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Evaluating Key Barriers and Drivers in Manufacturing Data Analytics: A Fuzzy DEMATEL-Based Strategic Map Approach

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ABSTRACT

Purpose – This study aims to explore the strategic and operational challenges affecting the adoption of Manufacturing Data Analytics (MDA), defined as the systematic use of manufacturing data to support decision-making and performance improvement in industrial environments. Focusing on expert insights from manufacturing sectors in Türkiye, the study examines key technology management decisions such as resource allocation, technology selection, and organizational transformation and identifies the primary drivers and barriers influencing successful MDA implementation.

Design/methodology/approach – The study applies the Fuzzy DEMATEL (Decision-Making Trial and Evaluation Laboratory) method based on evaluations from 14 industry experts in Türkiye to identify and analyze the cause-and-effect relationships among critical drivers and barriers to MDA integration. This approach enables a systematic evaluation of how technological, managerial, and organizational factors interact during the adoption process.

Findings – The results reveal that high investment costs for data analysis and simulation (B4), lack of technical infrastructure in operational processes (B6), and insufficient top management support (B10) are the most significant barriers. Conversely, the primary drivers belong to the cause group and include problem identification (D1), operational efficiency improvement (D2), transparency (D3), observability (D4), coordination (D5), data management (D6), readiness of Industry 4.0 infrastructure (D9), prediction (D10), and agility (D13).

Discussion – The findings demonstrate that addressing cost, infrastructure, and leadership barriers particularly in the context of expert insights from Türkiye's manufacturing sectors while strengthening analytical and organizational capabilities is essential for effective MDA adoption. The study contributes to technology and innovation management literature by providing practical insights for engineering managers to enhance digital transformation, improve operational performance, and achieve a sustainable competitive advantage.

1. Introduction

Recently, the proliferation of big data and digital technologies in the manufacturing sector has made data analytics applications a strategic necessity for businesses (Saraswat & Choudhari, 2025). However, the adoption and effective use of Manufacturing Data Analytics (MDA) applications in businesses is directly related not only to the existence of technological infrastructure, but also to organizational transformation, resource management, and administrative support. MDA refers specifically to analytics applications focused on operational manufacturing processes and production-related supply chain activities, rather than broader Big Data Analytics (BDA) or purely AI-driven decision systems. While BDA and AI encompass cross-functional and predictive intelligence across domains, MDA concentrates on extracting actionable insights from production, process, and shop-floor data to improve operational performance. Although MDA has the potential to increase efficiency in manufacturing processes, prevent losses, and provide a sustainable competitive advantage, many businesses struggle to fully integrate these systems (Wu et al., 2024).

In other words, data diversity is currently increasing significantly as new internet technologies enable the production of data on an individual level (Sahoo, 2021). Especially in manufacturing supply chains, for

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example, manually operated tools have become smart devices that generate data from embedded sensors (Raut et al., 2021a). The rapid diffusion of IoT devices, sensorization, Manufacturing Execution Systems (MES), and Enterprise Resource Planning (ERP) systems has led to an unprecedented growth of production-related data. However, this expansion has also created a “data-rich but insight-poor” paradox in many manufacturing environments. Transforming these data into information has become a significant source of competitive advantage in manufacturing supply chains, which are becoming increasingly complex, thereby making it harder to achieve perfection in business processes (Majeed et al., 2021). For manufacturing supply chains, prevention of losses and innovativeness now depend on processing information (Chavez et al., 2017). Information can thus be defined as data that has been transformed into a valuable form for supply chains through transformational and analytical processes, achieving specific goals or gaining a specific understanding (Sahoo, 2021).

Accordingly, it is crucial for the sustainability of manufacturing operations that manufacturing supply chains take a data-based approach to making strategic decisions (My, 2021). However, processing and handling data through business analytics has become a critical problem, especially for manufacturing processes in supply chains (Ren et al., 2019). In other words, even though there is many data, when it is not collected and processed correctly, meaningless data piles up. Poor data integration across systems may result in unplanned machine downtime, increased scrap rates, quality deviations, delayed deliveries, and higher operational costs, thereby eroding the expected value of digital investments. Therefore, one of the most important elements to focus on in supply chains is the operational data and analysis of these data. Every stage of the product life cycle now generates massive production-related data about the product itself, its manufacturing processes, and its supply chain, among other things. In turn, these data must be managed by information systems, such as manufacturing execution systems, enterprise resource planning systems, and customer relationship management systems. This creates the need to integrate the production-related data managed by different systems on a common platform. In addition, big data plays a vital role in manufacturing processes, enabling better demand and manufacturing forecasting, improved factory performance, and faster after-sales service and customer support Consequently, there is a growing need for manufacturing data analytics (MDA) to ensure effective management of manufacturing operations.

MDA enables the rapid analysis and reporting of data, allowing businesses to obtain accurate information and make informed decisions regarding their manufacturing processes (Ma et al., 2020). These data are critical for both understanding customer behaviors and demands and evaluating business performance (Mageto, 2021). MDA can be defined as the multidisciplinary science of turning data into information within manufacturing operations (Escobar et al., 2021). It directly influences how data is gathered and how business decisions are made in manufacturing operations (Lutfi et al., 2022). As mentioned before, implementing MDA can minimize losses and maximize operational efficiency in manufacturing processes (Saleem et al., 2020). In complex manufacturing operations, it is essential to collect, store, and analyze data from every step (Ren et al., 2019).

Managers need to recognize the importance of MDA and prioritize data analytics applications in their company's management strategy. This will enable the enterprise to adapt its technologies to implement MDA and thereby remain competitive during the digital transformation. While MDA can support effective decision-making in almost all sectors, it is especially valuable in strategic sectors. Therefore, managers must follow developments in MDA and adapt the enterprise to avoid falling in the current competitive business environment. Given the apparent need to adopt MDA to analyze the massive data generated during manufacturing processes, very few businesses have fully adopted and implemented it (Moktadir et al., 2019). Possible barriers include insufficient awareness and knowledge within enterprises, as well as an unwillingness to accept high investment costs (Gupta & Goyal, 2021). Importantly, prior studies tend to focus either on barriers or on drivers of adoption, and rarely examine both dimensions within a unified analytical framework. Moreover, the causal interrelationships among these factors namely which factors trigger or intensify others have remained largely underexplored.

In emerging economies such as Türkiye, the digital transformation of manufacturing processes has become a strategic priority in terms of both economic growth and increasing global competitiveness (Rashid et al., 2025). However, this transformation process faces challenges such as technical infrastructure deficiencies, high investment costs, an insufficiently qualified workforce, and a lack of awareness about digitalization (Narwane & Priyadarshinee, 2025). In emerging economies, factors such as infrastructure readiness, financial constraints, and top management commitment may become even more critical compared to developed contexts. These barriers, especially in the adoption of innovative applications such as MDA, stand out as critical factors that delay companies' digital transformation processes. Despite these barriers, the operational efficiency, cost optimization, and speed provided by MDA in decision-making processes offer a significant opportunity for sustainable development in emerging economies. MDA not only enhances the efficiency of business processes but also provides environmental benefits, including waste management and resource savings, by improving quality in industrial manufacturing (Tanpoco & Magnaye, 2025). While the empirical setting of this study is Türkiye, the aim is to reveal cross-sectoral common patterns that may characterize similar emerging economy contexts, rather than making universal generalizations. Therefore, this study aims to identify the primary barriers and driving factors that affect the applicability of MDA in emerging economies and to develop recommendations to accelerate the digital transformation processes of these economies. Moreover, this study aims to reveal general trends and commonalities in MDA applications rather than barriers and drivers specific to different contexts, sectors, and operations. The study offers three main contributions: (1) identifying barriers and drivers within a single integrated framework, (2) separately analysing their causal networks to determine influence direction, and (3) providing a strategic prioritization map that supports actionable managerial decision-making. This broad perspective contributes to both the literature and practice by providing a comprehensive basis for understanding the basic factors that shape MDA Considering the heterogeneity of the current manufacturing structure in Türkiye, these findings provide a starting point that can form the basis for narrower-scope studies in the future.

Recently, although studies are conducted to make sense of the data, this is not something that every company can afford to adopt. The applicability of MDA has both theoretical and practical significance in terms of identifying common trends and fundamental factors across different contexts and sectors. This study provides a general framework that can guide more focused and sector-specific research on integrating MDA into business processes. In this context, the primary motivation of the study is to understand why MDA has not been fully adopted, to analyse in detail the barriers encountered in this process and the driving factors supporting success, and to shed light on sectoral applications. As the literature review presented below reveals, there is a significant lack of information in the literature on the barriers and driving factors encountered in the implementation of MDA. Existing studies generally focus on specific sectors or contexts, but fail to provide a comprehensive understanding of the factors affecting MDA adoption across different sectors and organizational structures.

Furthermore, the causal relationships among these barriers and drivers have been largely ignored. This creates a critical gap in understanding how these factors hinder or facilitate the implementation of MDA. To address this gap, the study employs the Fuzzy DEMATEL method, which enables not only the prioritization of factors but also the identification of cause–effect directions and influence intensities. The fuzzy extension is particularly appropriate given the ambiguity and subjectivity inherent in expert judgments regarding technological and organizational factors.

Accordingly, this study addresses the following research questions in an integrated manner: **RQ1:** What are the barriers and drivers to implementing MDA? **RQ2:** How do these barriers causally affect MDA implementation? **RQ3:** How do these drivers causally affect MDA implementation? The rest of the paper is organized as follows. Section 2 presents the literature review. Section 3 outlines the methodology, while Section 4 presents the implementation and results. Section 5 discusses the findings, including their implications, and draws some conclusions.

2. Literature Review of MDA Research

Recently, big data has become a crucial and widespread resource. However, enterprises are not yet analysing and managing it effectively, especially for manufacturing processes (Dubey et al., 2019). Moreover, databases are growing in size due to the extensive use of information systems and technologies in manufacturing operations (Belhadi et al., 2019). This rapid growth of big data related to manufacturing processes highlights the need for data analysis (Psarommatis et al., 2022). In manufacturing, big data refers to data sets that are too large and complex for traditional databases to process within acceptable time constraints (Raut et al., 2021a; Narwane & Priyadarshinee, 2025). Consequently, MDA is becoming a prominent approach for handling large datasets in manufacturing processes (Cui et al., 2020). Therefore, MDA relies on big data, which refers to large and rapidly growing volumes of data that can occur in various forms without a specific structure (Bi & Cochran, 2014).

Use of MDA can increase manufacturing quality, improve performance, optimize supply chains, and reduce costs (Tanpoco & Magnaye, 2025). It can enable better tracking of operations and, in some cases, automate decisions by analyzing various types of data, including real-time, historical, unstructured, structured, and qualitative data (Yuan et al., 2022). MDA includes forecasting models that extract information from geographical, graphical, textual, and temporal data (Wang et al., 2021). This can support decision-making processes in manufacturing and sourcing, providing a competitive advantage (Sajadieh et al., 2022). Finally, MDA enables real-time monitoring of manufacturing devices and advanced detection of malfunctions by utilizing device data from device alarms, event logs, and status notifications (Ungermann et al., 2019).

As mentioned earlier, MDA has become a significant issue due to rapid technological advancements and the accelerating transition from traditional to data-driven manufacturing (Dubey et al., 2019; Narwane & Priyadarshinee, 2025). Given these technological developments and the current focus on the internet in manufacturing, enterprises must now measure and monitor real-time data from their manufacturing processes.

Several studies have examined the application of data analytics in manufacturing, concentrating on key themes. These include predictive analytics (Krumeich et al., 2014; Jain et al., 2017), process optimization (Ungermann et al., 2019), shop floor scheduling (Ji & Wang, 2017; Zhong et al., 2017), sustainable manufacturing (Bi & Cochran, 2014; Mani et al., 2017; Jasiulewicz-Kaczmarek & Gola, 2019; Ren et al., 2019; Ma et al., 2020; Rashid et al., 2025), intelligent manufacturing (Zhong et al., 2017; Ma et al., 2020; Wang et al., 2020), and smart manufacturing (Narwane & Priyadarshinee, 2025; Tanpoco & Magnaye, 2025). Most of these studies highlight the areas that require data analytics and explain how data analytics can be used.

Several researchers have conducted systematic literature reviews of big data and data analytics. For example, Cui et al. (2020) identified important areas for MDA applications. Moreover, Mrida et al. (2025) examine AI-driven manufacturing data analytics and automation in industrial applications through a systematic literature review. They assess the role and impact of AI in various sectors within the context of strategic data management and innovation.

Upon reviewing the literature, it becomes apparent that although studies discussed in practice or systematic literature reviews are available, a gap remains in the literature regarding the identification of permanent solutions by pinpointing the barriers and drivers of MDA applications and establishing a relationship analysis between them. Moreover, this study fills an important gap in the literature on MDA applications by simultaneously addressing both barriers and push factors and determining the causal relationships between them. While the literature typically focuses on a specific sector or context, this study offers a broader perspective, providing important theoretical and practical implications regarding the general acceptance processes of MDA applications. Therefore, this study aims to first determine the barriers and drivers to implementing MDA, then to specify the relationship between these barriers and drivers, and finally to find permanent solutions to this problem. Hence, firstly, barriers and drivers to implementing MDA are explained in detail.

2.1. Determining the Barriers and Drivers to Implementing MDA

Few studies have investigated the barriers and drivers to implementing MDA for operational processes in manufacturing. Therefore, the most important contribution of this study is that it will simultaneously compare these factors in this specific area. Tables 1 and 2 identify, respectively, the barriers (B) and drivers (D) to implementing MDA in operational processes, as identified from the literature review and experts' opinions.

Table 1. Barriers to implementing MDA

Barriers to MDA	**Author(s)**
Lack of Veracity in Data Collected from Operational Processes (B1)	Zhong et al., 2016; Belhadi et al., 2019
Lack of Skilled Personnel for Processing Data in Manufacturing (B2)	Moktadir et al., 2019; Gupta & Goyal,2021
Lack of Data Scalability (B3)	Bi & Cochran, 2014; Gupta & Goyal,2021
High Investment Costs for Data Analysis And Simulation in Manufacturing Processes (B4)	Jain et al., 2017; Moktadir et al., 2019
Lack of Data Integration (B5)	Dai et al., 2019; Raut et al., 2021a
Lack of Technical Infrastructure in Operational Processes (B6)	Alharthi et al., 2017; Moktadir et al., 2019; Gupta & Goyal,2021
Lack of Information Sharing (B7)	Omar et al., 2019
Long Term Investment Return (B8)	Raut et al., 2021a; Raut et al., 2021b
Lack of Data Security (B9)	Alharthi et al., 2017; Gangwar, 2018
Lack of Top Management Support (B10)	Raut et al., 2021b
Lack of Traceability (B11)	Chen et al., 2022

The barriers listed in Table 1 can be explained as follows.

Lack of Veracity in Data Collected from Operational Processes (B1): Not all data collected from manufacturing processes is valid or accurate, which makes it more challenging to incorporate adaptive data analytics into manufacturing.

Lack of Skilled Personnel for Processing Data in Manufacturing (B2): More qualified employees with knowledge of MDA are needed to implement data analytics in manufacturing operations (Moktadir et al., 2019).

Lack of Data Scalability (B3): To implement MDA, the data must be scalable and adaptable. Otherwise, it cannot be located, processed, classified, or accessed from the collected data stack promptly (Gupta & Goyal, 2021).

High Investment Costs for Data Analysis and Simulation in Manufacturing Processes (B4): The required technology and analytical methods for MDA have high investment costs (Jain et al., 2017).

Lack of Data Integration (B5): Different systems must be integrated to make sense of the data collected from different operational processes (Raut et al., 2021a).

Lack of Technical Infrastructure in Operational Processes (B6): Without the required technical infrastructure, MDA cannot be implemented in manufacturing processes (Alharthi et al., 2017).

Lack of Information Sharing (B7): MDA cannot be implemented without accurate and transparent information sharing between manufacturing processes (Omar et al., 2019). Additionally, implementation will be hindered if managers and data scientists do not collaborate to understand the process.

Long-Term Investment Return (B8): MDA investments yield a return only in the long run (Raut et al., 2021b).

Lack of Data Security (B9): It can be challenging to ensure data security because MDA requires that data is shareable across all manufacturing processes (Gangwar, 2018).

Lack of Top Management Support (B10): Implementing MDA becomes more challenging if top management fails to adopt a strategic perspective or provides insufficient support for MDA (Raut et al., 2021b).

Lack of Traceability (B11): Even if accurate data is obtained from manufacturing processes, these processes should be traceable. Otherwise, the expected outputs will not be obtained due to variations in the dynamics of the systems comprising manufacturing operations (Chen et al., 2022). Consequently, end-to-end system control is required.

The drivers identified from the literature review and expert opinions listed in Table 2 can be explained as follows.

Table 2. Drivers to implementing MDA

Drivers of MDA	**Author(s)**
Problem Identification (D1)	Zhong et al.,2016; Belhadi et al., 2019; Dubey et al., 2019
Operational Efficiency Improvement (D2)	Jain et al., 2017; Belhadi et al., 2019; Dai et al., 2019; Bag et al., 2020
Transparency (D3)	Kampker et al., 2018; Woo et al., 2018; Omar et al., 2019
Observability (D4)	Yadegaridehkordi et al., 2018; Woo et al., 2018
Coordination (D5)	Groggert et al., 2017; Siddique et al., 2020; Kumar et al., 2021
Data Management (D6)	Fahmideh and Beydoun, 2019; Gangwar, 2018
Competitive Advantage (D7)	Gangwar, 2018; Zaki et al., 2019
Quality (D8)	Dai et al., 2019
Readiness of Industry 4.0 Infrastructure (D9)	Sahoo, 2021; Kampker et al., 2018
Prediction (D10)	Cui et al., 2020
Sustainable Manufacturing (D11)	Zhang et al., 2016; Cui et al., 2020
Effective Use of Resources (D12)	Dubey et al., 2019; Kumar et al., 2021
Agility (D13)	Barlette & Baillette, 2022

Problem Identification (D1): By refining the problem definition, MDA ensures that the right decisions are made (Belhadi et al., 2019). Given that the perspectives and problem-solving techniques of data-based systems and organizational structures are changing, MDA enables more creative solutions (Dubey et al., 2019).

Operational Efficiency Improvement (D2): Through improved analysis of data obtained from manufacturing processes, MDA enhances manufacturing efficiency (Dai et al., 2019).

Transparency (D3): MDA makes the data required for operational processes more accessible and reliable (Woo et al., 2018).

Observability (D4): MDA makes operational processes more visible, thereby making them easier to track (Yadegaridehkordi et al., 2018).

Coordination (D5): For smooth operations, manufacturing processes must work in an integrated manner (Kumar et al., 2021). MDA enables the required coordination.

Data Management (D6): MDA ensures effective collection, classification, and analysis of data, which enables accurate and effective data management of manufacturing processes (Fahmideh & Beydoun, 2019).

Competitive Advantage (D7): Through rapid adaptation to changing technological or operational conditions, MDA enables enterprises to gain a competitive advantage (Zaki et al., 2019).

Quality (D8): MDA minimizes error rates to ensure operational excellence.

Readiness of Industry 4.0 Infrastructure (D9): MDA meets the main criterion of Industry 4.0, namely the use of big data analytical infrastructure (Sahoo, 2021).

Prediction (D10): MDA enables effective estimation analyses of manufacturing processes (Cui et al., 2020).

Sustainable Manufacturing (D11): MDA enables the conversion of manufacturing outputs back into inputs, thereby ensuring environmental, economic, and social improvements (Zhang et al., 2016). That is, the results from data analytics in manufacturing can reduce the use of raw materials, energy consumption, and waste generation while maintaining or increasing product value.

Effective Use of Resources (D12): MDA ensures the efficient use of resources through improved manufacturing activities, including manufacturing planning, demand forecasting, and stock management (Kumar et al., 2021).

Agility (D13): MDA eliminates delays between problem formation, understanding, and acting through the use of real-time structures in data-based systems. Structures become more agile due to increased operational speed and flexibility (Barlette & Baillette, 2022).

To provide a stronger theoretical foundation for the barriers and drivers framework, this study draws on established technology adoption and strategic management perspectives. Specifically, the Technology–Organization–Environment (TOE) framework, the Resource-Based View (RBV), and dynamic capabilities literature highlight how organizational, technological, and environmental factors influence MDA adoption. In addition, digital transformation maturity provides insight into why certain factors act as barriers while others serve as drivers. This theoretical grounding justifies the causal analysis performed with Fuzzy DEMATEL, which is particularly suitable for revealing perceived relationships between complex, interdependent factors.

Moreover, although this study focuses on leading companies in Türkiye, it provides insights into common barriers and drivers that may apply across sectors. Future studies can extend the analysis to sector-specific contexts to address intra-sector heterogeneity while maintaining a shared baseline of critical factors. By determining these barriers and drivers to implementing MDA, the first research question is answered. Despite the growing significance of MDA, there is a lack of comprehensive studies that identify and analyze both the barriers and drivers of MDA implementation across various sectors. Existing research often focuses on specific industries or contexts, failing to establish causal relationships between these factors and their outcomes. This study fills this gap by systematically examining both barriers and drivers while providing applicable solutions to enhance MDA adoption and effectiveness. In the following section, the causal relationships between these barriers and drivers are determined, respectively.

3. Method

The first stage in the study was a detailed literature review. The identified barriers and drivers to implementing MDA in operational processes were then validated by three vendors and two experts working in manufacturing processes to justify the barriers and drivers list correctly. After the set of barriers and drivers was identified, separate fuzzy DEMATEL analyses were conducted for the barriers and drivers with 14 experts. The following section explains the steps in fuzzy DEMATEL.

3.1. Fuzzy DEMATEL

DEMATEL (Decision-Making Trial and Evaluation Laboratory) was developed to solve complex, intertwined problem groups in research (Hosseini et al., 2022). DEMATEL is a method for structural model analysis that identifies causal relationships between a set of factors using diagrams and matrices (Agi & Jha, 2022). The method defines the relationships between components using diagrams and matrices, and quantifies these relationships to reveal their strength (Kumar et al., 2021). However, it is challenging to determine the degree of interaction between the factors in these relationships (Lin et al., 2021) because it is difficult to quantify the interaction (Agi & Jha, 2022). Therefore, DEMATEL has been extended to fuzzy environments (Hosseini et al., 2022). This method offers superior performance compared to other methods in terms of revealing the causal relationships between complex and interrelated factors and evaluating the strength of these relationships. For example, the WINGS method focuses on the weighting of individual factors, but is insufficient in analysing the interactions between factors (Amiri et al., 2025). While the Analytical Hierarchy Process (AHP) method is effective for prioritizing and weighting factors, it cannot analyse the bidirectional cause-and-effect relationships between factors (Wu et al., 2025). Similarly, TOPSIS does not consider the interactions between factors when determining the proximity of alternatives to the ideal solution (Seifi et al., 2025). Although the Interpretive Structural Modelling (ISM) method is effective in establishing a hierarchy between factors, it cannot reveal the intensity and direction of the interactions between these factors (Wu et al., 2025). Fuzzy DEMATEL was selected as the most appropriate method in line with the objectives of this study because it can comprehensively analyse not only the importance of factors, but also their effects on each other and their causal relationships (Min et al., 2025).

The Fuzzy DEMATEL method was preferred in this study over the traditional DEMATEL method because fuzzy logic offers the ability to effectively manage the uncertainties and subjectivity that arise in expert opinions (Tian et al., 2025). While the traditional DEMATEL method requires experts to express the relationships between factors with precise numbers, this can create difficulties in MDA applications, which are complex and multidimensional subjects. Fuzzy DEMATEL, on the other hand, allows experts to express their opinions through linguistic terms (e.g., "weak," "medium," "strong") and quantifies these expressions with fuzzy numbers. This approach allows better management of uncertainties and more reliable and realistic analysis results. In addition, the Fuzzy DEMATEL method can evaluate not only the direction of the relationships between factors, but also the intensity of these relationships. Therefore, the method used in this study is the most appropriate choice to analyse the complex interactions between barriers and driving factors in the application of MDA more accurately.

Before applying fuzzy DEMATEL in the present study, the expert opinions were normalized using the CFCS (Converting Fuzzy data into Crisp Scores) method. Specifically, the CFCS defuzzification method, as proposed by Opricovic and Tzeng (2003), was adopted. This method is suitable for fuzzy aggregation processes and was originally applied in course selection problems, offering more accurate crisp values compared to the traditional centroid method. The CFCS procedure begins with normalizing the fuzzy triangular numbers by calculating the relative positions of the lower, middle, and upper values with respect to the minimum and maximum of the fuzzy set. Then, the normalized left and right scores are computed to capture the asymmetry of each fuzzy number. These scores are combined to calculate the total normalized crisp value, which is subsequently transformed into the final crisp score by adding back the minimum bound. Finally, the crisp values from all experts are aggregated as a weighted average to obtain a single precise value for each factor. The CFCS method determines the left and right scores bounded by the minimum and maximum of the fuzzy number, and the total crisp score is calculated as a weighted average based on the membership functions. This approach allows the fuzzy linguistic evaluations from the experts to be converted into precise numerical values for subsequent DEMATEL analysis while preserving the relative importance indicated by the participants.

DEMATEL was then conducted with the normalized values according to the following steps:

Step 1: Determining the problem purpose, establishing the decision group, and determining the initial direct-relation matrix

The initial direct-relation matrix is symbolized with Z. Z could be a n x n framework that's procured by pair-wise comparisons from the point of impacts and headings among the criteria, in which zij is communicated as the degree to which the measure i influences the measure j, i.e. in Equation 1.

$$Z = [Z_{ij}]_{nxn} \qquad (1)$$

Step 2: The normalized direct relationship matrix $X = [X_{ij}]_{nxn}$, where $0 \leq x_{ij} \leq 1$, can be calculated using Equations 2 and 3.

$$X = s \cdot Z \tag{2}$$

$$s = \frac{1}{max_{1 \le i \le n} \sum_{j=1}^{n} z_{ij}}, \; i,j = 1,2,\cdots,n \tag{3}$$

Step 3: The total relationship matrix (T) is calculated by using Equation 4.

$$T = X\,(I - X)^{-1} \tag{4}$$

Step 4: The overall lines and the entirety of columns are characterized autonomously as D and R interior the total-relation matrix T through the equations (5)–(6):

$T = t_{ij}, \quad i,j = 1,2,\ldots,n,$

$$D = \sum_{j=1}^{n} t_{ij}, \tag{5}$$

$$R = \sum_{i=1}^{n} t_{ij}, \tag{6}$$

D is the sum of rows and R is the sum of columns.

Step 5: Establishing and analysing the cause-effect structural model based on (D+R) and (D-R) values.

4. Findings

In Türkiye, data analytics in manufacturing is relatively new and currently at a low level due to several factors, with particular concerns regarding high investment costs and the lack of necessary infrastructure. However, the current structure of eligible companies in Türkiye, combined with the knowledge of experts in the field, indicates that it is necessary to concentrate more on data analytics in manufacturing (Sarı et al., 2020). Few studies of MDA in Türkiye have been conducted, so it is necessary to investigate the barriers and drivers of MDA in Türkiye.

This study was conducted with leading companies in Türkiye. For Fuzzy DEMATEL data collection process, the opinions of 14 experts, who were manufacturing and IT managers working in Türkiye, were collected through face-to-face interviews. The experts were selected based on their extensive experience in the manufacturing sector and their involvement in decision-making processes related to MDA applications. The experts were selected based not only on their extensive experience in the manufacturing sector (each having at least 10 years of professional experience) but also on their direct involvement in MDA-related decision-making processes within their companies, ensuring that their insights reflected both operational and strategic perspectives. The experts were selected based on their extensive experience in the manufacturing sector and their involvement in decision-making processes related to MDA applications. Each expert had at least 10 years of professional experience, and these experts were in managerial or technical roles. The participating companies represented a range of sectors—including automotive, textile, iron and steel, food, tobacco, lighting, and abrasive covering both highly mature and developing MDA contexts, which allowed capturing variations in infrastructure, investment, and organizational readiness across industries.

The interviews were conducted in a semi-structured format, covering the experts' direct experiences with MDA adoption and their views on general industry challenges. To ensure data reliability, all participants were informed about the study's objectives and fundamental concepts prior to the interviews. The selection of experts was based on their knowledge of MDA applications and their active role in these processes. The participants were selected from major manufacturing sectors in Türkiye, such as automotive, textile, iron and steel, and food. To increase the representativeness of the study, opinions from experts across various sectors were included, and these experts have direct work experience related to data analytics and manufacturing processes. This careful selection ensured that the expert judgments used in the DEMATEL analysis were grounded in both technical expertise and sectoral diversity, enhancing the reliability and applicability of the causal relationships identified.

To sum up, during the interviews, experts were asked to assess the relationships between each driver and barrier individually, based on their own experiences. Each expert provided qualitative assessments of the direction and intensity of the interaction between each driver and barrier, resulting in a wealth of verbal and conceptual data.

Due to the nature of the FUZZY DEMATEL method, these qualitative comments were first translated into linguistic expressions. Expressions such as "very high, "high," "low," and "very low", "no influence" were categorized according to the fuzzy linguistic scales defined within the method. These expressions and their corresponding triangular fuzzy numbers are shown in Table 3.

Table 3. Triangular Fuzzy Numbers

Linguistics Scale	Fuzzy Numbers
Very High	(0.75, 1.0, 1.0)
High	(0.5, 0.75, 1.0)
Low	(0.25, 0.5, 0.75)
Very Low	(0, 0.25, 0.5)
No Influence	(0, 0, 0.25)

During this process, all driver-barrier relationships were individually evaluated for each expert, and the linguistic expressions were converted into quantitative forms by matching them with fuzzy triangular numbers for analysis. In the final stage, the fuzzy matrices obtained from the linguistic expressions were subjected to fuzzification, normalization, total effects calculation, and defuzzification steps in accordance with the FUZZY DEMATEL procedure, revealing the causal effects of driver-barrier relationships. The data obtained from these processes are described below, respectively.

Table 4 presents the characteristics of the companies and the participating experts.

Table 4. Expert Characteristics

Expert	Sector	Firm Size	Expert	Sector	Firm Size
Expert 1	Machinery	Large	**Expert 8**	Lighting	Large
Expert 2	Textile	Large	**Expert 9**	Lighting	Large
Expert 3	Automotive	Medium	**Expert 10**	Metal	Medium
Expert 4	Iron Steel	Large	**Expert 11**	Food	Large
Expert 5	Automotive	Medium	**Expert 12**	Textile	Large
Expert 6	Abrasive	Medium	**Expert 13**	Tobacco	Large
Expert 7	Lighting	Large	**Expert 14**	Automotive	Large

The experts for this study were selected from the most important manufacturing sectors in Türkiye, such as automotive, textile, iron and steel, food, tobacco, and lighting. The expert opinions encompassed diverse perspectives, gathering input from service providers and data analytics professionals involved in manufacturing processes.

The expert opinions regarding the barriers and drivers of MDA were analysed separately using fuzzy DEMATEL by making pairwise comparisons of the MDA barriers and drivers. The analysis identified 11 barriers and 13 drivers to implementing MDA. Tables IV and V show an example of the pairwise comparisons by Expert 1. In these tables, No Influence is represented as NO, Very Low Influence is represented as VL, Low Influence is represented as L, High Influence is represented as H, Very High Influence is represented as VH.

Table 5. Example of Expert 1's Linguistic Assessment of Barriers to Implementing MDA

	B1	**B2**	**B3**	**B4**	**B5**	**B6**	**B7**	**B8**	**B9**	**B10**	**B11**
B1		NO	VL	VL	NO	NO	VL	L	VL	H	H
B2	VL		VL	NO	L	VL	VL	NO	VL	NO	VL
B3	H	L		VL	H	L	NO	H	NO	H	VL
B4	NO	H	VL		VL	H	VL	NO	NO	NO	L
B5	VL	VL	VL	VL		VL	VL	NO	NO	VL	VL
B6	H	H	H	VL	VL		VL	NO	L	NO	NO
B7	NO	NO	VL	NO	VL	VL		L	VL	VL	VL

B8	VL	L	VL	VL	NO	L	VL		NO	VL	H
B9	NO	VL	L	L	VL	VL	NO	H		H	H
B10	L	H	VL	L	NO	H	L	L	NO		VL
B11	NO	VL	H	VL	H	H	NO	VL	NO	H	

Table 6. Example of Expert 1's Linguistic Assessment of Drivers for Implementing MDA

	D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**	**D11**	**D12**	**D13**
D1		L	L	VL	VH	NO	VL	VL	H	VL	NO	NO	NO
D2	L		L	L	VL	VH	L	VH	L	H	NO	VL	VH
D3	VL	H		VL	VH	VL	NO	L	VH	L	VH	VH	VH
D4	VL	H	VL		L	NO	L	VH	L	NO	L	NO	NO
D5	VH	VH	VL	L		VL	H	VL	L	H	VH	NO	VH
D6	VH	H	VH	NO	H		VL	L	L	NO	VL	VH	NO
D7	L	L	NO	VL	VL	VH		VH	NO	L	VH	VH	H
D8	VL	VH	H	VL	VL	VH	H		VL	H	H	VH	VH
D9	NO	NO	VH	VL	VH	NO	L	H		VL	H	H	NO
D10	VL	NO	H	L	VL	VL	NO	H	VL		L	H	L
D11	VH	VH	NO	VH	VH	VL	VH	VH	NO	L		VL	VH
D12	H	VH	H	NO	L	H	H	VH	NO	VL	H		H
D13	VL	H	H	VH	VL	VH	VL	VL	NO	VL	H	L	

Fuzzy DEMATEL was implemented in accordance with the four steps outlined in Section 3. The D and R vectors were calculated to determine the importance (D+R) of each factor and their relationships (D-R). The results are presented in Tables 7 and 8, which outline the barriers and drivers, respectively. In the causal relationship matrix, the D+R value is plotted on the horizontal axis and represents the total importance or prominence of a criterion. The D−R value is plotted on the vertical axis and indicates the causal role of the criterion. A positive D−R value means the criterion belongs to the cause group, while a negative D−R value means it belongs to the effect group.

Table 7. D+R and D-R Values for Barriers to Implementing MDA

Barriers	**D+R**	**D-R**
B1	9.8	-0.1
B2	8.3	-0.1
B3	9.1	-0.5
B4	8.6	0.6
B5	9.3	-0.2
B6	10.1	0.8
B7	8.0	-0.6
B8	9.0	-0.2
B9	8.0	-0.3
B10	8.8	0.7
B11	10.4	-0.1

Table 8. D+R and D-R Values for Drivers to Implement MDA

Drivers	**D+R**	**D-R**
D1	15.5	0.9
D2	16.9	0.1
D3	15.5	1.6
D4	15.7	1.0
D5	15.4	0.5
D6	16.4	0.7
D7	13.7	-3.7
D8	15.9	-0.8

D9	16.1	0.9
D10	13.9	0.4
D11	15.9	-1.2
D12	16.2	-1.0
D13	16.9	0.6

Causal diagrams for the barriers and drivers were then obtained, as shown in Figures 1 and 2, respectively. In the DEMATEL method, cause-and-effect criteria are identified by examining the Cause-and-Effect Relationship Diagram. More specifically, the criteria are located, respectively, above and below the horizontal axis. The horizontal axis represents prominence (D+R), indicating the total importance of a criterion, while the vertical axis represents causal role (D−R). A positive D−R value places a criterion in the cause group, and a negative D−R value places it in the effect group.

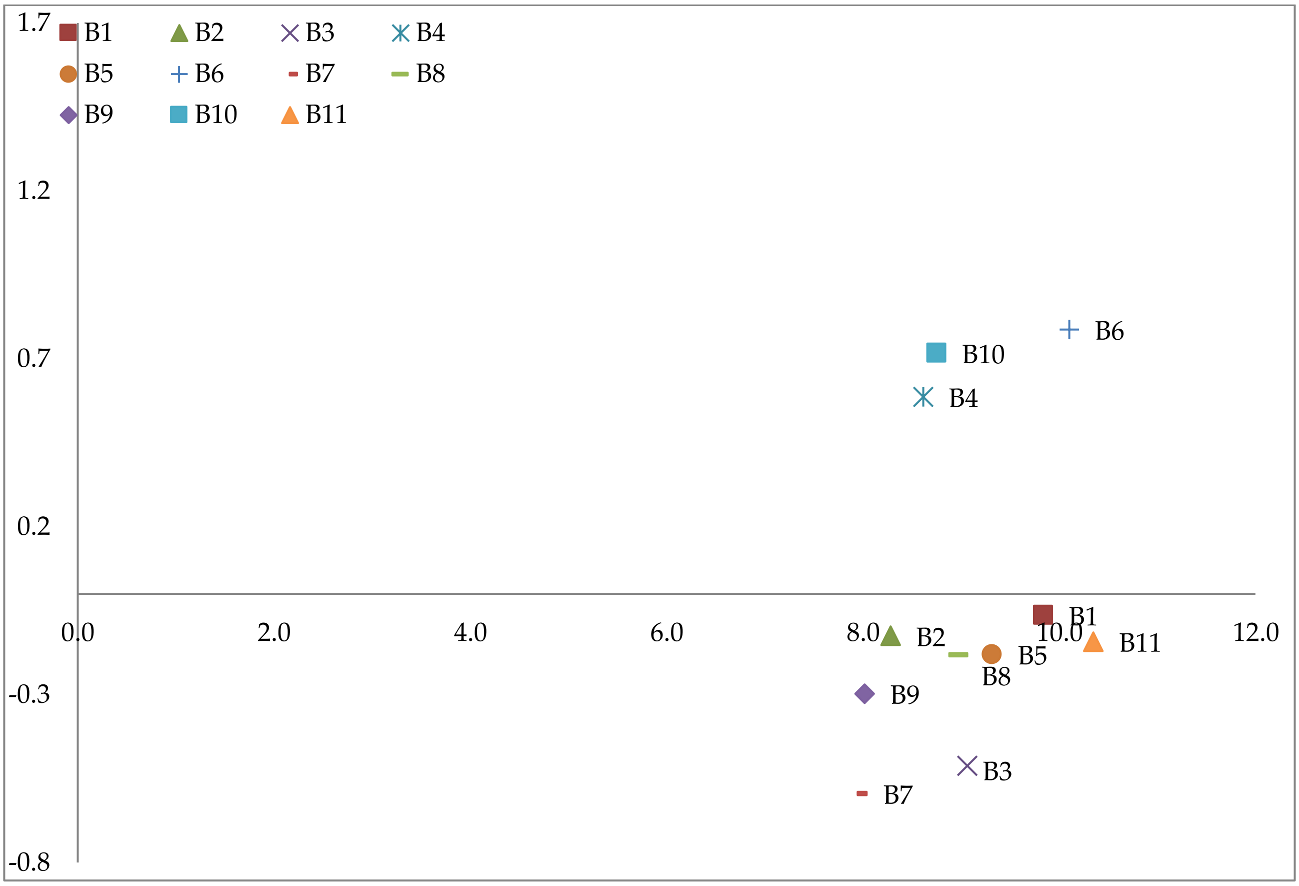

Figure 1. Causal Diagram for Barriers to Implementing MDA

Figure 1 shows that the cause group included three out of 11 identified barriers, namely High Investment Costs for Data Analysis and Simulation in Manufacturing Processes (B4), Lack of Technical Infrastructure in Operational Processes (B6), and Lack of Top Management Support (B10). For example: since B6 has a positive D−R, it belongs to the cause group. Therefore, "most important" in terms of cause refers to D−R, not D+R.

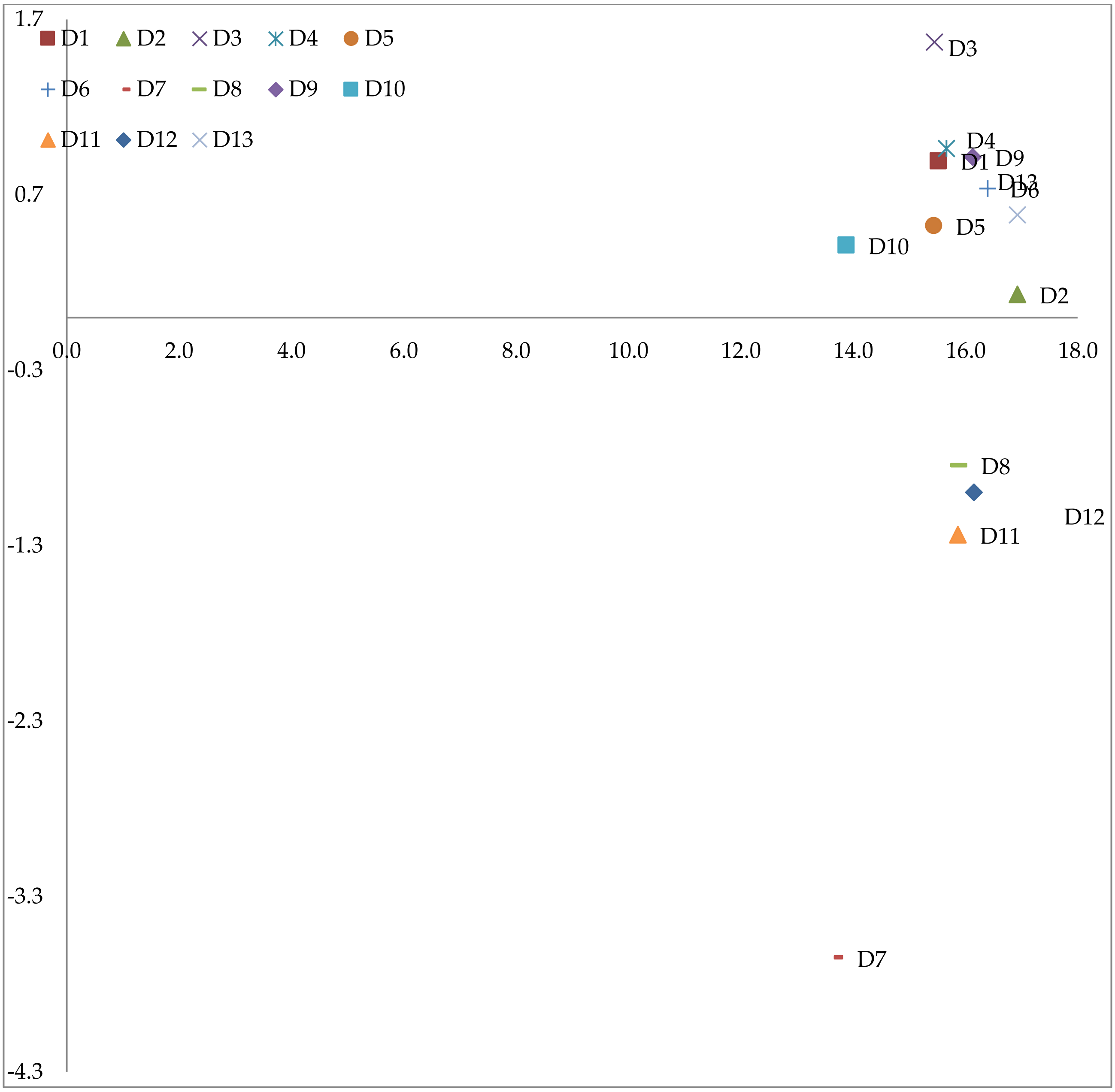

Figure 2. Causal Diagram for Drivers to Implementing MDA

Figure 2 shows that the cause group included 9 out of 13 drivers. These were Problem Identification (D1), Operational Efficiency Improvement (D2), Transparency (D3), Observability (D4), Coordination (D5), Data Management (D6), Readiness of Industry 4.0 Infrastructure (D9), Prediction (D10), and Agility (D13). In the driver table, D7 (Competitive Advantage) has a strongly negative D−R value (-3.7), placing it clearly in the effect group. While it is an important effect, its D+R value is relatively low, indicating that its overall prominence or total connectedness in the network is limited. Therefore, D7 is a strong effect, but its influence on other drivers is moderate.

Using Fuzzy DEMATEL, a strategic map can be created for the barriers and drivers. By revealing the causal relationships, the strategic map helps decision-makers adopt the most effective strategies in line with these relationships. Based on the literature, it was deemed appropriate to determine the threshold values first (Yang et al., 2008). Yang et al. (2008) recommend calculating the threshold (α) by taking the average of all values in the total-relation matrix. Accordingly, values below this threshold are considered to have low causal influence and are therefore excluded from the strategic map. These were set at $\alpha = 0.4140$ for barriers and $\alpha = 0.603$ for drivers. Factors falling below these thresholds were considered insignificant and removed from the strategic map. Figures 3 and 4 show the maps for the remaining barriers and drivers to implementing MDA. In other words, In the context of MDA, a strategic map serves as a visual tool to represent the relationships between critical barriers and drivers, helping decision-makers understand how different factors influence one another. This enables managers to identify priorities, focus on the most impactful elements, and design interventions that account for the interdependencies among operational, technological, and organizational factors. Overall, the strategic map provides a systematic and actionable framework for implementing MDA effectively, ensuring that decisions are informed by both the strength and direction of relationships among barriers and drivers. In this study, no values fell below the threshold, meaning that all relationships among the barriers and drivers were retained in the analysis.

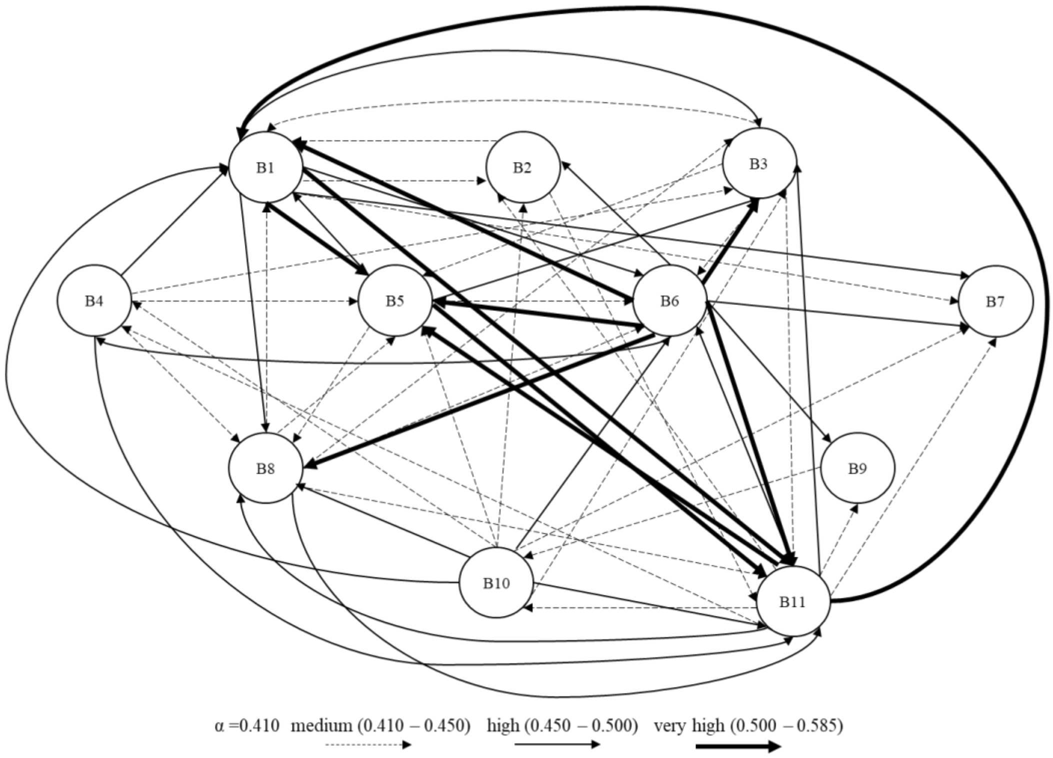

Figure 3. Strategic Map for Barriers to Implementing MDA

As Figure 3 shows, the following barriers mutually affect each other firmly or very strongly: Lack of Veracity in Data Collected from Operational Processes (B1), Lack of Data Scalability (B3), Lack of Data Integration (B5), Lack of Technical Infrastructure in Operational Processes (B6), and Lack of Traceability (B11).

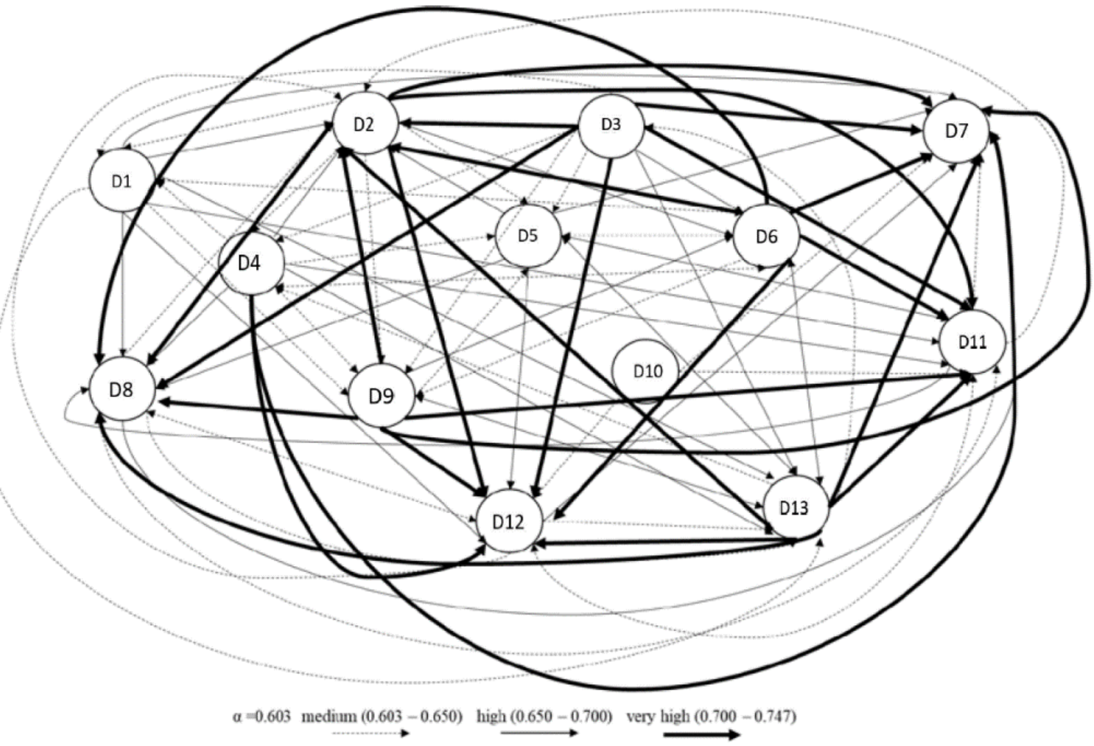

Figure 4. Strategic Map for Drivers to Implement MDA

As Figure 4 shows, the following drivers affect each other firmly or very strongly: Operational Efficiency Improvement (D2), Transparency (D3), Observability (D4), Data Management (D6), Competitive Advantage (D7), Quality (D8), Readiness of Industry 4.0 Infrastructure (D9), Sustainable Manufacturing (D11), Effective Use of Resources (D12), and Agility (D13). The results shown in Figures 3 and 4 show that it is essential to consider bilateral relations in the strategy map.

5. Discussions and Implications

Based on the results of this study, the most important cause criterion among the barriers to implementing MDA is the *Lack of Technical Infrastructure in Operational Processes (B6)*. In contrast, the most important effect criterion is *the Lack of Information Sharing (B7).* Similarly, Moktadir et al. (2019) identified *Lack of Technical Infrastructure in Operational Processes (B6)* as the most important cause criterion among the barriers. In addition, Raut et al. (2021a) identified a lack of top management support as one of the most important barriers. According to Ajayi et al. (2023), the following barriers were identified in their study: financial constraints, lack of governmental and management support, and a lack of resilience against changes. They suggested that digitalization should be adopted in all manufacturing processes.

In contrast, Singh & Bhanot (2018) identified *Long Term Investment Return (B8)* as a cause barrier, whereas it appeared in the effect group in the present study. In the context of this study, based on expert perceptions derived from the DEMATEL analysis, *Long Term Investment Return (B8)* is positioned in the effect group, indicating that concerns about delayed financial returns are perceived to be influenced by more fundamental barriers such as infrastructure inadequacy and limited managerial support. That is, although MDA implementations require high investment, according to expert valuations they are perceived to generate returns when appropriate infrastructural and organizational conditions are ensured. However, this interpretation reflects perceived causal influence rather than objective financial performance evidence. Regarding drivers to implementing MDA, the most important cause criterion in the present study is *Transparency (D3)*, while *Competitive Advantage (D7)* is the most important effect criterion. Similar to our study, Al-Khatib (2023) stated that data analytics has a positive impact on supply chain visibility.

The most significant barrier preventing companies from implementing MDA in their manufacturing processes is an inability to provide the appropriate infrastructure. The primary reasons for this include a lack of awareness, difficulties in interpreting existing data, and challenges in integrating data. Although the overall maturity level of MDA adoption in Türkiye remains relatively limited, this study draws on expert insights from leading companies that are comparatively more aware of digital transformation practices. The severity of the technical infrastructure insufficiency differs according to the size of the companies. In large companies, MDA implementations should be adopted for their technical infrastructure, accompanied by appropriate investments, to ensure profitability through profit and loss analyses.

Moreover, it is recommended to encourage infrastructure investments on a sectoral basis and to establish standard data management systems in industrial zones. Such sectoral infrastructure initiatives directly address the *Lack of Technical Infrastructure in Operational Processes (B6),* which emerged as the most influential cause barrier in this study. It is possible to minimize the infrastructure investment costs of SMEs by developing data center-based solutions, especially in organized industrial zones. These shared data center models can simultaneously mitigate *High Investment Costs for Data Analysis and Simulation (B4)* by distributing fixed infrastructure expenses across multiple firms. Such solutions are expected to accelerate the adoption of MDA and enable companies to transition to digital transformation processes at a lower cost. To address these barriers, managers should implement small-scale pilot projects to test MDA solutions before full-scale investments, enabling risk reduction and early insight into potential ROI. This phased implementation strategy is particularly relevant for mitigating financial uncertainty associated with B4, as it reduces the perceived risk of large upfront investments. Sector-wide consortia or shared data centers can reduce infrastructure costs and facilitate faster adoption of new technologies.

A lack of top management support is often viewed as a significant barrier to implementing MDA. Hence, managers' approaches need to become more constructive and motivating. Given that *Lack of Top Management Support (B10)* emerged as a cause-type barrier influencing other organizational factors, executive-level awareness programs, data governance frameworks, and ROI-based performance dashboards should be interpreted as targeted interventions addressing this specific causal constraint. Additionally, technological opportunities can be achieved by organizing training, especially for operations managers. Although high investment costs make it challenging to implement MDA, the investment can quickly pay for itself, contrary to common belief. Given appropriate planning, the highest profit can be obtained with the least investment cost. In particular, the use of simulations to analyse and evaluate the proposed investments can prevent poor planning. The results of this study emphasize that MDA should be considered not only as a technological investment but also as an organizational change and transformation process. It is challenging to implement MDA applications without the support of top management successfully. While the role of top management is generally examined from a strategic decision-making perspective in the literature, this study reveals that the active role of top management is a critical factor in terms of the development of technical infrastructure and organizational adaptation. Managers should establish precise data governance mechanisms and dashboards to monitor investment outcomes. Regular training programs and ROI simulations can improve top management engagement and ensure effective implementation of MDA initiatives. To increase top management support, data analytics awareness programs should be organized within businesses, and the contributions of MDA to operational efficiency should be demonstrated with concrete data. Additionally, training that helps managers evaluate the cost-benefit analyses of MDA applications can ensure that these processes are managed more effectively.

Regarding the drivers, it is almost impossible to collect data from manufacturing processes if they are not traceable, as reflected in the importance given to this criterion. To ensure such traceability, it is first necessary to determine the amount of data and its associated value. This, in turn, highlights the importance of observability, which is another key driving force. Data from manufacturing processes should be observed instantly using technological aids, such as barcode readers and touch terminals.

Although a lack of infrastructure is often seen as a barrier, MDA implementation is one of the most important drivers for organizations that incorporate Industry 4.0 infrastructure into their operations. If intellectual capital can be effectively provided in institutions that offer the appropriate infrastructure, processes can progress more efficiently. In addition to infrastructure, the company's goals must be determined correctly to develop appropriate action plans. Managers should set clear, measurable goals for MDA adoption and align action plans accordingly. Tracking performance metrics and providing feedback loops ensures that initiatives contribute effectively to organizational transformation.

The adoption of digital transformation and MDA applications offers a significant opportunity to increase Türkiye’s competitiveness in the global market. The development of data-based decision-making mechanisms in production processes can help businesses adapt to rapidly changing market conditions and develop more efficient production models. Especially for Türkiye, which is pursuing an export-based growth strategy, the adoption of data analytics in production processes is a crucial factor in raising quality standards and gaining a competitive advantage in the international market. Therefore, data analytics should play a central role in Türkiye’s industrial policies and be integrated into digital transformation strategies. From a policy perspective, government incentives and R&D funding mechanisms should be strategically aligned with the empirically identified cause barriers namely B4 (high investment costs), B6 (lack of technical infrastructure in operational processes), and B10 (lack of top management support). Designing incentive schemes that subsidize infrastructure modernization, reduce capital burden, and promote executive digital leadership development would ensure that national policy tools directly correspond to the causal structure revealed by the study. At the national and sectoral level, managers should leverage government incentives and R&D funds to accelerate digital transformation. For export-driven sectors, integrating data analytics into quality control, supply chain management, and demand forecasting can strengthen competitiveness in international markets.

6. Conclusions

To survive in today's highly competitive business environment, the need for sectors to capitalize on new opportunities becomes increasingly apparent. In particular, MDA can enable innovations that offer a better service and product portfolio, prompting companies to invest more in data analytics to gain a competitive advantage in critical areas such as efficiency, profitability, and sustainable manufacturing processes. MDA enables companies to access the information and tools they need to unlock this potential by integrating statistical science and modern quantitative computing methods to create business value from large data volumes.

This study’s main contribution is that it identified current barriers and drivers to implementing MDA, and determined the respective cause-and-effect relationships between them. It thus indicates how MDA implementations can be implemented by eliminating these barriers and encouraging the drivers. Based on the literature review and 14 expert opinions, the study identified 11 barriers and 13 drivers. Separate fuzzy DEMATEL analyses were conducted for these barriers and drivers.

The results indicate that the cause group of barriers comprises High Investment Costs for Data Analysis and Simulation in Manufacturing Processes (B4), Lack of Technical Infrastructure in Operational Processes (B6), and Lack of Top Management Support (B10). In contrast, the cause group of drivers comprises Problem Identification (D1), Operational Efficiency Improvement (D2), Transparency (D3), Observability (D4), Coordination (D5), Data Management (D6), Readiness of Industry 4.0 Infrastructure (D9), Prediction (D10), and Agility (D13).

To sum up, high investment costs constitute a significant obstacle, especially in developing economies such as Türkiye. This situation makes it difficult for small and medium-sized enterprises (SMEs), which are the locomotives of the economy, to implement digitalization projects. However, financial support from the government and financial institutions plays a critical role in supporting the digital transformation of these enterprises. Supports that can cover high investment costs (B4) can make a significant difference in the digitalization processes of SMEs. At the same time, such support will provide infrastructure improvements and enhance technological adaptation to address technical infrastructure deficiencies encountered in production processes (B6).

Minimizing barriers will enable the effective activation of drivers who are affected by these barriers. For example, the prominence of elements such as increased efficiency, transparency, and observability will make production processes more competitive, enabling businesses in Türkiye to gain a stronger position in global markets. As a result of the successful implementation of MDA projects, positive effects will be created not only for individual enterprises but also for the economic development of all sectors and ultimately for the country. As a result, accelerating the digitalization processes of SMEs in Türkiye offers excellent opportunities for the country's overall economic growth and technological advancement. This process will create a development effect at the national level and increase Türkiye's global competitiveness.

The main limitation of this study is that data collection was constrained due to difficulties in finding companies in Türkiye that have implemented MDA or are even aware of it. Moreover, the findings rely on perceptual expert evaluations within the Fuzzy DEMATEL framework, which is inherently based on subjective judgments rather than objective performance data. The cross-sectoral structure of the sample may also reflect sectoral heterogeneity, and the results are limited to the Türkiye context; therefore, generalizations should be made cautiously. Regarding future research, the same methodology can be applied to separate sectors at the same level of manufacturing to create unique roadmaps for each. In addition, future studies could conduct comparative analyses with different implementations instead of Fuzzy DEMATEL.

References

Agi, M. A., & Jha, A. K. (2022). Blockchain technology for supply chain management: An integrated theoretical perspective of organizational adoption. *International Journal of Production Economics*, 108458.

Ajayi, M. O., & Laseinde, O. T. (2023). A review of supply chain 4IR management strategy for appraising the manufacturing industry's potentials and shortfalls in the 21st century. *Procedia Computer Science*, *217*, 513-525.

Alharthi, A., Krotov, V., & Bowman, M. (2017). Addressing barriers to big data. *Business Horizons*, *60*(3), 285–292. https://doi.org/10.1016/j.bushor.2017.01.002

Al-Khatib, A. W. (2023). Internet of things, big data analytics and operational performance: the mediating effect of supply chain visibility. *Journal of Manufacturing Technology Management*, *34*(1), 1-24.

Amiri, A. S., Torabi, S. A., & Tavana, M. (2025). An assessment of the prominence and total engagement metrics for ranking interdependent attributes in DEMATEL and WINGS. *Omega*, 130, 103176.

Bag, S., Wood, L. C., Xu, L., Dhamija, P., & Kayikci, Y. (2020). Big data analytics as an operational excellence approach to enhance sustainable supply chain performance. *Resources, Conservation and Recycling*, 153, 104559.

Barlette, Y., & Baillette, P. (2022). Big data analytics in turbulent contexts: towards organizational change for enhanced agility. *Production Planning & Control*, *33*(2-3), 105-122.

Belhadi, A., Zkik, K., Cherrafi, A., & Sha'ri, M. Y. (2019). Understanding big data analytics for manufacturing processes: insights from literature review and multiple case studies. *Computers & Industrial Engineering*, *137*, 106099.

Bi, Z., & Cochran, D. (2014). Big data analytics with applications, *Journal of Management Analytics*, 1(4), 249-265.

Chavez, R., Yu, W., Jacobs, M.A., & Feng, M. (2017). Data driven supply chains, manufacturing capability and customer satisfaction, *Production Planning & Control*, 28(11-12), 906–918.

Chen, C., Choi, H. S., & Ractham, P. (2022). Data, attitudinal, and organizational determinants of big data analytics systems use. *Cogent Business & Management*, *9*(1), 2043535.

Cui, Y., Kara, S., & Chan, K. C. (2020). Manufacturing big data ecosystem: A systematic literature review. *Robotics and Computer-Integrated Manufacturing*, 62.

Dai, H. N., Wang, H., Xu, G., Wan, J., & Imran, M. (2020). Big data analytics for manufacturing internet of things: opportunities, challenges, and enabling technologies. *Enterprise Information Systems*, *14*(9-10), 1279–1303.

Dubey, R., Gunasekaran, A., Childe, S.J., Blome, C., Papadopoulos, T. (2019). Big data and predictive analytics and manufacturing performance: Integrating institutional theory, Resource-based View, and Big data culture. *British J. Manag*. 30(2), 341–361.

Escobar, C. A., McGovern, M. E., & Morales-Menendez, R. (2021). Quality 4.0: a review of big data challenges in manufacturing. *Journal of Intelligent Manufacturing*, *32*(8), 2319-2334.

Fahmideh, M., & Beydoun, G. (2019). Big data analytics architecture design—An application in manufacturing systems. *Computers & Industrial Engineering*, *128*, 948–963.

Gangwar, H. (2018). Understanding the determinants of big data adoption in India: An analysis of the manufacturing and services sectors. *Information Resources Management Journal (IRMJ)*, *31*(4), 1-22.

Groggert, S., Wenking, M., Schmitt, R. H., & Friedli, T. (2017, December). Status quo and future potential of manufacturing data analytics—an empirical study. In *2017, the IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)* (pp. 779–783). IEEE.

Gupta, A. K., & Goyal, H. (2021). Framework for implementing big data analytics in Indian manufacturing: ISM-MICMAC and Fuzzy-AHP approach. *Information Technology and Management*, *22*(3), 207–229.

Hosseini, S. M., Soltanpour, Y., & Paydar, M. M. (2022). Applying the Delphi and fuzzy DEMATEL methods for identification and prioritization of the variables affecting Iranian citrus exports to Russia. *Soft Computing*, *26*(18), 9543-9556.

Jain, S., Shao, G. & Shin, S. (2017). Manufacturing data analytics using a virtual factory representation. *International Journal of Production Research*. 55. 1–15.

Jasiulewicz-Kaczmarek, M., & Gola, A. (2019). Maintenance 4.0 technologies for sustainable manufacturing-an overview. *IFAC-PapersOnLine*, *52*(10), 91-96.

Ji, W., & Wang, L. (2017). Big data analytics-based fault prediction for shop floor scheduling. *Journal of Manufacturing Systems*, *43*, 187–194.

Kampker, A., Heimes, H., Bührer, U., Lienemann, C., & Krotil, S. (2018). Enabling data analytics in large scale manufacturing. *Procedia Manufacturing*, *24*, 120-127.

Krumeich, J., Jacobi, S., Werth, D., & Loos, P. (2014, June). Big data analytics for predictive manufacturing control-a case study from process industry. In *2014, the IEEE International Congress on Big Data* (pp. 530-537). IEEE.

Kumar, N., Kumar, G., & Singh, R. K. (2021). Big data analytics application for sustainable manufacturing operations: analysis of strategic factors. *Clean Technologies and Environmental Policy*, 23(3), 965–989.

Lin, A. J., Chang, H. Y., Huang, S. W., & Tzeng, G. H. (2021). Improving Service Quality of Wealth Management Bank for High-Net-Worth Customers During COVID-19: A Fuzzy-DEMATEL Approach. *International Journal of Fuzzy Systems,* 1-18.

Lutfi, A., Alsyouf, A., Almaiah, M. A., Alrawad, M., Abdo, A. A. K., Al-Khasawneh, A. L., ... & Saad, M. (2022). Factors Influencing the Adoption of Big Data Analytics in the Digital Transformation Era: Case Study of Jordanian SMEs. *Sustainability*, *14*(3), 1802.

Ma, S., Zhang, Y., Liu, Y., Yang, H., Lv, J., & Ren, S. (2020). Data-driven sustainable intelligent manufacturing based on demand response for energy-intensive industries. *Journal of Cleaner Production*, *274*, 123155.

Mageto, J. (2021). Big Data Analytics in Sustainable Supply Chain Management: A Focus on Manufacturing Supply Chains. *Sustainability*, *13*(13), 7101.

Majeed, A., Zhang, Y., Ren, S., Lv, J., Peng, T., Waqar, S., & Yin, E. (2021). A big data-driven framework for sustainable and smart additive manufacturing. *Robotics and Computer-Integrated Manufacturing*, *67*, 102026.

Mani, V., Delgado, C., Hazen, B. T., & Patel, P. (2017). Mitigating supply chain risk via sustainability using big data analytics: Evidence from the manufacturing supply chain. *Sustainability*, *9*(4), 608.

Min, Q., Zhao-Xian, R., Can, W., & Li, X. (2025). Integrating user feedback into air purifier innovation: The FKANO-DEMATEL-VIKOR decision framework. *Engineering Management Journal*, 38(1), 81–98.

Moktadir, M. A., Ali, S. M., Paul, S. K., & Shukla, N. (2019). Barriers to big data analytics in manufacturing supply chains: A case study from Bangladesh. *Computers & Industrial Engineering*, *128*, 1063–1075.

Mrida, M. S. H., Rahman, M. A., & Alam, M. S. (2025). AI-Driven Data Analytics and Automation: A Systematic Literature Review of Industry Applications. *Strategic Data Management and Innovation*, *2*(01), 21–40.

My, C. A. (2021). The Role of Big Data Analytics and AI in Smart Manufacturing: An Overview. *Research in Intelligent and Computing in Engineering*, 911-921.

Narwane, V. S., & Priyadarshinee, P. (2025). Examining the effect of AI-BDA on manufacturing firm performance: An Indian approach. *International Journal of Information Management Data Insights*, *5*(1), 100306.

Omar, Y. M., Minoufekr, M., & Plapper, P. (2019). Business analytics in manufacturing: Current trends, challenges, and pathway to market leadership. *Operations Research Perspectives*, *6*, 100127.

Opricovic, S. & Tzeng, G.H. (2003). Defuzzification within a Multicriteria Decision Model, International Journal of Uncertainty. *Fuzziness and Knowledge-Based Systems,* 11(5), 635-652.

Psarommatis, F., Dreyfus, P. A., & Kiritsis, D. (2022). The role of big data analytics in the context of modeling design and operation of manufacturing systems. In *Design and Operation of Production Networks for Mass Personalization in the Era of Cloud Technology* (pp. 243-275). Elsevier.

Rashid, A., Baloch, N., Rasheed, R., & Ngah, A. H. (2025). Big data analytics-artificial intelligence and sustainable performance through green supply chain practices in manufacturing firms of a developing country. *Journal of Science and Technology Policy Management*, *16*(1), 42–67.

Raut, R. D., Yadav, V. S., Cheikhrouhou, N., Narwane, V. S., & Narkhede, B. E. (2021a). Big data analytics: implementation challenges in Indian manufacturing supply chains. *Computers in Industry*, *125*, 103368.

Raut, R., Narwane, V., Mangla, S. K., Yadav, V. S., Narkhede, B. E., & Luthra, S. (2021b). Unlocking causal relations of barriers to big data analytics in manufacturing firms. *Industrial Management & Data Systems,* 121(9), 1939-1968.

Ren, S., Zhang, Y., Liu, Y., Sakao, T., Huisingh, D., & Almeida, C. M. (2019). A comprehensive review of big data analytics throughout product lifecycle to support sustainable smart manufacturing: A framework, challenges and future research directions. *Journal of Cleaner Production*, *210*, 1343–1365.

Sahoo, S. (2021). Big data analytics in manufacturing: a bibliometric analysis of research in the field of business management. *International Journal of Production Research*, *60*(22), 6793-6821.

Sajadieh, S. M. M., Son, Y. H., & Noh, S. D. (2022). A Conceptual Definition and Future Directions of Urban Smart Factory for Sustainable Manufacturing. *Sustainability*, *14*(3), 1221.

Saleem, H., Li, Y., Ali, Z., Ayyoub, M., Wang, Y., & Mehreen, A. (2020). Big data use and its outcomes in the supply chain context: the roles of information sharing and technological innovation. *Journal of Enterprise Information Management,* 34(4), 1121-1143.

Saraswat, J. K., & Choudhari, S. (2025). Integrating big data and cloud computing into the existing system and performance impact: A case study in manufacturing. *Technological Forecasting and Social Change*, *210*, 123883.

Sarı, T., Güleş, H. K., & Yiğitol, B. (2020). Awareness and readiness of Industry 4.0: The case of Turkish manufacturing industry. *Advances in Production Engineering & Management*, *15*(1), 57-68.

Seifi, N., Keshavarz, M., Kalhor, H., Shahrakipour, S., & Adibifar, A. (2025). Ranking of criteria affecting the implementation readiness of Internet of Things in industries using TISM and fuzzy TOPSIS analysis. *Journal of Operations Intelligence*, *3*(1), 46–66.

Siddique, M. N. A., Hasan, K. W., Ali, S. M., Moktadir, M. A., Paul, S., & Kabir, G. (2021). Modeling drivers to big data analytics in supply chains. *Journal of Production Systems and Manufacturing Science*, 2(1), 4-25.

Singh, R., & Bhanot, N. (2020). An integrated DEMATEL-MMDE-ISM based approach for analysing the barriers of IoT implementation in the manufacturing industry. *International Journal of Production Research*, *58*(8), 2454–2476.

Tanpoco, M. R., & Magnaye, R. P. (2025). Fostering Business Analytics Success: Examining Leadership Support, Data Quality, and User Skills in Philippine Manufacturing Companies. *Review of Integrative Business and Economics Research*, *14*(1), 237-253.

Tian, B., He, L., Xu, Y., Fu, J., & Wu, H. (2025). Critical success factors for blockchain implementation in the AEC industry: An integrated ISM and DEMATEL Approach. *Engineering Management Journal*, 1-17.

Ungermann, F., Kuhnle, A., Stricker, N., & Lanza, G. (2019). Data analytics for manufacturing systems–a data-driven approach for process optimization. *Procedia CIRP*, *81*, 369-374.

Wang, J., Xu, C., Zhang, J., & Zhong, R. (2021). Big data analytics for intelligent manufacturing systems: A review. *Journal of Manufacturing Systems*, 62, 738-752.

Woo, J., Shin, S. J., Seo, W., & Meilanitasari, P. (2018). Developing a big data analytics platform for manufacturing systems: architecture, method, and implementation. *The International Journal of Advanced Manufacturing Technology*, *99*(9), 2193–2217.

Wu, C. H., Chou, C. W., Chien, C. F., & Lin, Y. S. (2024). Digital transformation in manufacturing industries: Effects of firm size, product innovation, and production type. *Technological Forecasting and Social Change*, *207*, 123624.

Wu, H., Zhong, W., Zhong, B., Li, H., Guo, J., & Mehmood, I. (2025). Barrier identification, analysis and solutions of blockchain adoption in construction: a fuzzy DEMATEL and TOE integrated method. *Engineering, Construction and Architectural Management*, *32*(1), 409–426.

Yadegaridehkordi, E., Hourmand, M., Nilashi, M., Shuib, L., Ahani, A., & Ibrahim, O. (2018). Influence of big data adoption on manufacturing companies' performance: An integrated DEMATEL-ANFIS approach. *Technological Forecasting and Social Change*, *137*, 199–210.

Yang, Y. P. O., Shieh, H. M., Leu, J. D., and Tzeng, G. H. (2008). A Novel Hybrid MCDM Model Combined with DEMATEL And ANP With Applications. *International Journal of Operations Research*, 5(3), 160-168.

Yuan, C., Li, G., Kamarthi, S., Jin, X., & Moghaddam, M. (2022). Trends in intelligent manufacturing research: a keyword co-occurrence network-based review. *Journal of Intelligent Manufacturing*, 1–15.

Zaki, M., Theodoulidis, B., Shapira, P., Neely, A., & Tepel, M. F. (2019). Redistributed manufacturing and the impact of big data: a consumer goods perspective. *Production Planning & Control*, *30*(7), 568–581.

Zhong, R. Y., Newman, S. T., Huang, G. Q., & Lan, S. (2016). Big Data for supply chain management in the service and manufacturing sectors: Challenges, opportunities, and future perspectives. *Computers & Industrial Engineering*, *101*, 572–591.