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Revolutionizing Manufacturing Decision-Making with Data-Driven Insights: A Case Study Approach

[1]Sulartopo, [2]Miftahurrohman, [3]Agus Wibowo
ORCHID[1]: 0000-0001-8594-7938; ORCHID[2]: 0000-0002-7603-5977, ORCHID[3]: 0000-0002-1251-0468
[1,2,3] University of Science and Computer Technology (STEKOM University), Semarang, 50192, Indonesia

ABSTRACT: Information is pivotal in decision-making across various sectors, including the manufacturing industry. A robust framework is required to amalgamate information from diverse sources, conduct thorough analyses, and provide actionable insights to support an effective decision process. This study proposes a comprehensive information-driven decision process (DD-DM) framework tailored for the manufacturing industry within the context of Industry 4.0. Employing a case study methodology focused on a small and medium-sized enterprise (SME) within the electronics manufacturing sector, we identify and address the multifaceted challenges associated with implementing DD-DM. The study integrates qualitative and quantitative information collection methods, including interviews, observations, and information analysis from various manufacturing processes. The findings reveal that implementing the DD-DM framework significantly enhances decision process efficiency, improves product quality, and increases responsiveness to market changes. Four critical factors essential for the successful adoption of DD-DM are ensuring information quality, integrating advanced technologies, optimizing operational processes, and addressing human factors. This research contributes valuable insights for managers, engineers, and employees in the manufacturing industry by offering a practical and theoretical framework for transitioning to an information-driven decision process. By facilitating the integration of Industry 4.0 technologies, the proposed framework enables manufacturing companies to achieve higher levels of operational efficiency and competitive advantage in a rapidly evolving market environment.

KEYWORDS: *Manufacturing industry, data analysis, data-driven, industry 4.0, decision making.*

1. INTRODUCTION

The advent of Industry 4.0 has brought complex challenges to the manufacturing sector, requiring them to remain competitive and sustainable. Rapid technological advancements, global market shifts, and changing consumer preferences compel manufacturing firms to make more intelligent, data-driven decisions. The ability to make accurate and timely decisions has become crucial in optimizing operations, enhancing product quality, reducing costs, and responding efficiently to market changes. Previous research has shown that DD-DM (Data-Driven Decision Making) can improve production performance and decision-making in the manufacturing sector (Kalla & Smith, 2024; Raptis et al., 2019). (Jamwal et al., 2021) they emphasized the importance of data generated by Industry 4.0 technologies in efficiently managing factory resources. (Awan et al., 2021; Shahid et al., 2021) and (Vafaei-Zadeh et al., 2024) defined DD-DM as the practice of making decisions based on automatically analyzed data, which can enhance productivity and competitive advantage.

(Awan et al., 2021; Fanelli et al., 2023; Nisar et al., 2020) highlighted the importance of collecting, processing, and storing data in ways that support effective decision-making. (Bammidi et al., 2024; Wu et al., 2021) emphasized that data quality is crucial for the effectiveness of DD-DM. Challenges in managing big data include assessing data quality and converting unstructured data into structured formats within a reasonable time frame. (Bammidi et al., 2024; Fanelli et al., 2023) indicated that effective integration of technology and data management is essential to support sound decision-making. (Liu et al., 2023) identified that resistance to change and a lack of understanding of new technologies can hinder the effective implementation of DD-DM. (Neumann et al., 2021; Pollini et al., 2022) added that human factors play a significant role in decision-making, and systems should integrate both technological and human aspects.

Furthermore, (Abikoye et al., 2021; Tao et al., 2018) discussed the concept of the Smart Factory, which combines with the Internet of Things (IoT) to create more intelligent and responsive manufacturing systems. (Awan et al., 2021; Ryalat et al., 2023; Sarker, 2021) emphasized the importance of predictive analytics in DD-DM for formulating decisions based on prospective scenarios. This research aims to propose an integrated DD-DM framework in the manufacturing industry by combining data analysis, information technology, operational management, and business strategy. The main contributions of this study are:

- Development of an Integrated DD-DM Framework: Providing a comprehensive framework that integrates data analysis, information technology, operational management, and business strategy to support decision-making in the manufacturing industry.
- DD-DM Maturity Model: Developing a maturity model that manufacturing companies can use to assess and enhance their DD-DM capabilities.
- Empirical Case Study: Present an in-depth case study on the implementation of DD-DM in a manufacturing company, offering practical insights and recommendations for implementation.
- Multidisciplinary Approach: Integrating various disciplines such as data analysis, operational management, and business strategy to create holistic and applicable solutions.

2. RESEARCH METHOD

Approach

The research utilizes a case study method to gain a detailed understanding of how the DD-DM framework is implemented in the manufacturing sector. The case study approach allows for an in-depth exploration of phenomena within real-world contexts and provides practical insights for other manufacturing companies.

Research Design

The research design comprises several key stages:

1. Case Selection: The study selects a small and medium-sized enterprise (SME) in the electronics sector. This case was chosen based on the company's involvement in implementing Industry 4.0 technologies and its commitment to DD-DM.
2. Data Collection: Data were collected using various methods to ensure a comprehensive understanding of current decision-making practices and challenges. Methods include:
    a. In-depth Interviews: Interviews with managers, engineers, and operational employees to identify their needs, barriers, and expectations regarding DD-DM.
    b. Field Observations: Direct observations in the factory to understand workflows, production processes, and the use of information technology.
    c. Documentation Analysis: Analysis of internal documents such as production reports, data management policies, and strategic plans.
    d. Questionnaire Surveys: Distribution of questionnaires to employees to collect quantitative data on their perceptions of DD-DM and related technologies.
3. Data Analysis: The gathered data were examined through both qualitative and quantitative methods. The techniques used for analysis included descriptive, diagnostic, and predictive analysis.
    a. Descriptive analysis: This method is utilized to comprehend the fundamental attributes of the gathered data. It involves summarizing the data using descriptive statistics like mean, median, mode, and frequency distribution. The outcomes of this analysis offer a general snapshot of the data's initial condition, which is crucial for grasping the wider context.
    b. Diagnostic analysis: This technique aims to identify the causes of the problems faced by the company. Regression and correlation analysis are used to find relationships between key variables. In this case, the study uses linear regression to identify factors that affect operational efficiency and product quality.
    c. Predictive analysis: This technique uses statistical models and machine learning algorithms to predict future trends and patterns. The study employs multiple linear regression and decision tree models to predict operational performance and product quality based on historical data.

Framework Development

This framework was then validated through discussions with experts and stakeholders in the company. In Data Collection, data gathered includes sources such as IoT sensors, production reports, employee surveys, and ERP systems. In Data Management, data will be stored and managed through validation and cleaning processes to ensure data quality. Subsequently, in Data Analysis, various analysis techniques such as descriptive, diagnostic, and predictive analysis are used to support decision-making. In Technology Integration, various information systems and technologies are integrated to enable smooth and real-time data flow throughout the organization. Finally, in Employee Training, continuous training is provided to employees to enhance analytical skills and understanding of DD-DM

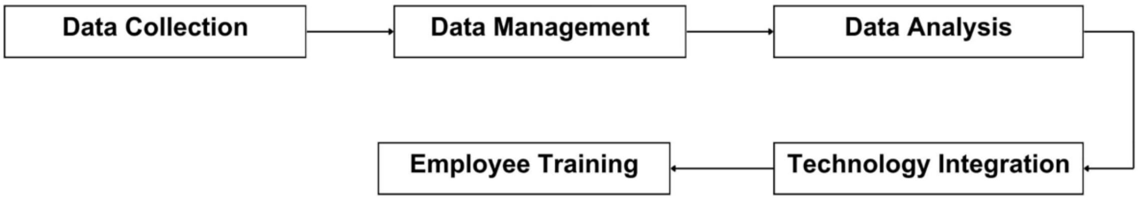

Figure 1. Framework of DD-DM

DD-DM Maturity Model

The proposed maturity model consists of several levels, as shown in Figure 2. Each level reflects the development of a company's DD-DM capabilities. Level 1: Data Collection: Focuses on basic data collection from various sources. Level 2: Data Integration: Integrates data from various systems and sources. Level 3: Data Analysis: Applies data analysis techniques to support decision-making. Level 4: Prediction: Uses predictive analytics to forecast future trends and patterns. Lastly, Level 5: Adaptation: Applies analysis results to adapt processes and strategies in real time.

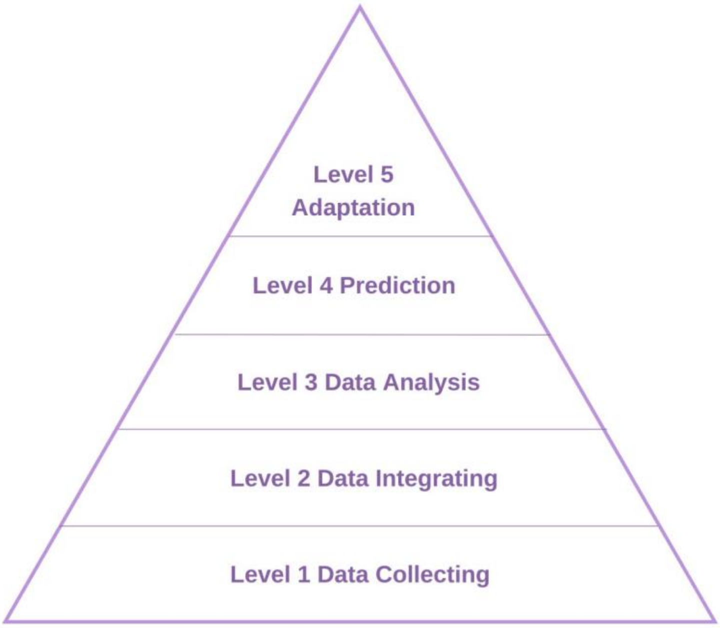

Figure 2. DD-DM Maturity Model

Validation and Testing

The developed framework and maturity model were then tested in a case study company to assess their effectiveness and suitability for the company's needs. Feedback from end-users and stakeholders was used to optimize the framework.

3. RESULT AND DISCUSSION

Empirical Result

The company focused on in this case study is an SME operating in the electronics sector. This company has around 150 employees and uses various advanced technologies in its operations, including ERP systems, IoT, and sensors. These technologies are used to enhance production efficiency, monitor equipment conditions, and collect operational data in real time. Despite having adopted several Industry 4.0 technologies, the company still faces challenges in integrating data from various sources and leveraging this data for more effective decision-making.

Table 1. Case Study Description

Aspect	Description
Industrial Sensor	Electronic
Size of Company	Medium-sized enterprise (MSE)
Total Employee	150
Technology Use	ERP, IoT, Sensor

Current Decision-Making Practices

In-depth interviews and field observations at the case study company revealed several key findings related to data-driven decision-making (DD-DM) practices. These findings are supported by the information shown in Table 2. One of the primary obstacles encountered is the problem of data quality. The available data is often incomplete, inaccurate, or outdated, making effective analysis difficult. This low data quality hampers the company's ability to make informed decisions based on accurate information. Additionally, the company faces difficulties in integrating the various information technology systems it uses. Diverse data sources and different systems create data flow barriers and result in information silos. This adds complexity to the overall data collection and analysis process. Resistance to change among employees is also a significant challenge. Many employees are comfortable with traditional working methods and are reluctant to switch to data-driven methods. This reluctance is compounded by a lack of understanding of the benefits of DD-DM, leading to uncertainty and concern among employees.

However, the research also identified important opportunities to enhance DD-DM implementation. One such opportunity is to provide comprehensive training and education to employees about the benefits and use of DD-DM, which can help reduce resistance and increase the adoption of new technologies. Additionally, investing in upgrading technological infrastructure, including hardware and software that support data integration, can help overcome existing technical challenges. Adopting a phased approach to DD-DM implementation, starting with small projects that can demonstrate tangible results, can also build trust and support throughout the organization. Despite the significant challenges in implementing DD-DM, there are substantial opportunities for improvement that can help the company achieve more effective and data-driven decision-making.

Table 2. Key Findings from Interviews and Observations

Key finding	Description
Data Quality	Data is often incomplete and inaccurate
Technology Integration	Difficulty in integrating various systems
Resistance to Change	Employees are reluctant to adopt new methods
Opportunities for DD-DM	Training, technology investment, phased approach

Development of the DD-DM Framework

Based on empirical findings, the proposed DD-DM framework consists of several key components: Data Collection, Data Analysis, Technology Integration, Employee Training and Development, and Evaluation and Feedback. The development of the DD-DM framework in the manufacturing industry begins with understanding the specific needs and challenges faced by the case study company. Based on empirical findings from interviews, observations, and data analysis, a comprehensive and integrated DD-DM framework is designed to encompass several key components.

Data Management and Collection

The initial phase of the framework involves gathering data from multiple pertinent sources, including IoT sensors, production reports, employee surveys, and ERP systems. The collected data must be validated and cleaned to ensure its quality. This validation and cleaning process involves checking for consistency, removing duplicate data, and handling missing or incomplete data. Once the data is collected and validated, the next step is efficient data storage. A robust database management system is necessary to store and organize the data in a way that facilitates easy access and future analysis.

Data Analysis

Once data is collected and appropriately managed, the subsequent step is to analyze the data. This involves employing various techniques such as descriptive analysis to comprehend the fundamental characteristics of the data, diagnostic analysis to pinpoint problem causes, predictive analysis to anticipate future trends, and prescriptive analysis to offer optimal action recommendations. The use of advanced data analysis software and machine learning algorithms can enhance the accuracy and speed of the analysis. The results of this analysis should be presented in an easily understandable form for decision-makers, such as informative data visualizations and detailed reports.

Technology Integration

Technology integration is a crucial component of the DD-DM framework. Companies need to integrate the various information systems and technologies they use, including ERP, IoT, sensors, and data analysis software, to ensure smooth and real-time data flow throughout the organization. This integration process involves setting up communication protocols, data standards, and network infrastructure that support data exchange between systems. With integrated technology, companies can obtain a comprehensive view of their operations and make quicker and more accurate decisions.

Employee Training and Development

Another important component of the framework is employee training and development. Employees must be equipped with analytical skills and an understanding of DD-DM concepts. Comprehensive and ongoing training programs should be provided to ensure employees can effectively use new tools and technologies. This training can include workshops, online courses, and practical training sessions. Furthermore, companies should cultivate a culture of learning and innovation among their employees to improve the adoption and successful implementation of DD-DM.

Evaluation and Feedback

The final step in the DD-DM framework is continuous evaluation and feedback. Companies should implement evaluation mechanisms to assess the effectiveness of the framework and identify areas needing improvement. This evaluation can include measuring operational performance, product quality, and market response. Feedback from end-users and stakeholders should be routinely collected to ensure the framework remains relevant and effective. Companies can make adjustments and enhancements to the framework to achieve optimal results based on the evaluation outcomes and feedback.

By developing a comprehensive and integrated DD-DM framework, manufacturing companies can improve operational efficiency, product quality, and adaptability to market changes. This framework provides practical guidance for companies to implement effective and sustainable data-driven decision-making.

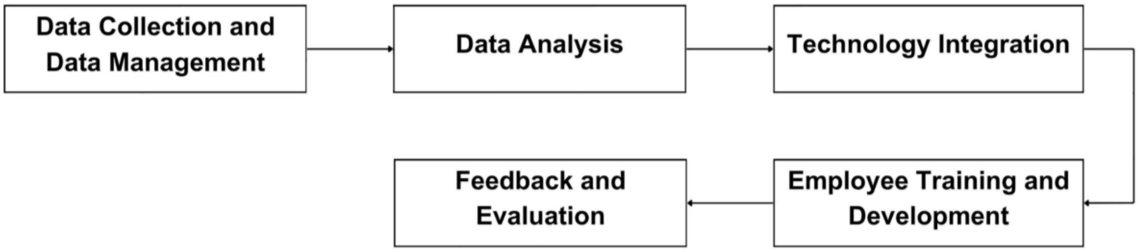

Figure 3. The Developed DD-DM Framework

Performance Improvement After Implementing the Developed DD-DM

The results of performance improvement after implementing DD-DM are shown in Table 3. After the implementation of the data-driven decision-making (DD-DM) framework, the company experienced significant improvements in its operational performance. One of the most notable improvements was in operational efficiency. Before implementing DD-DM, the company's operational efficiency was at 70%. However, after the framework was implemented, operational efficiency increased to 85%, reflecting a 15% improvement. Additionally, product quality saw a significant enhancement. Before implementation, the product defect rate was recorded at 10%. With the implementation of DD-DM, the product defect rate was reduced to 8%, showing a 20% decrease in the defect rate. This demonstrates that data-driven decision-making can help companies identify and address quality issues more effectively.

Moreover, the company became more responsive to changes in market demand. The response time to changes in demand was reduced 2 days after implementing DD-DM, representing a 40% improvement in responsiveness. With faster response times, the company can more easily adapt to market fluctuations and customer needs, ultimately increasing customer satisfaction and the company's competitiveness in the market. The implementation of DD-DM in this company has had a significant positive impact, improving efficiency, product quality, and response speed to market demands. These results highlight the great potential of DD-DM in helping manufacturing companies achieve better and more competitive performance.

Table 3. Performance Improvement After Implementing the Proposed DD-DM

Performance Metrics	Before Implementation	After Implementation	Improvement (%)
Operational efficiency	70%	85%	15%
Product Defect Rate	10%	8%	20%
Market Response Time	5 days	3 days	40%

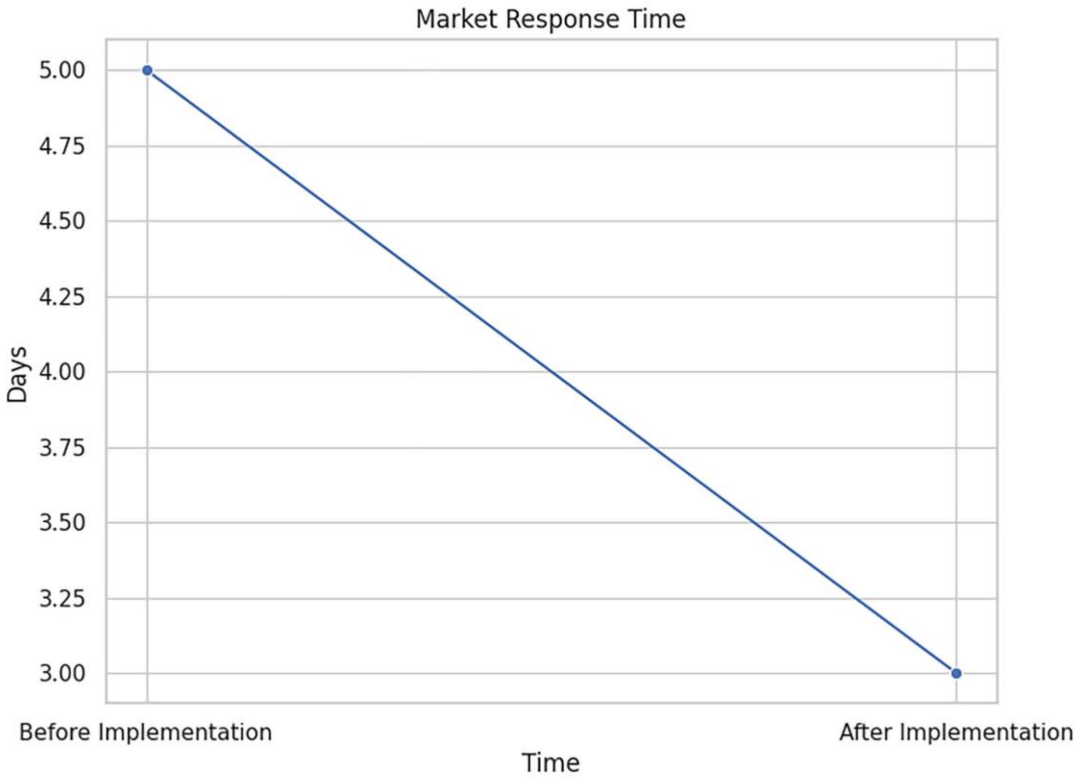

Figure 4. Market response time after Implementing the Proposed DD-DM

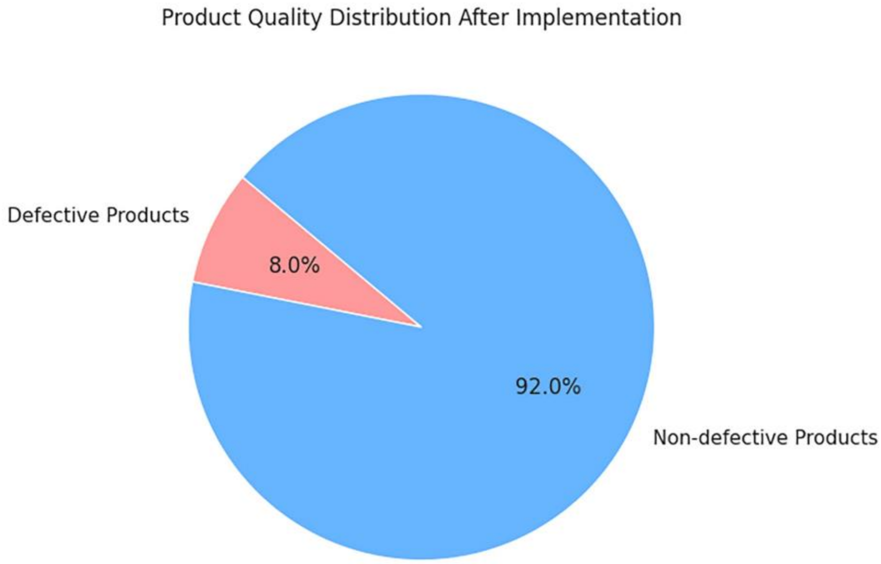

Figure 5. Product Quality Distribution After Implementing the Proposed DD-DM

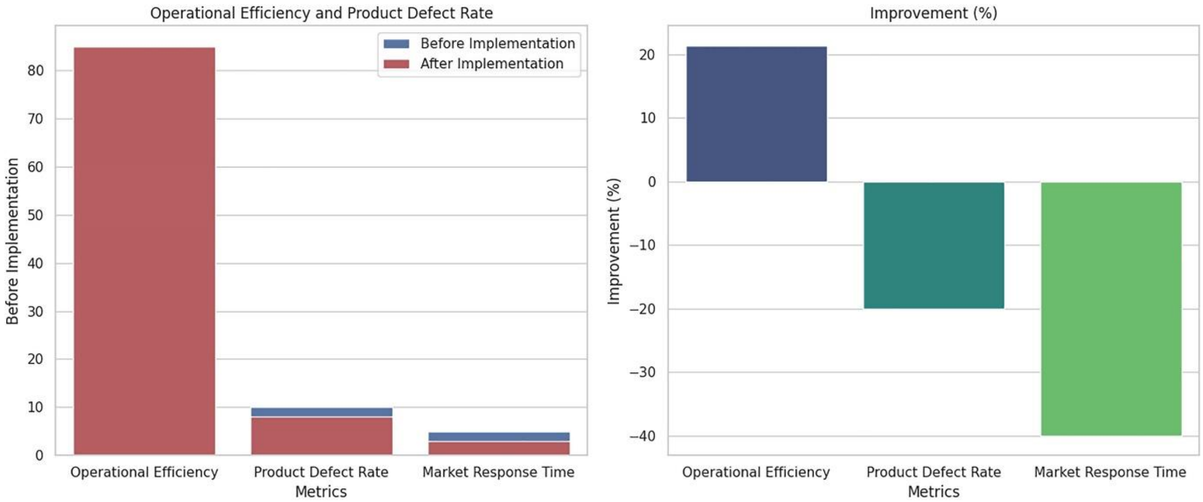

Figure 6. Operation Efficiency After Implementing the Proposed DD-DM

Opportunities in Using DD-DM

Despite facing various challenges, this study also identified several significant opportunities to enhance the implementation of data-driven decision-making (DD-DM). One of the main opportunities is to provide comprehensive training and education to employees on the benefits and use of DD-DM. This training can help reduce resistance to change and increase the adoption of new technologies among employees. Additionally, companies can invest in upgrading technological infrastructure, including hardware and software that support smooth and real-time data integration. This investment will help overcome existing technical challenges and enable companies to manage and analyze data more effectively.

Adopting a phased approach to DD-DM implementation is also a potential strategy. Starting with small projects that can demonstrate tangible results can build trust and support throughout the organization, as well as provide valuable lessons for larger projects in the future. By leveraging these opportunities, companies can achieve more effective and data-driven decision-making, ultimately improving operational efficiency and market competitiveness.

Discussion

The study's findings indicate that the implementation of the DD-DM framework in the manufacturing industry can yield significant benefits. This aligns with the existing literature, such as (Kalla & Smith, 2024), who emphasize the importance of data generated by Industry 4.0 technologies for efficient resource management. This study shows that by integrating data analysis, information technology, operational management, and business strategy, companies can enhance operational efficiency, product quality, and responsiveness to market changes. The empirical findings from this case study support previous research by (Jamwal et al., 2021), which indicates that Industry 4.0 technologies can improve manufacturing performance. The results are also consistent with the views of (Awan et al., 2021) and (Vafaei-Zadeh et al., 2024) that DD-DM can enhance productivity and competitive advantage.

However, the study also identifies key challenges, such as poor data quality, difficulties in technology integration, and employee resistance to change. These challenges align with findings by (Bammidi et al., 2024) and (Wu et al., 2021), who highlight that incomplete or inaccurate data can impede effective decision-making. To address these issues, validation, and cleaning of data are critical steps. Technological integration remains a significant challenge. Various information systems and technologies need to be integrated to ensure smooth and real-time data flow, as highlighted by (Raptis et al., 2019). Investing in technological infrastructure, including hardware and software that support data integration, can help overcome this challenge

Human factors also play a crucial role in the success of DD-DM implementation. As identified by (Neumann et al., 2021) and (Pollini et al., 2022), resistance to change and lack of understanding of new technologies can hinder effective adoption. Extensive training and education can mitigate resistance and enhance the adoption of new technologies among employees. The proposed DD-DM framework encompasses essential elements like data collection, data management, data analysis, technology integration, and employee training. Each component is crafted to promote more effective DD-DM. The development of a DD-DM maturity model, which includes five levels of maturity, also provides a roadmap for companies to assess and enhance their DD-DM capabilities progressively.

This study provides practical and theoretical contributions for manufacturing companies seeking to adopt DD-DM. By understanding and addressing existing challenges and leveraging available opportunities, companies can achieve better performance and competitiveness in an evolving market. Future research could explore the reliability and flexibility of the proposed DD-DM framework in different contexts and with more in-depth approaches.

4. CONCLUSION AND RECOMMENDATION

This study proposes an integrated data-driven decision-making (DD-DM) framework for the manufacturing industry, focusing on data analysis, information technology, operational management, and business strategy. The case study on an SME in the electronics sector demonstrates the significant benefits of implementing the DD-DM framework. Empirical findings indicate that implementing the DD-DM framework can improve operational efficiency by 15%, reduce product defect rates by 20%, and enhance market responsiveness by 40%. However, challenges such as data quality issues, technology integration difficulties, and employee resistance to change must be addressed. To overcome these challenges, companies should focus on improving data quality through validation and cleaning processes, investing in technology infrastructure that supports data integration, and providing comprehensive training for employees to enhance analytical skills.

Future Research Recommendation

1. Further Research on Data Quality: Future studies should explore effective methods and techniques for improving information quality, including validation, information cleaning, and big information management.
2. Case Studies in Various Sectors: Conduct additional case studies in different industrial sectors to test the flexibility of the DD-DM framework proposed. This will help us understand how the framework can be applied in diverse contexts.
3. Influence of Organizational Factors: Further research on the impact of organizational factors such as corporate culture and change management on the success of DD-DM implementation. Understanding these factors can help design more effective strategies to overcome resistance to change.

Author contributions Conceptualization, implementation, and execution of experiments, MR; Execution of experiments, SP; Conceptualization and review writing, AW; All authors have read and agreed to the final version of the manuscript.

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