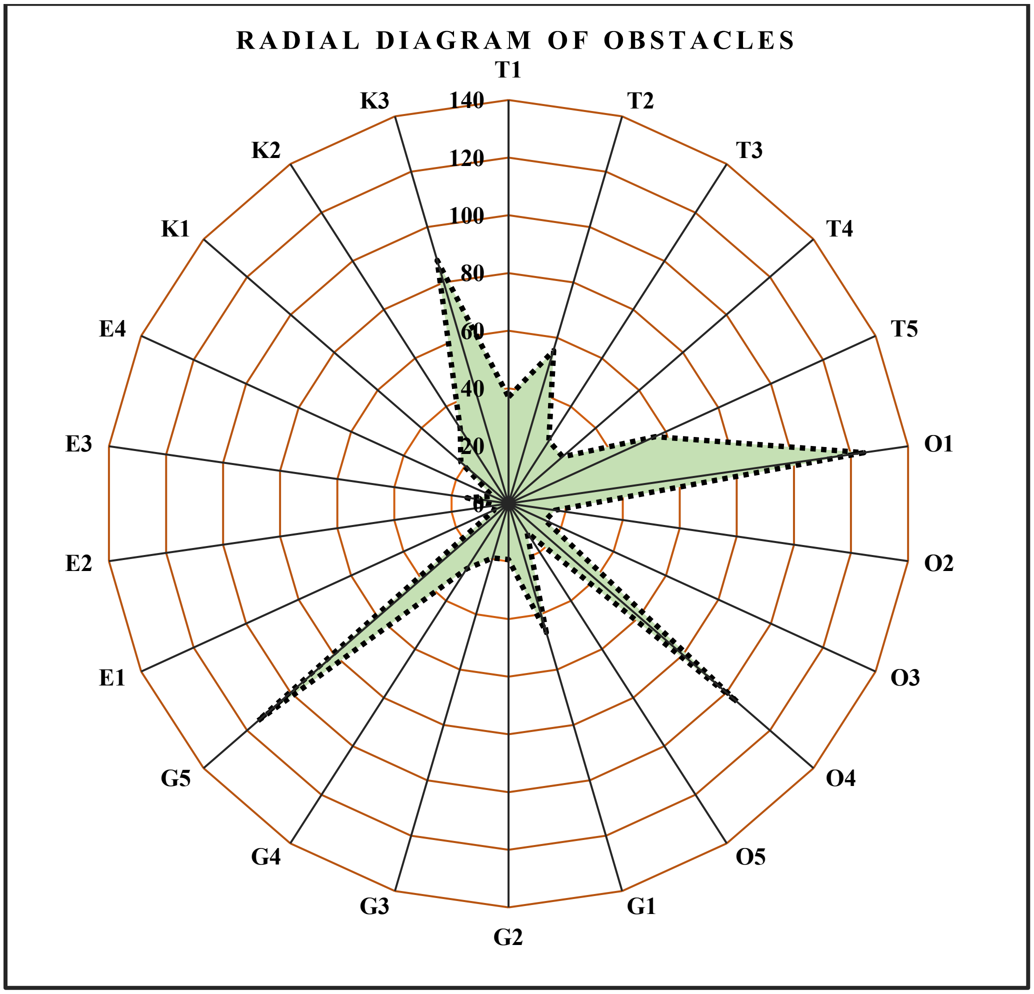

Figure 7. Weighted Crisp Obstacle Ratings (Created by authors)

The crisp obstacle rating shown in Table 11 is used to determine the relative importance or weight of the obstacle. The importance of each obstacle is determined based on its correlation with the overall goal shown in Figure 7. The rationale behind this approach is that the more correlated an obstacle is with another obstacle, the more important it is in the decision-making process. Figure 7 reveals that "Stagnant Regulatory Framework (G4)" and "Cost Reduction in CBU vs. Local Manufacturing (O1)" are the most significant obstacles to smart manufacturing implementation, as evidenced by their highly weighted crisp obstacle ratings. This underscores the need to address outdated regulations and cost disparities to facilitate the adoption of smart manufacturing technologies.

Table 12: Weights and Ranks obtained for CSFs by integrated AHP-DEA

CSF	Weights	Rank
CSF 9	1.0000	1
CSF 7	0.9137	2
CSF 11	0.8840	3
CSF 1	0.8597	4
CSF 12	0.8578	5
CSF 5	0.8517	6
CSF 10	0.7833	7
CSF 6	0.7822	8
CSF 8	0.7645	9
CSF 3	0.7432	10
CSF 2	0.5865	11
CSF 4	0.5690	12

*(Created by authors)

Table 12 is analyzed to draw insights regarding the CSFs. The fourth CSF, "Government Support", has garnered a maximum level of resource efficiency, which is rated as 1. This means that the government allocates the best possible support in terms of resource usage to get the desired outcome from smart manufacturing. To enhance local creativity, the government can provide incentives like the imposition of import duties on foreign manufactured mobiles, liberal trading policies, and the use of patents and copyrights. This finding corroborates previous work which shows the need for government involvement in the enhancement of local industries as well as in localizing technologies (Chen et al., 2020).

In smart manufacturing, consistent quality control is crucial, spanning from the procurement of raw materials to the actual delivery of the finished goods. CSF 11, which is "Develop a robust supply chain," ranked third with an efficiency score of 0.8840, also stresses the need for consistent quality control in the smart manufacturing process. This need for quality control is also reflected in the literature, which has established that there is a relationship between good supply chain management practices and the quality of the product (Sachan et al., 2022). On top of that, CSF 4, has the lowest efficiency while remaining in the twelfth place on the ranking system with an efficiency score of 0.5689. This is because Multiple Carrier Aggregation works best with stable systems rather than flexible systems as it is inherently process driven by data which has to be accurate and timely. Lastly, Assuming this, CSF 2 and CSF 3 are in the second and the third last positions with efficiency scores of 0.7432 and 0.5864 respectively.

6. Discussion

The study employed the IVSFS-AHP integrated with DEA to analyze critical success factors (CSFs) and obstacles. Through this methodology, the weightage of 22 identified obstacles was determined, alongside the efficiency levels of the CSFs in addressing these challenges. The insights derived from the application of this novel approach are detailed below, providing a comprehensive understanding of the interplay between obstacles and CSFs in the context under investigation.

Smart manufacturing offers a transformative opportunity for manufacturers in developing economies by enhancing efficiency, cost optimization, and product quality. Aligned with prior research by (Nguyen et al., 2022), this study identifies over-reliance on foreign technologies (obstacle O4) and the delayed adoption of emerging trends (obstacle T1) as critical barriers that escalate costs, constrain local innovation, and undermine competitiveness. Technological dependence and policy stagnation obstruct sustainable industrialization and the adoption of energy-efficient practices (Patterson et al., 2022). Building on these findings, this manuscript study uncovers the compounding role of rigid regulatory frameworks and insufficient policy incentives for green investments, revealing the critical interplay between policy, market readiness, and technological adoption. Policymakers should focus on implementing targeted subsidies for green technology adoption, establishing clear regulatory frameworks for smart manufacturing standards, and incentivizing R&D in localized manufacturing technologies.

The identification of critical success factors (CSFs), such as government support (CSF 9) and robust supply chain management (CSF 11), builds on and reinforces earlier findings in the literature. Goodarzian et al. (2020) highlighted the role of resilient supply chains in mitigating disruptions and ensuring the continuous and sustainable flow of resources. Similarly, (Stefán, 2023) emphasized the importance of proactive government policies in fostering technology adoption and advancing sustainability in manufacturing. This study reveals that government incentives not only directly support innovation but also strengthen supply chain resilience by creating an enabling ecosystem for smart technologies. Reports like the World Economic Forum further support this connection by underscoring the importance of integrated public-private collaborations in fostering industrial innovation (Nguyen, 2024). Governments and private sectors must work together to develop a dual strategy where public investment supports long-term infrastructure and private entities lead innovation in tools like predictive maintenance and digital twins. Integrated networks can accelerate the deployment of advanced manufacturing technologies.

This study demonstrates that smart manufacturing can position developing economies as competitive players on the global stage by driving innovation, improving product quality, and achieving cost efficiency. While earlier studies, such as (Bonfanti et al., 2023), emphasized the alignment of manufacturing strategies with the United Nations Sustainable Development Goals (SDGs) as a broad conceptual framework. This research provides empirical evidence of how such alignment directly enhances global competitiveness. Additionally, strategic investments in fostering local innovation ecosystems and reducing dependencies on foreign technologies. Supported by reports from the UNIDO Industrial Development Report, these findings highlight the dual role of smart manufacturing in achieving sustainable growth and enhancing economic self-reliance, thereby charting a clear path toward long-term global competitiveness (Santiago et al., 2024). Policymakers should establish innovation hubs, enforce technology transfer agreements, and Develop benchmarking systems to assess local manufacturers' progress against global standards. This includes facilitating cross-border collaborations to adopt best practices from regions leading in smart manufacturing.

The findings of this research underscore the transformative potential of smart manufacturing for developing economies, revealing a multifaceted interplay between critical success factors (CSFs) and obstacles in achieving global competitiveness. The integration of the Interval-Valued Spherical Fuzzy Sets (IVSFS) with AHP and DEA models has illuminated key pathways for overcoming challenges such as over-reliance on foreign technologies, rigid regulatory frameworks, and skill gaps, which hinder innovation and sustainable industrial growth. Notably, government support, cost optimization, and resilient supply chain management emerge as pivotal CSFs, enabling local manufacturers to align with global standards while promoting sustainable practices in line with the United Nations Sustainable Development Goals (SDGs). This study highlights the importance of localized innovation ecosystems, reducing dependencies on foreign imports, and leveraging user-centric design to enhance competitiveness. By providing actionable insights, this research paves the way for policymakers to develop inclusive, innovation-driven strategies that integrate advanced technologies and build resilient, sustainable manufacturing ecosystems capable of thriving on the global stage.

7. Sensitivity Analysis:

A sensitivity study was carried out to account for any variability and guarantee reliable findings. This widely used technique evaluates how small adjustments to input values affect the stability of a solution. Sensitivity analysis is essential to the validity of this study since it depends on human input, which may contain personal biases (Agrawal, 2022). Changing the weights given to the preferences of the decision-makers was part of the sensitivity analysis. Six other examples (s = 1, 2, 3,...6) were made in which the input of one DM was set to "Very Important" and that of the others to "Unimportant." The baseline is the initial scenario (s = 7), in which the DM weights were changed. The weight distributions are shown in Table 13. After that Ranking value of the CSFs was calculated and contrasted for every example The results, as displayed in Table 14, strongly concur with patterns found in the baseline study, demonstrating the validity of the conclusions.

Figure 8 reveals a remarkable trend – despite variations in decision-maker weights across the six cases, CSF rankings remained remarkably consistent. This compelling evidence suggests the robustness of our results, demonstrating the minimal influence of individual DM preferences on the overall outcome (Prashar and Sunder M, 2024). The largest fluctuation occurred in CSF 4 (Intelligent Manufacturing) due to its reliance on rapidly changing technologies and varying levels of adoption across systems, making it highly sensitive to dynamic industry and technological conditions. Similarly, The fluctuation for CSF 3 (Stop Grey Marketing of Products) unpredictability is due to varying decision-maker priorities influenced by regional enforcement, market exposure, and the perceived financial impact of grey marketing. In many cases, the ranking of CSFs changes as decision-makers adjust their weights based on priorities and perspectives. However, the overall trend of the results remains consistent, reflecting the relative importance of each CSFs across the analysis.

The sensitivity analysis results reinforce the crucial need for comprehensive guidelines for domestic mobile manufacturers. Policymakers must carefully evaluate regulations impacting operations within the Indian sector. Importantly, the sensitivity analysis demonstrates the validity of this study. By revealing the consistent trends in CSFs, regardless of decision-maker weighting, this study confidently concludes that our results remain largely unaffected by potential observer bias.

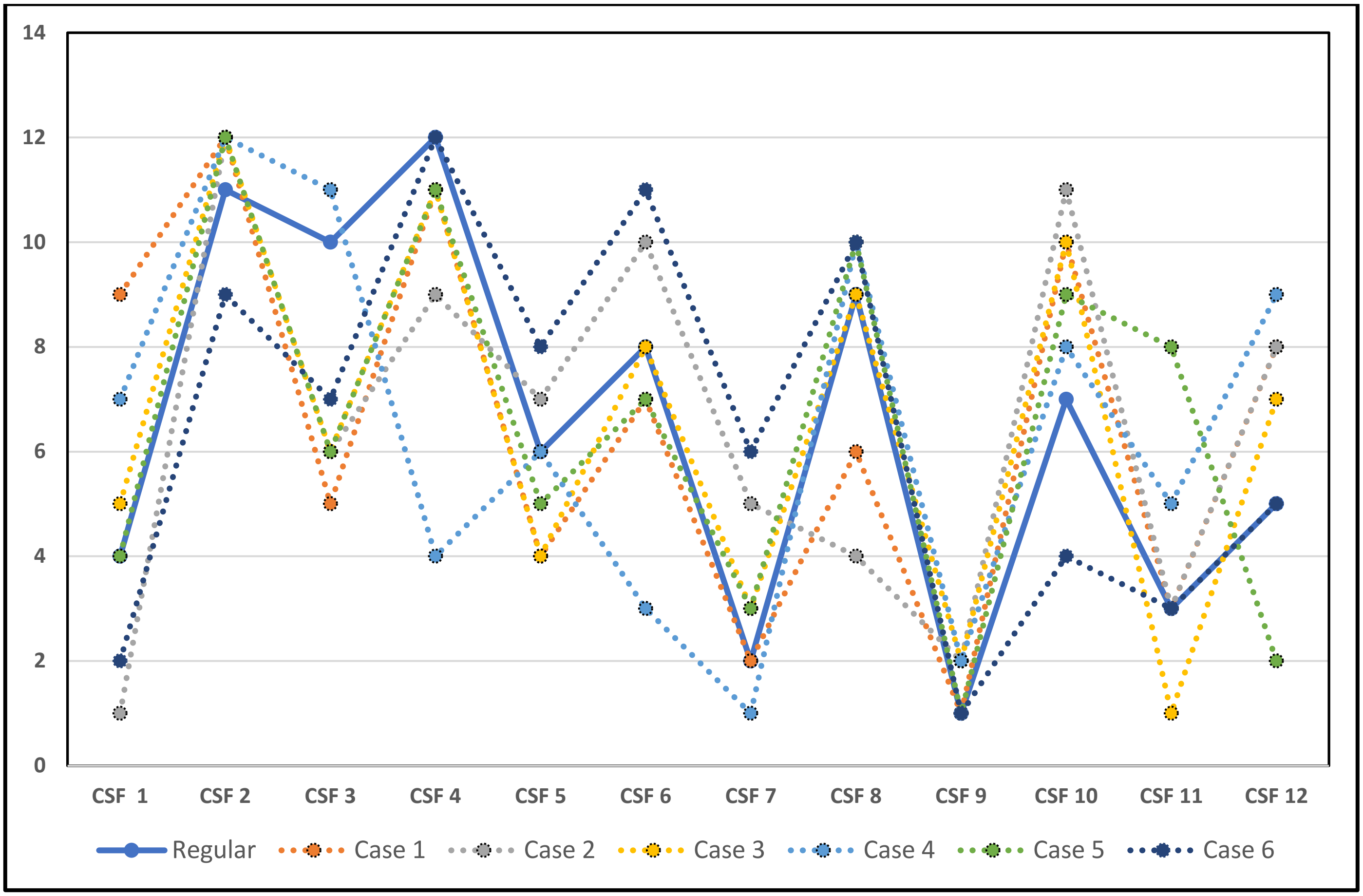

Figure 8. Efficiency Ranking" Movements for CSFs during Sensitivity (Created by authors)

Table 13. Weightage Allocated to DMs in Sensitivity Analysis

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Regular
DM 6	*Less important*	*Less important*	*Less important*	*Less important*	*Less important*	*Very Important*	*Less important*
DM 5	*Less important*	*Less important*	*Less important*	*Less important*	*Very Important*	*Less important*	*Less important*
DM 4	*Less important*	*Less important*	*Less important*	*Very Important*	*Less important*	*Less important*	*Less important*
DM 3	*Less important*	*Less important*	*Very Important*	*Less important*	*Less important*	*Less important*	*Less important*
DM 2	*Less important*	*Very Important*	*Less important*	*Less important*	*Less important*	*Less important*	*Less important*
DM 1	*Very Important*	*Less important*	*Less important*	*Less important*	*Less important*	*Less important*	*Very Important*

*(Created by authors)

Table 14. Efficiency of CSFs with Changing DM's Weightage

	Regular	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
CSF 1	4	9	1	5	7	4	2
CSF 2	11	12	12	12	12	12	9
CSF 3	10	5	6	6	11	6	7
CSF 4	12	11	9	11	4	11	12
CSF 5	6	4	7	4	6	5	8
CSF 6	8	7	10	8	3	7	11
CSF 7	2	2	5	3	1	3	6
CSF 8	9	6	4	9	10	10	10
CSF 9	1	1	2	2	2	1	1
CSF 10	7	10	11	10	8	9	4
CSF 11	3	3	3	1	5	8	3
CSF 12	5	8	8	7	9	2	5

*(Created by authors)

8. Implications

8.1. Theoretical implications

This research introduces a novel hybrid methodological framework combining IVSFs-AHP with DEA to address obstacles and CSFs for local manufacturers' global expansion, particularly in the mobile manufacturing sector, through smart manufacturing. The use of IVSFs is particularly unique as it captures uncertainty and imprecision in decision-making more effectively than traditional fuzzy sets, enhancing the reliability of pairwise comparisons and achieving high consistency (Stoilova and Munier, 2021). Combined with DEA, this approach ensures comprehensive efficiency evaluations, outperforming previous linear programming techniques. By addressing trade-offs such as the cost dynamics of completely built units versus local manufacturing, this framework aligns micro-level firm strategies with macro-level policy objectives, resonating with SDG 9's goals of sustainable industrialization. Beyond providing a replicable model for other sectors, this study offers actionable insights for policymakers to design targeted interventions, such as trade deals and import duties while enabling local mobile manufacturers to benchmark their performance and enhance global competitiveness. This hybrid approach fills gaps in existing literature and provides a transformative framework for achieving sustainable global success. Future research could extend this framework to other industries, such as automotive or electronics manufacturing, to validate its applicability and effectiveness. Additionally, integrating emerging technologies like artificial intelligence or blockchain could further enhance decision-making precision and efficiency evaluations.

8.2. Practical and research implications

The research employed the integration of IVSFs AHP with the DEA model in determining the prioritization of CSFs and investigating the obstacles that local mobile companies face in trying to compete globally. The findings of this study give rise to several implications as detailed below:

i. In this study, cost optimization (CSF 12) is identified as a crucial factor for the global expansion of local manufacturers. Low-cost strategies with smart manufacturing performance will more quickly allow and respond to market changes instead of larger conglomerates which tend to be slower and more cumbersome in their decision-making processes. The adoption of agile and cost-efficient manufacturing practices is imperative for small and medium enterprises (SMEs) to sustain competitive parity in the global marketplace, as underscored by Carmona et al. (2024). This increased focus on competitiveness is also in line with SDG 9 for expanding sustainable industrialization. The evidence presented in this paper also corroborates previous research that cost-minimization strategies are fundamentally important in enabling local manufacturers to compete globally (Khan et al., 2020). Furthermore, the Industrial Development Report underscores the importance of sustainable industrial practices, especially for emerging manufacturers aiming to scale internationally (Patterson et al., 2022).

ii. Evolving to shift from global to local exports has a significant economic effect on domestic manufacturing (O4) as it decreases the time and cost associated with transportation. This approach aligns with the emphasis on the economic benefits of reducing logistical complexities and strengthening local production networks (Gössling and Reinhold, 2024). Local manufacturers focusing on glocalization by minimizing their dependence on foreign products not only contribute to sustainable economic growth but also reduce carbon footprints associated with long-distance trade (Yang, 2024). This sustainable development agenda, particularly in terms of mitigating environmental impacts caused by global trade (Kamran et al., 2021). Moreover, the method reinforces sustainable economic growth by fostering domestic supply chains and networks, thereby creating resilient local economies that support both economic and environmental sustainability.

iii. The findings of this manuscript highlight that local manufacturers face significant challenges in meeting user-centric design expectations (Obstacle K2), which are often scrutinized by technologically equipped patrons. This result supports the World Bank Digital Development Report, which emphasizes the necessity of designing inclusive and user-friendly technology interfaces to bridge the digital divide (Johri et al., 2024). As SDG 10 highlights, making technology accessible to a greater range of users not only promotes functional literacy but also fosters both global and local engagement. Local differentiation from foreign companies is achieved by focusing on and exaggerating specialized characteristics, which enhances customers' perception of the company's products (Patterson et al., 2022). This approach aligns with insights from the OECD Digital Economy Outlook on leveraging design innovations to improve brand perception (Young, 2024). Furthermore, this finding corroborates previous research demonstrating that user-centered design significantly influences brand perception and loyalty (Chen et al., 2020).

iv. The same matrix also provides a robust framework for goal-setting in low disruptive innovation takeovers, with potential applications extending beyond business strategy into public policy. This offers policymakers a strategic tool to design and implement industrial policies that support local initiatives aiming to integrate modern technological advancements (Yang, 2024). The OECD Science, Technology, and Innovation Outlook underscores the significance of aligning innovation-driven policies with local economic ecosystems to catalyze technology-driven growth (Young, 2024). Such an approach is consistent with the principles advocated by SDG 9, which emphasizes fostering innovation, promoting sustainable industrialization, and enhancing infrastructural capabilities. Furthermore, the UNIDO Industrial Development Report highlights the transformative potential of inclusive and sustainable industrial policy frameworks in leveraging advanced technologies for diversified and equitable industrial growth, reaffirming the model's broader applicability (Santiago et al., 2024).

9. Conclusion

The central endeavor of this paper is devoted to the delineation of obstacles besetting the growth of the local mobile phone industry within the context of smart manufacturing. These challenges also affect customer satisfaction, repurchase intention, and the likelihood of recommendation. Some manufacturers are beginning to build a domestic ecosystem for mobile phone components and procurement, but they struggle to become part of the global supply chain. This paper offers some valuable insights that could be useful to the mobile phone industry in these countries as they seek to shift from local to global markets employing smart manufacturing techniques.

This study employs a sophisticated MCDM technique and assessment process to derive estimates of the selected variables which integrate both qualitative and quantitative dimensions. Such AHP and DEA techniques are employed as a hybrid model integrating IVSFs. Results of the proposed integrated model confirm that the framework developed in this study enables the construction of a prioritized list of CSFs designed to satisfy particular needs, making sure that the proposed solution addresses multiple interacting factors and is solving the problem holistically. The hierarchy structure is established and the successive levels are ranked using AHP. Likewise, DEA is used to assess the competency of the CSFs. The IVSFs AHP-DEA facilitates generating a sorted list of appropriate alternatives, assigning individual weights to each option which is how this fuzzy combines the two approaches. The resulting ranking lists provide various strategies regarding the assessment of fractal dimensions of the supply chain ensuring the promotion of sustainability, profit maximization, and environmental friendliness in the smartphone production processes.

This research shows that Indian manufacturers can enhance their competitiveness in the global market by prioritizing cost optimization and leveraging government support. Interval-valued spherical fuzzy sets can be combined with other decision-making tools to compare different decision-making approaches, as inconsistencies in the matrices and the lack of comprehensive examination can pose tangible risks and limit the study's conclusions. This study offers a framework for benchmarking smart manufacturing, implementation faces challenges such as infrastructure limitations, high costs, and workforce skill gaps. Addressing these requires investments in infrastructure, upskilling, and cost-efficient solutions. Emerging trends like digital twins, AI, and IoT can further enhance benchmarking and drive adaptive manufacturing systems. Future research ought to concentrate on devising a novel approach that can complement the existing ranking system by facilitating decision-makers in visualizing any inconsistencies in the matrix. This approach should also enable them to iteratively rank the alternatives for optimal outcomes.

References

Abate, M., Christidis, P. & Purwanto, A. J. 2020. Government support to airlines in the aftermath of the COVID-19 pandemic. *Journal of Air Transport Management,* 89**,** 101931.

Abonyi, J., Nagy, L. & Ruppert, T. 2024. Data Sharing in Industry 4.0—AutomationML, B2MML and International Data Spaces-Based Solutions. *In:* ABONYI, J., NAGY, L. & RUPPERT, T. (eds.) *Ontology-Based Development of Industry 4.0 and 5.0 Solutions for Smart Manufacturing and Production: Knowledge Graph and Semantic Based Modeling and Optimization of Complex Systems.* Cham: Springer Nature Switzerland.

Adhikari, K. & Roy, A. S. 2024. E-waste by mobile Phones: A Case Study on the Consumption, Disposal Behavior, and Awareness of Consumers in Kolkata, India. *Bulletin of Science, Technology & Society***,** 02704676231224700.

Agrawal, N. 2022. Multi-criteria decision-making toward supplier selection: exploration of PROMETHEE II method. *Benchmarking: An International Journal,* 29**,** 2122-2146.

Aguado, A., Lopez, V., Lopez, D., Peev, M., Poppe, A., Pastor, A., Folgueira, J. & Martin, V. 2019. The Engineering of Software-Defined Quantum Key Distribution Networks. *IEEE Communications Magazine,* 57**,** 20-26.

Ahmad, M. S., Jamil, A., Latif, K. F., Ramayah, T., Ai Leen, J. Y., Memon, M. & Ullah, R. 2020. Using food choice motives to model Pakistani ethnic food purchase intention among tourists. *British Food Journal,* 122**,** 1731-1753.

Alatise, M. B. & Hancke, G. P. 2020. A Review on Challenges of Autonomous Mobile Robot and Sensor Fusion Methods. *IEEE Access,* 8**,** 39830-39846.

Arcidiacono, F. & Schupp, F. 2024. Investigating the impact of smart manufacturing on firms' operational and financial performance. *Journal of Manufacturing Technology Management,* 35**,** 458-479.

Arora, C., Kamat, A., Shanker, S. & Barve, A. 2022. Integrating agriculture and industry 4.0 under “agri-food 4.0” to analyze suitable technologies to overcome agronomical barriers. *British Food Journal,* 124**,** 2061-2095.

Bachir, D., Khodabandelou, G., Gauthier, V., El Yacoubi, M. & Puchinger, J. 2019. Inferring dynamic origin-destination flows by transport mode using mobile phone data. *Transportation Research Part C: Emerging Technologies,* 101**,** 254-275.

Baryshnikova, N., Kiriliuk, O. & Klimecka-Tatar, D. 2021. Enterprises’ strategies transformation in the real sector of the economy in the context of the COVID-19 pandemic. *Production Engineering Archives,* 27**,** 8-15.

Beikmirza, M., Shen, Y., Vreede, L. C. N. D. & Alavi, M. S. 2023. A Wideband Energy-Efficient Multi-Mode CMOS Digital Transmitter. *IEEE Journal of Solid-State Circuits,* 58**,** 677-690.

Best, R. E., Rezazadeh Kalehbasti, P. & Lepech, M. D. 2020. A novel approach to district heating and cooling network design based on life cycle cost optimization. *Energy,* 194**,** 116837.

Bhagwan, N. & Evans, M. 2023. A review of industry 4.0 technologies used in the production of energy in China, Germany, and South Africa. *Renewable and Sustainable Energy Reviews,* 173**,** 113075.

Bocken, N. M. P. & Geradts, T. H. J. 2020. Barriers and drivers to sustainable business model innovation: Organization design and dynamic capabilities. *Long Range Planning,* 53**,** 101950.

Bonfanti, A., Mion, G., Brunetti, F. & Vargas-Sánchez, A. 2023. The contribution of manufacturing companies to the achievement of sustainable development goals: An empirical analysis of the operationalization of sustainable business models. *Business Strategy and the Environment,* 32**,** 2490-2508.

Bortoloti, M. a. A., Fernandes, T. A. & Ferreira, O. P. 2022. An efficient damped Newton-type algorithm with globalization strategy on Riemannian manifolds. *Journal of Computational and Applied Mathematics,* 403**,** 113853.

Bucknell Bossen, C. & Kottasz, R. 2020. Uses and gratifications sought by pre-adolescent and adolescent TikTok consumers. *Young Consumers,* 21**,** 463-478.

Buran, B. & Erçek, M. 2022. Public transportation business model evaluation with Spherical and Intuitionistic Fuzzy AHP and sensitivity analysis. *Expert Systems with Applications,* 204**,** 117519.

Carmona, S., Filatotchev, I., Fisch, J. H. & Livne, G. 2024. Integrating contemporary accounting and international business research: progress so far and opportunities for the future. *Accounting and Business Research,* 54**,** 369-391.

Chaudhuri, S., Roy, M., Mcdonald, L. M. & Emendack, Y. 2021. Reflections on farmers' social networks: a means for sustainable agricultural development? *Environment, Development and Sustainability,* 23**,** 2973-3008.

Chen, J., Markowitz, J. E., Lilascharoen, V., Taylor, S., Sheurpukdi, P., Keller, J. A., Jensen, J. R., Lim, B. K., Datta, S. R. & Stowers, L. 2021. Flexible scaling and persistence of social vocal communication. *Nature,* 593**,** 108-113.

Chen, Z., Ming, X., Zhou, T. & Chang, Y. 2020. Sustainable supplier selection for smart supply chain considering internal and external uncertainty: An integrated rough-fuzzy approach. *Applied Soft Computing,* 87**,** 106004.

Cui, K., Hong, Z., Feng, Y., Li, Z., Song, X., Lou, S. & Tan, J. 2024. Extraction of evolutionary factors in smart manufacturing systems with heterogeneous product preferences and trust levels. *Engineering Applications of Artificial Intelligence,* 129**,** 107655.

De Matos, E., Viegas, E., Tiburski, R. & Hessel, F. Context-Aware Security in the Internet of Things: A Review. *In:* BAROLLI, L., ed. Advanced Information Networking and Applications, 2023// 2023 Cham. Springer International Publishing, 518-531.

Dube, A. S. & Gawande, R. S. 2016. Analysis of green supply chain barriers using integrated ISM-fuzzy MICMAC approach. *Benchmarking: An International Journal,* 23**,** 1558-1578.

Dutta, D., Cheela, V. R. S., Dubey, B., Kumar, S. & Goel, S. 2024. Evaluation of environmental impacts of mobile phones in India using life cycle assessment technique. *International Journal of Environmental Science and Technology*.

Farahbakhsh, F., Shahidinejad, A. & Ghobaei-Arani, M. 2021. Context-aware computation offloading for mobile edge computing. *Journal of Ambient Intelligence and Humanized Computing*.

Fathi, M. R., Torabi, M. & Razi Moheb Saraj, S. 2022. The future of apitourism in Iran based on critical uncertainty approach and DEMATEL/COPRAS techniques. *Journal of Tourism Futures,* ahead-of-print.

Finlay, A., Robinson, E., Jones, A., Maden, M., Cerny, C., Muc, M., Evans, R., Makin, H. & Boyland, E. 2022. A scoping review of outdoor food marketing: exposure, power and impacts on eating behaviour and health. *BMC Public Health,* 22**,** 1431.

Ghosh, S., Roy, S. K., Ebrahimnejad, A. & Verdegay, J. L. 2021. Multi-objective fully intuitionistic fuzzy fixed-charge solid transportation problem. *Complex & Intelligent Systems,* 7**,** 1009-1023.

Goodarzian, F., Hosseini-Nasab, H., Muñuzuri, J. & Fakhrzad, M.-B. 2020. A multi-objective pharmaceutical supply chain network based on a robust fuzzy model: A comparison of meta-heuristics. *Applied Soft Computing,* 92**,** 106331.

Gössling, S. & Reinhold, S. 2024. Accelerating small and medium sized tourism enterprises' engagement with climate change. *Journal of Sustainable Tourism***,** 1-18.

Goswami, M. & Daultani, Y. 2022. Make-in-India and Industry 4.0: technology readiness of select firms, barriers and socio-technical implications. *The TQM Journal,* 34**,** 1485-1505.

Gupta, P. & Mittal, A. 2023. Realising leadership in Indian market by Deming awarded original equipment manufacturing industry through TQM. *International Journal of Services and Operations Management,* 44**,** 426-441.

Hilton, B., Hajihashemi, B., Henderson, C. M. & Palmatier, R. W. 2020. Customer Success Management: The next evolution in customer management practice? *Industrial Marketing Management,* 90**,** 360-369.

Hu, Y., Jia, Q., Yao, Y., Lee, Y., Lee, M., Wang, C., Zhou, X., Xie, R. & Yu, F. R. 2024. Industrial Internet of Things Intelligence Empowering Smart Manufacturing: A Literature Review. *IEEE Internet of Things Journal,* 11**,** 19143-19167.

Ignatov, A. 2018. AI benchmark: running deep neural networks on android smartphones. *In:* LEAL-TAIXÉ, L. & ROTH, S. (eds.) *Computer Vision – ECCV 2018 Workshops.* Cham: Springer.

Imran, M., Siddiqui, H. U. R., Raza, A., Raza, M. A., Rustam, F. & Ashraf, I. 2023. A performance overview of machine learning-based defense strategies for advanced persistent threats in industrial control systems. *Computers & Security,* 134, 103445.

Johri, A., Asif, M., Tarkar, P., Khan, W., Rahisha & Wasiq, M. 2024. Digital financial inclusion in micro enterprises: understanding the determinants and impact on ease of doing business from World Bank survey. *Humanities and Social Sciences Communications,* 11, 361.

Kamble, S. S., Gunasekaran, A. & Gawankar, S. A. 2020. Achieving sustainable performance in a data-driven agriculture supply chain: A review for research and applications. *International Journal of Production Economics,* 219, 179-194.

Kamran, R., Khan, N. & Sundarakani, B. 2021. Blockchain technology development and implementation for global logistics operations: a reference model perspective. *Journal of Global Operations and Strategic Sourcing,* 14, 360-382.

Kasmad, K. 2022. Analysis of Purchase Decision Estimates Based on Store Atmosphere and Affordable Prices. *AKADEMIK: Jurnal Mahasiswa Ekonomi & Bisnis,* 2, 27-34.

Khan, S., Haleem, A. & Khan, M. I. 2020. Enablers to Implement Circular Initiatives in the Supply Chain: A Grey DEMATEL Method. *Global Business Review,* 25, 68-84.

Khezrimotlagh, D., Zhu, J., Cook, W. D. & Toloo, M. 2019. Data envelopment analysis and big data. *European Journal of Operational Research,* 274, 1047-1054.

Kim, J., Yang, S. & Kim, N. 2023. Effect of plasticizer dosage on properties of multiple recycled aggregate concrete. *Journal of Material Cycles and Waste Management*.

Kocsis, G. & Xydis, G. 2019. Repair Process Analysis for Wind Turbines Equipped with Hydraulic Pitch Mechanism on the U.S. Market in Focus of Cost Optimization. *Applied Sciences* [Online], 9.

Kou, G., Olgu Akdeniz, Ö., Dinçer, H. & Yüksel, S. 2021. Fintech investments in European banks: a hybrid IT2 fuzzy multidimensional decision-making approach. *Financial Innovation,* 7, 39.

Kou, G., Yüksel, S. & Dinçer, H. 2022. Inventive problem-solving map of innovative carbon emission strategies for solar energy-based transportation investment projects. *Applied Energy,* 311, 118680.

Kumar, S., Swarnakar, V., Phanden, R. K., Antony, J., Jayaraman, R. & Khanduja, D. 2024. Analyzing critical success factors of Lean Six Sigma for implementation in Indian manufacturing MSMEs using best-worst method. *Benchmarking: An International Journal,* 31, 2960-2983.

Kutlu Gündoğdu, F. & Kahraman, C. 2019. A novel fuzzy TOPSIS method using emerging interval-valued spherical fuzzy sets. *Engineering Applications of Artificial Intelligence,* 85, 307-323.

Ledro, C., Nosella, A. & Vinelli, A. 2022. Artificial intelligence in customer relationship management: literature review and future research directions. *Journal of Business & Industrial Marketing,* 37, 48-63.

Leramo, R. O., Adekoya, L. O., Kilanko, O., Oyedepo, S. O., Eluwa, S. E., Babalola, P. O., Adeosun, S. O., Leramo, N. T., Aiyedun, P. O., Ohunakin, O. S., Ajayi, O. O. & Fayomi, O. S. I. 2022. A comparative analysis of the chemical composition and compliance level to established standards of concrete reinforcement steel rods rolled in Nigeria. *Heliyon,* 8, e09597.

Li, D. & Malerba, F. 2024. Technological change and the evolution of the links across sectoral systems: The case of mobile communications. *Technovation,* 130, 102936.

Li, G. & Branstetter, L. G. 2024. Does “Made in China 2025” work for China? Evidence from Chinese listed firms. *Research Policy,* 53, 105009.

Li, G., Kou, G. & Peng, Y. 2018. A Group Decision Making Model for Integrating Heterogeneous Information. *IEEE Transactions on Systems, Man, and Cybernetics: Systems,* 48, 982-992.

Li, Y., Kou, G., Li, G. & Peng, Y. 2022. Consensus reaching process in large-scale group decision making based on bounded confidence and social network. *European Journal of Operational Research,* 303, 790-802.

Lim, Y.-M., Leong, C.-M., Lau, T.-C. & Pek, C.-K. Experience with Mobile Phone Technology: A Comparison Between Two Brands. *In:* AL-SHARAFI, M. A., AL-EMRAN, M., AL-KABI, M. N. & SHAALAN, K., eds. Proceedings of the 2nd International Conference on Emerging Technologies and Intelligent Systems, 2023// 2023 Cham. Springer International Publishing, 240-250.

Lu, L. & Menezes, M. B. C. 2024. Supply chain vertical competition and product proliferation under different power structures. *International Journal of Production Economics,* 267**,** 109097.

Luo, Y. 2021. New OLI advantages in digital globalization. *International Business Review,* 30**,** 101797.

Mahmoodi, E., Fathi, M., Tavana, M., Ghobakhloo, M. & Ng, A. H. C. 2024. Data-driven simulation-based decision support system for resource allocation in industry 4.0 and smart manufacturing. *Journal of Manufacturing Systems,* 72**,** 287-307.

Makaya, A., Pambaguian, L., Ghidini, T., Rohr, T., Lafont, U. & Meurisse, A. 2023. Towards out of earth manufacturing: overview of the ESA materials and processes activities on manufacturing in space. *CEAS Space Journal,* 15**,** 69-75.

Malaga, A. & Vinodh, S. 2021. Benchmarking smart manufacturing drivers using Grey TOPSIS and COPRAS-G approaches. *Benchmarking: An International Journal,* 28**,** 2916-2951.

Malagihal, S. S. 2021. Strategic Options for Automobile OEMs of Indian Origin to have Sustained Competitive Advantage: A Case of Tata Motors. *International Journal of Global Business and Competitiveness,* 16**,** 139-152.

Mangla, S. K., Luthra, S., Jakhar, S. K., Tyagi, M. & Narkhede, B. E. 2018. Benchmarking the logistics management implementation using Delphi and fuzzy DEMATEL. *Benchmarking: An International Journal,* 25**,** 1795-1828.

Mardanya, D., Maity, G. & Kumar Roy, S. 2022. The multi-objective multi-item just-in-time transportation problem. *Optimization,* 71**,** 4665-4696.

Mehrotra, S. 2020. 'Make in India': The Components of a Manufacturing Strategy for India. *The Indian Journal of Labour Economics,* 63**,** 161-176.

Menekşe, A. & Camgöz Akdağ, H. 2022. Distance education tool selection using novel spherical fuzzy AHP EDAS. *Soft Computing,* 26**,** 1617-1635.

Monika & Sangwan, O. P. 2022. A framework for evaluating cloud computing services using AHP and TOPSIS approaches with interval valued spherical fuzzy sets. *Cluster Computing,* 25**,** 4383-4396.

Muñoz, C., De Miguel, M., Rochera, M. I., Dorda, M. D., Caubet, E. & González, O. 2021. Ultrasound diagnosis of a case of transient bilateral vocal cord paralysis secondary to local anesthetic infiltration. *Revista Española de Anestesiología y Reanimación (English Edition),* 68**,** 235-238.

Musa, A., Chojenta, C., Geleto, A. & Loxton, D. 2019. The associations between intimate partner violence and maternal health care service utilization: a systematic review and meta-analysis. *BMC Women's Health,* 19**,** 36.

Narkhede, G. B., Pasi, B. N., Rajhans, N. & Kulkarni, A. 2024. Industry 5.0 and sustainable manufacturing: a systematic literature review. *Benchmarking: An International Journal,* ahead-of-print.

Nguyen, J. 2024. Beyond policy impacts: Internal strategic capabilities as determinants of industrial energy efficiency implementation. *Energy Policy,* 184**,** 113898.

Nguyen, T.-L., Nguyen, P.-H., Pham, H.-A., Nguyen, T.-G., Nguyen, D.-T., Tran, T.-H., Le, H.-C. & Phung, H.-T. 2022. A Novel Integrating Data Envelopment Analysis and Spherical Fuzzy MCDM Approach for Sustainable Supplier Selection in Steel Industry. *Mathematics* [Online], 10.

Patterson, M., Singh, P. & Cho, H. 2022. The current state of the industrial energy assessment and its impacts on the manufacturing industry. *Energy Reports,* 8**,** 7297-7311.

Pierson, T. J., Liang, X., Peterson, R. & Kotz, D. Wanda: Securely introducing mobile devices. IEEE INFOCOM 2016 - The 35th Annual IEEE International Conference on Computer Communications, 10-14 April 2016 2016. 1-9.

Prashar, A. & Sunder M, V. 2024. Blockchain barriers in hospitals: a stakeholder theoretic perspective. *Benchmarking: An International Journal,* ahead-of-print.

Qayyum, F., Jamil, H., Iqbal, N. & Kim, D.-H. 2024. IoT-orchestrated optimal nanogrid energy management: Improving energy trading performance and efficiency via virtual operations. *International Journal of Electrical Power & Energy Systems,* 155**,** 109668.

Rajabpour, E., Fathi, M. R. & Torabi, M. 2022. Analysis of factors affecting the implementation of green human resource management using a hybrid fuzzy AHP and type-2 fuzzy DEMATEL approach. *Environmental Science and Pollution Research,* 29**,** 48720-48735.

Rajak, S., Mathiyazhagan, K., Agarwal, V., Sivakumar, K., Kumar, V. & Appolloni, A. 2022. Issues and analysis of critical success factors for the sustainable initiatives in the supply chain during COVID- 19 pandemic outbreak in India: A case study. *Research in Transportation Economics,* 93**,** 101114.

Robustelli, U., Baiocchi, V. & Pugliano, G. 2019. Assessment of Dual Frequency GNSS Observations from a Xiaomi Mi 8 Android Smartphone and Positioning Performance Analysis. *Electronics* [Online], 8.

Rodriguez, C. L., Zevin, M., Amaro-Seoane, P., Chatterjee, S., Kremer, K., Rasio, F. A. & Ye, C. S. 2019. Black holes: The next generation---repeated mergers in dense star clusters and their gravitational-wave properties. *Physical Review D,* 100**,** 043027.

Roudometof, V. 2023. Globalization, glocalization and the ICT revolution. *Global Media and Communication,* 19**,** 29-45.

Sachan, S., Barve, A., Kamat, A. & Shanker, S. 2022. Assessing the Barriers Towards the Glocalization of India's Mobile Industry: An IVIFs-DEMATEL with Choquet Integral Method. *International Journal of Information Technology & Decision Making,* 21**,** 1821-1858.

Sahoo, S. & Lo, C.-Y. 2022. Smart manufacturing powered by recent technological advancements: A review. *Journal of Manufacturing Systems,* 64**,** 236-250.

Santiago, F., Haraguchi, N. & Lavopa, A. 2024. Global Trends and World Order: Implications for New Industrial Policies in Developing Countries. *Journal of Industry, Competition and Trade,* 24**,** 5.

Sarraf, F. & Nejad, S. H. 2020. Improving performance evaluation based on balanced scorecard with grey relational analysis and data envelopment analysis approaches: Case study in water and wastewater companies. *Evaluation and Program Planning,* 79**,** 101762.

Shang, S. S. C. & Chiu, L. S. L. 2023. A RACE pathway for inventing and sustaining mobile payment innovation - A case study of a leading Bank in Taiwan. *Asia Pacific Management Review*.

Shaw, Y., Bradley, M., Zhang, C., Dominique, A., Michaud, K., Mcdonald, D. & Simon, T. A. 2020. Development of Resilience Among Rheumatoid Arthritis Patients: A Qualitative Study. *Arthritis Care & Research,* 72**,** 1257-1265.

Shokouhyar, S., Dehkhodaei, A. & Amiri, B. 2022. A mixed-method approach for modelling customer-centric mobile phone reverse logistics: application of social media data. *Journal of Modelling in Management,* 17**,** 655-696.

Shukla, M. & Shankar, R. 2024. Impact Assessment of Smart Manufacturing System Implementation in Small and Medium Enterprises: Moderating Role of Enabling Technology and Government Support. *Global Journal of Flexible Systems Management,* 25**,** 533-557.

Stefán, C. I. 2023. The World Economic Forum. *In:* MARTON, P., THOMASEN, G., BÉKÉS, C. & RÁCZ, A. (eds.) *The Palgrave Handbook of Non-State Actors in East-West Relations.* Cham: Springer International Publishing.

Stoilova, S. & Munier, N. 2021. A Novel Fuzzy SIMUS Multicriteria Decision-Making Method. An Application in Railway Passenger Transport Planning. *Symmetry* [Online], 13.

Sunny, J., Undralla, N. & Madhusudanan Pillai, V. 2020. Supply chain transparency through blockchain-based traceability: An overview with demonstration. *Computers & Industrial Engineering,* 150**,** 106895.

Trejos, T., Koch, S. & Mehltretter, A. 2020. Scientific foundations and current state of trace evidence—A review. *Forensic Chemistry,* 18**,** 100223.

Turienzo, J. & Lampón, J. F. 2022. New mobility technologies as incentive to location decisions: relocation strategy in the automotive industry. *Kybernetes,* ahead-of-print.

Van Der Valk, M. J. M., Marijnen, C. a. M., Van Etten, B., Dijkstra, E. A., Hilling, D. E., Kranenbarg, E. M.-K., Putter, H., Roodvoets, A. G. H., Bahadoer, R. R., Fokstuen, T., Ten Tije, A. J., Capdevila, J., Hendriks, M. P., Edhemovic, I., Cervantes, A. M. R., De Groot, D. J. A., Nilsson, P. J., Glimelius, B., Van De Velde, C. J. H. & Hospers, G. a. P. 2020. Compliance and tolerability of short-course radiotherapy followed by preoperative chemotherapy and surgery for high-risk rectal cancer – Results of the international randomized RAPIDO-trial. *Radiotherapy and Oncology,* 147**,** 75-83.

Vijh, M., Chandola, D., Tikkiwal, V. A. & Kumar, A. 2020. Stock Closing Price Prediction using Machine Learning Techniques. *Procedia Computer Science,* 167**,** 599-606.

Witt, M. A. 2019. China's Challenge: Geopolitics, De-Globalization, and the Future of Chinese Business. *Management and Organization Review,* 15**,** 687-704.

Wu, Z., Lu, J., Fu, Q., Sheng, L., Liu, B., Wang, C., Li, C. & Li, T. 2021. A smartphone-based enzyme-linked immunochromatographic sensor for rapid quantitative detection of carcinoembryonic antigen. *Sensors and Actuators B: Chemical,* 329**,** 129163.

Yan, X. & Huang, M. 2022. Leveraging university research within the context of open innovation: The case of Huawei. *Telecommunications Policy,* 46**,** 101956.

Yang, B., Wei, T., Fang, X., Deng, Z., Li, F. W. B., Ling, Y. & Wang, X. 2019. A Color-Pair Based Approach for Accurate Color Harmony Estimation. *Computer Graphics Forum,* 38**,** 481-490.

Yang, L., Zou, H., Shang, C., Ye, X. & Rani, P. 2023. Adoption of information and digital technologies for sustainable smart manufacturing systems for industry 4.0 in small, medium, and micro enterprises (SMMEs). *Technological Forecasting and Social Change,* 188**,** 122308.

Yang, Q. 2024. Heterogeneous impact of non-tariff measures on import margins through global value chains: Firm-level evidence from China. *International Review of Economics & Finance,* 92**,** 533-562.

Yilmaz, M. K., Kusakci, A. O., Aksoy, M. & Hacioglu, U. 2022. The evaluation of operational efficiencies of Turkish airports: An integrated spherical fuzzy AHP/DEA approach. *Applied Soft Computing,* 119**,** 108620.

Young, A. R. 2024. Governing the digital economy: transatlantic accommodation and cooperation. *Journal of European Integration,* 46**,** 973-992.

Zheng, P., Wang, H., Sang, Z., Zhong, R. Y., Liu, Y., Liu, C., Mubarok, K., Yu, S. & Xu, X. 2018. Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives. *Frontiers of Mechanical Engineering,* 13**,** 137-150.

Zhou, J., Huang, B., Fan, W., Cheng, Z., Zhao, Z. & Zhang, W. 2023. Text-based person search via local-relational-global fine grained alignment. *Knowledge-Based Systems,* 262**,** 110253.

Zimmermann, M., Bledsoe, C. & Papa, A. 2021. Initial impact of the COVID-19 pandemic on college student mental health: A longitudinal examination of risk and protective factors. *Psychiatry Research,* 305**,** 114254.

Appendix 1: Detailed Information about Experts

Sr. No.	Year of Experience	Qualification	Designation & Job Description	
1.	16	PhD in manufacturing and Management	Director of Operations	Oversees operations
2.	14	Master's Degree in smart manufacturing	Head of Logistics and Supply Chain	Manages logistics, supply chain
3.	13	MBA	Senior Program Manager	Leads program implementation
4.	11	Master's Degree in Engineering	Supply Chain Director	Directs supply chain strategy
5.	12	Master's Degree in Globalization	Head of Procurement	Oversees procurement processes
6.	11	PhD in Local to global export	Director of Emergency Response	Manages resilense operations
7.	10	Master's Degree in Engineering	Humanitarian Affairs Advisor	Advises on humanitarian policies
8.	19	PhD in Industry 4.0	Supply Chain Advisor	Guides supply chain optimization

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