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In Data We Trust: Opportunities & Challenges in Promoting Data-Driven Decision-Making in Organizations

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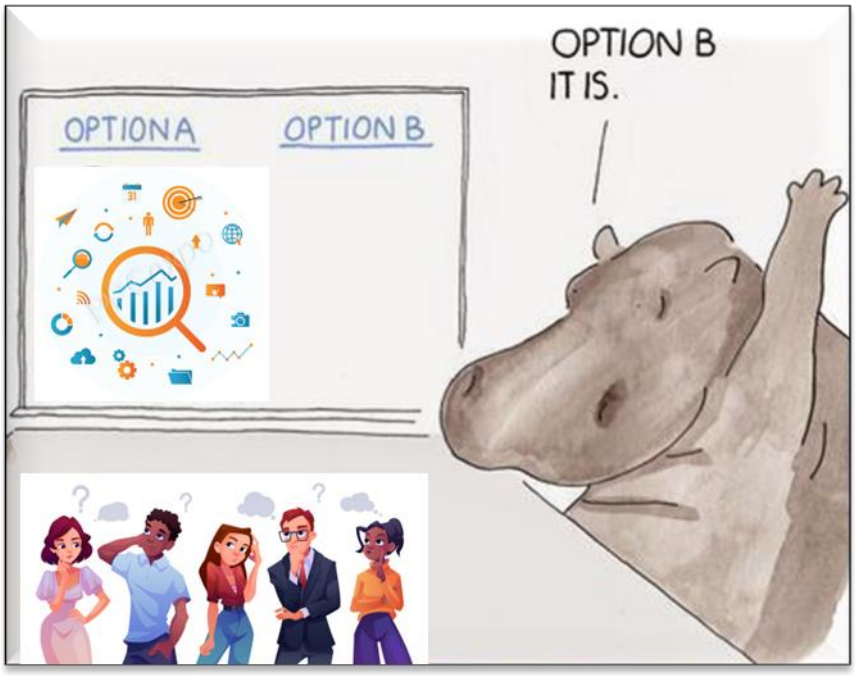
Abstract

This study explores the landscape of data-driven decision-making and the adoption of artificial intelligence in organizations, focusing on the challenges and opportunities encountered in promoting a data-driven culture. Through surveys and interviews with executives and managers, insights were gathered regarding the perceptions and experiences of data-driven strategies and AI technologies. The results highlighted a growing recognition of the benefits of data-driven approaches alongside concerns about cultural barriers and technological integration challenges. Our thesis offers a nuanced understanding of the similarities and discrepancies in perspectives on data-driven decision-making. Future research directions include long-term studies to assess the sustained impact of data-driven strategies, sector-specific investigations to tailor best practices and deeper exploration of ethical considerations in AI adoption. This comprehensive approach contributes to advancing knowledge and practice in data-driven decision-making and AI adoption within organizations.



Let data drive decisions, not the Highest Paid Person's Opinion

On importance of data-driven decision-making

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Keywords

Data-driven decision-making, Artificial intelligence, Organizational culture, Adoption barriers, Skills and expertise, Data-driven organization.

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1. Introduction

Decision-making is a critical task within organizations, significantly influencing their overall performance (Sharma et al., 2014). The pressure on decision-makers to ensure timely and accurate decisions has intensified due to the inherent errors and inconsistencies of human decision-makers (Clemons et al., 2017). Consequently, substantial research has been into decision-making theories, expanding to include data-driven decision-making (DDDM), which leverages analytics to make informed choices (Elgendy et al., 2021).

Data-driven organizations empower their employees with data-driven capabilities, prioritizing data over intuition to optimize processes and drive continuous improvement (Buitelaar, 2018). Research indicates that DDDM is associated with superior decision-making, increased firm performance, and the identification of valuable business opportunities (Brown et al., 2011; Chaudhuri et al., 2021). For instance, companies identifying as data-driven achieve superior financial and operational performance (McAfee & Brynjolfsson, 2012a).

The core characteristics of data-driven organizations include data access and sharing, data literacy, clear goals and indicators, an inquisitive culture, and strong data leadership (Anderson, 2015). These organizations apply DDDM across all types of analytics (descriptive, predictive, prescriptive) and decisions (operational, tactical, strategic) to encourage stakeholders to make data-driven choices (Dodman et al., 2021).

Despite the economic significance of data, many businesses struggle to transition to a data-driven approach, often relying on the "HiPPO"—the opinion of the highest-paid person—rather than data (McAfee & Brynjolfsson, 2012b). The drive for DDDM has led organizations to adopt strategies such as prioritizing data, investing in tools like Self-Service Business Intelligence (BI), and leveraging AI to support or replace human decision-makers (Berndtsson et al., 2020; Edwards et al., 2000).

Artificial intelligence (AI)'s role in decision-making has become prominent due to advancements in Generative AI, Big Data, algorithms, and computing power (Duan et al., 2019). AI-enabled systems are transforming businesses, enhancing decision-making processes, and presenting both challenges and opportunities (Miller, 2018a; Daugherty & Wilson, 2018).

The aim of this thesis is to explore how managers promote DDDM within their organizations and to identify the opportunities and challenges they face, including technological limitations and cultural resistance to change. The research seeks to address the following questions:

1. What are the opportunities and the challenges in implementing DDDM?

2. How does the adoption of AI technologies within organizations enhance decision-making processes, and what specific challenges and opportunities do these technologies present in the context of DDDM?

Our contribution to the field of DDDM and AI adoption within organizations lies in our exploration of how executives and managers drive DDDM, the challenges and opportunities in transitioning to a data-driven culture, and the practical applications of AI. By incorporating real-world examples and insights from empirical research, interviews, and surveys, we offer a unique perspective on promoting DDDM and leveraging AI technologies for competitive advantage. Our thesis aims to provide a practical roadmap for executives seeking to enhance decision-making processes through data-driven strategies, ultimately contributing to the advancement of organizational decision-making practices in the digital age.

To address the aim of our study and provide a comprehensive analysis of DDDM and the adoption of AI technologies in organizations, a rigorous mixed-methods approach was used, combining quantitative and qualitative research methods. An online survey and semi-structured interviews were conducted, targeting managers and executives from various industries and geographical locations. Questions were designed to gather insights on DDDM practices and AI integration, as well as the associated benefits and challenges. The survey data was quantitatively analyzed to reveal key trends and perceptions, whereas the complimentary semi-structured interviews provided qualitative data on managerial experiences and challenges. The Gioia method was used to identify and analyze patterns and themes from the interview transcripts, ensuring a robust and nuanced understanding of the human side of DDDM. This methodological approach not only triangulates findings from multiple data sources but also addresses potential biases, ensuring the reliability and validity of research outcomes.

Overall, this thesis explores the significance of decision-making within organizations, emphasizing DDDM and the role of AI. It reviews relevant literature on these topics, examines

quantitative data from an online survey, and provides qualitative insights from semi-structured interviews with managers. The results reveal key trends, benefits, and challenges in DDDM and AI adoption, highlighting cultural and technological obstacles. Integrating these findings, our discussion addresses the research questions and proposes strategies to overcome identified barriers. Our thesis concludes with a summary of findings, theoretical and practical implications, study limitations, future research suggestions, and practical recommendations for managers.

2. Previous research

The success and failures of organizations have been attributed to fate-changing decisions managers have to make. Therefore, substantial pressure has been placed upon decision-makers to ensure that the best decision is made in a correct and timely manner (Bartkus et al., 2018). Over the years, data has significantly transformed the economy, helping organizations to make informed decisions and increase overall performance (Brown et al., 2011; Chaudhuri et al., 2021). For instance, within the economies of the Organization for Economic Co-operation and Development, there is an increasing divide in productivity and profitability between firms that heavily utilize data and those that do not (Brynjolfsson et al., 2021a; Bajgar et al., 2021; Coyle & Manley, 2023). Data-driven organizations are additionally more likely to capitalize on business insights more frequently compared to their non-data-driven counterparts (LaValle et al., 2011). Therefore, more and more organizations have a vision to become data-driven (Davenport & Bean, 2018; Watson, 2016).

Data-driven companies now account for seven out of the top ten firms according to the global stock market chaptalization in 2021. Examples of top giant data-driven companies include Disney, Netflix, Starbucks, Airbnb, Adobe, Google, Uber, Johnson & Johnson, Novartis, and AstraZeneca- all which harness data to innovate, optimize operations, and provide better services to customers. To build a data-driven organization, it is crucial for practitioners to focus on the strategic and business benefits of big data analytics rather than just the technical aspects (Wang et al., 2014). Despite this, only a small fraction of organizations effectively leverages big data analytics to enhance processes and strategies. Consequently, the adoption and benefits of big data analytics within organizations to enhance performance remain limited (Bormida, 2021; Capurro et al., 2021).

Enterprise Resource Planning (ERP), BI, and Customer Relationship Management (CRM) systems form the backbone of modern data-driven organizations. These systems facilitate the integration and analysis of data across various business functions, leading to more informed decision-making processes (Rajola, 2003; Martines Mestre, 2015). The integration of ERP, BI, and CRM systems provides a competitive advantage by enhancing decision-making capabilities and allowing organizations to leverage data insights for improved strategic decisions (Sturdy, 2012). CRM and BI can be conceptualized based on the principles of people,

process, and technology (Shinde & Sunjita, 2018). Such integration allows organizations to better utilize customer data in the context of customer-centricity and enterprise-wide strategy (Sturdy, 2012).

The significance of data literacy programs in bridging skill gaps and cultivating a data-literate workforce is well-documented in the literature. Data literacy, defined as the ability to read, understand, create, and communicate data as information, is increasingly recognized as a critical skill in the modern workplace. Di Fiore (2018) emphasizes that data literacy is essential for making informed decisions and driving business success. The gap between the data skills that companies demand, and the current proficiency level of their employees is a significant challenge, driven by factors such as budget constraints, inadequate training resources, and organizational culture (Crabtree, 2023). One study highlighted that 84% of decision-makers expect at least basic data literacy from their employees. However, only 51% of employees report having received basic data literacy training (Correlation One, 2023). Therefore, this discrepancy highlights the urgent need for comprehensive data literacy programs to ensure that employees are equipped to handle and interpret data effectively.

AI represents a significant frontier in this endeavour, with its application in decision-making standing out as one of AI's most profound contributions. AI systems are designed to either support or even replace human decision-makers, offering capabilities across strategic, tactical, and operational levels of organizational decision-making (Edwards et al., 2000).

Data analysis and learning, human cognition, emotions, and thinking are the three capabilities of AI (Nishat et al., 2020). After years of anticipation and expectation, AI is beginning to make significant headway within major corporations (Bean, 2018). Reports indicate that the adoption of AI-enabled systems in organizations is growing swiftly, and AI has a transformative impact on businesses (Miller, 2018a; Daugherty & Wilson, 2018). AI's popularity has surged due to Generative AI, Big Data, sophisticated algorithms, and enhanced computing power and storage capacity. Consequently, AI systems are increasingly becoming a fundamental component with a significant influence on human decision-making (Duan et al., 2019).

Given the increasing importance of data and AI in organizational decision-making, there is a critical need to explore the managerial challenges in implementing DDDM. Our thesis aims to fill this gap by focusing on how managers can promote DDDM and the obstacles they encounter, including technological limitations and cultural resistance to change. Our thesis

focuses on why DDDM is important and identifies managerial challenges in adopting it. It also delves into the role of AI in DDDM. While previous research has highlighted the potential of AI in decision-making, our thesis investigates how AI technologies are currently being adopted within organizations and the specific challenges and opportunities they present in the context of DDDM. And finally, by focusing on the strategic and business benefits of big data analytics and AI from a managerial perspective, this thesis will offer practical recommendations for organizations aiming to become data driven.

2.1 Conceptual framework

This conceptual framework sets the stage for our study on how DDDM can be effectively implemented in organizations. It aims to understand the key ideas, theories, and relationships that guide managers and executives in overcoming technological and cultural challenges to harness the power of data.

1. DDDM

Definition: DDDM involves making choices based on the outcomes and evidence derived from analytics (Elgendy et al., 2021).

According to Provost and Fawcett (2013), DDDM involves "the practice of basing decisions on the analysis of data rather than purely on intuition." This approach integrates data analytics into the decision-making process, allowing organizations to make more informed and objective choices.

Importance: The importance of DDDM in modern business environments cannot be overstated. Organizations that effectively implement DDDM tend to outperform their competitors and identify new business opportunities more readily. Companies utilizing DDDM tend to perform better and find new business opportunities more easily (Brown et al., 2011). For example, organizations identifying as data-driven have achieved superior financial and operational performance (McAfee & Brynjolfsson, 2012b). Müller et al. (2018) conducted a comprehensive study which revealed that organizations employing DDDM experienced improved decision quality, leading to enhanced organizational performance. This improvement was particularly notable in areas such as customer relationship management, supply chain optimization, and risk management.

The application of DDDM extends across various sectors. In healthcare, for instance, it has been demonstrated how data-driven approaches can lead to improved patient outcomes and more efficient resource allocation (Freitas, 2024). In the retail sector, Papanagnou et al. (2022) showed how DDDM can enhance customer experience and optimize inventory management.

2. AI

Definition: AI refers to smart machines that can mimic human thinking to assist or replace human decision-making (Duan et al., 2019).

Role in DDDM: AI plays a pivotal role in enhancing data analysis within the framework of DDDM. By providing predictive insights, AI supports strategic decision-making processes. Edwards et al. (2000) highlighted that AI technologies enable organizations to analyze vast amounts of data more efficiently and accurately, leading to more informed and timely decisions. The integration of AI into DDDM allows for the automation of complex analytical tasks, thereby freeing up human resources for more strategic activities. The adoption of AI technologies in organizations is growing rapidly. Miller (2018) and Daugherty & Wilson (2018) have documented the transformative impact of AI on businesses, noting that AI-driven analytics can uncover patterns and trends that would be difficult, if not impossible, for humans to detect on their own. This capability is particularly valuable in dynamic and competitive markets where timely and accurate decision-making is crucial.

Impact on Organizations: AI is widely recognized as a catalyst for enhanced data analysis and predictive capabilities. The adoption of AI significantly boosts organizational performance and competitiveness. Organizations leveraging AI technologies experience substantial improvements in efficiency, accuracy, and overall decision quality (Dwivedi et al., 2021). These improvements are attributed to AI's ability to process and analyze large datasets at unprecedented speeds, providing actionable insights that drive better business outcomes. However, the successful implementation of AI in organizations requires significant investment in AI training and education. One study emphasized the importance of developing comprehensive AI training programs to fully leverage these technologies (Jarrahi et al., 2022). Organizations that invest in AI education and training are better positioned to harness the full potential of AI, leading to enhanced decision-making capabilities and competitive advantages.

These programs help build a workforce that is proficient in AI tools and methodologies, ensuring that the organization can effectively integrate AI into its decision-making processes.

3. Organizational Culture

Definition: Organizational culture refers to the set of shared values, beliefs, and practices that shape how people behave and make decisions within an organization. Organizational culture has been defined as "a pattern of shared basic assumptions learned by a group as it solved its problems of external adaptation and internal integration, which has worked well enough to be considered valid and, therefore, to be taught to new members as the correct way to perceive, think, and feel in relation to those problems (Schein, 2010).

Impact on DDDM: The impact of organizational culture on the adoption and effectiveness of DDDM practices is profound. A culture resistant to change can significantly impede the implementation of DDDM. Buitelaar (2018) highlights that organizations with a rigid culture often struggle to embrace data-driven approaches, as they may prioritize traditional decision-making methods over innovative, data-centric strategies. The drive for DDDM necessitates a cultural shift towards valuing data over opinions. One study argued that many organizations find this shift challenging due to deeply ingrained practices and resistance from employees who are accustomed to making decisions based on intuition or experience (Berndtsson et al., 2020). This resistance can manifest in various forms, including scepticism towards data analytics, reluctance to adopt new technologies, and a general preference for maintaining the status quo.

Facilitating a Cultural Shift: To successfully implement DDDM, organizations must foster a culture that values data-driven insights. This involves promoting data literacy, encouraging a mindset that embraces change, and demonstrating the tangible benefits of DDDM. According to Gupta and George (2016), building a data-driven culture requires leadership commitment, continuous education, and the integration of data analytics into everyday business processes. Moreover, organizational leaders play a crucial role in driving this cultural shift. As noted by Kiron et al. (2014), leaders who champion data-driven decision-making and model data-centric behaviours can influence the broader organizational culture. By setting an example and actively promoting the use of data in decision-making, leaders can help mitigate resistance and foster a more receptive environment for DDDM.

4. Technological Barriers

Definition: Technological barriers in the context of DDDM refer to the challenges related to the tools, infrastructure, and expertise needed to effectively implement data-driven practices. These barriers can significantly impede an organization's ability to leverage data for strategic decision-making (Wegener & Sinha, 2013). These challenges encompass a wide range of issues, from data quality and management to the availability of skilled personnel and the adequacy of technological infrastructure.

Common Technological Barriers: One of the most significant technological barriers to DDDM is poor data quality. It has been shown that the effectiveness of data-driven decisions is directly dependent on the quality of the data used (Hazen et al., 2014). Issues such as incomplete, inaccurate, or inconsistent data can lead to flawed analyses and, consequently, misguided decisions. Ensuring data quality requires robust data governance practices, including data cleansing, validation, and standardization processes.

The lack of skilled personnel capable of managing and analyzing complex datasets is another critical barrier. The third barrier is the absence of appropriate technological infrastructure to support data collection, storage, and analysis. One study discussed the challenges organizations face in managing big data, including issues related to data volume, velocity, and variety (Chen et al., 2012). Addressing these technological barriers is crucial for the successful adoption and implementation of DDDM (Fanelli et al., 2023).

3. Method

3.1 Empirical selection

This is a mixed-method approach thesis where it benefits from both an online structured survey and a number of semi structured interviews (Tashakkori & Teddlie, 2010). Each method has unique and complementary strengths and weaknesses. In a structured survey, participants respond to prompts by selecting from predetermined answers and these data are typically analyzed quantitatively (Babbie, 2020). In a semi-structured interview, interviewers begin with a small set of open-ended questions, but spend a considerable amount of time probing participant responses, encouraging them to provide detail and clarification and the data are analyzed qualitatively (Harris & Brown, 2019). Utilizing both methods allows us to mitigate the limitation of each approach (Creswell & Clark, 2017).

In designing the structured survey (In thesis it is referred to as survey), we searched and identified relevant literature, and discussed the questions and the topic with several decision makers in different industries. This process informed the development of our survey (Groves et al., 2009).

The survey was distributed, and the interviews were conducted to a diverse group of executives and managers involved in decision-making processes within their organizations. Respondents were selected based on their roles and responsibilities related to data analysis, decision-making, and technology adoption.

Our goal was to target managers at all levels in any sector and size of organization. We assured survey and interview participants of the anonymity and confidentiality of their responses. Ethical considerations regarding data privacy and security were prioritized throughout the survey and interview processes, adhering to established guidelines (Kvale & Brinkmann, 2009). More details regarding our sample selection in both survey and interviews is discussed in this chapter.

3.2 Data collection

3.2.1 Survey

Data collection was conducted through the online survey platform Microsoft Forms, allowing participants to respond to the survey questions at their convenience. This survey was

developed to gather insights on DDDM practices within organizations. The survey comprised 23 multiple-choice questions aimed at assessing participants' familiarity with DDDM, perceptions of its importance, challenges in integrating data-driven approaches, participants' familiarity with AI technologies, perceptions of AI's potential impact on decision-making, challenges in integrating AI technologies, and recommendations for enhancing DDDM processes (Appendix 7.1). The survey was open for a specified period, and participants were encouraged to provide their responses by a set deadline.

The target population for our survey consisted of managers from diverse sectors (healthcare, manufacturing, technology, pharmaceutical, financial services, energy, retail and consumer goods, construction and real state, transportation and logistics, media and entertainments and professional services). The aim was to capture a broad spectrum of managerial insights across different fields. We also categorized managers based on their years of experience to ensure a comprehensive understanding of managerial perspectives at different career stages. The experience levels were segmented as follows:

Less than 5 years, 5 to 10 years, 11 to 20 years and more than 20 years.

Our survey respondents were from diverse countries including Belgium, Denmark, Finland, France, Germany, the Netherlands, Norway, Poland, Sweden, UK, Canada, USA, China, Iran, Malysia, and South Korea.

We assured respondents of the confidentiality of their responses. This was crucial in obtaining honest and candid feedback, especially from managers who might be concerned about the sensitivity of the information they were providing.

Post-survey, we performed data cleaning to remove any incomplete or inconsistent responses. This step was essential to maintain the integrity and reliability of the data collected. By following this structured approach, we ensured that our survey captured a diverse and representative sample of managerial insights across different sectors and experience levels. This methodology provided a robust foundation for analyzing the data and drawing meaningful conclusions.

Considering gender and age frequency, responses were received from 47 (79%) men and 13 (21%) women, the majority of which were in 35-54 age group (76.7%). The criteria used to determine the size of companies were based on the number of employees. Specifically, the classification employed was:

- Small Organizations: Companies with 1 to 50 employees (14 / 23.3%).

- Medium Organizations: Companies with 51 to 500 employees (11 / 18.3%).
- Large Organizations: Companies with 501 to 5000 employees (25 / 41.7%).
- Very Large Organizations: Companies with more than 5000 employees (10 / 16.7%).

The response rate was 60% and it was calculated according to the following formula:

Response Rate= (Number of responses/ Number of surveys distributed) ×100

Response Rate= (60/100) ×100= 60%

3.2.2 Interviews

Conducting interviews is a powerful tool to gather rich and detailed information about a topic. Semi structured interviews benefit from a mix of closed- and open-ended questions, often accompanied by follow-up "why" or "how" questions (Adams, 2015).

Interviews allow for a more in-depth exploration of people's experiences, opinions, and attitudes (Gubrium & Holstein, 2002). This is particularly relevant to this thesis as the research questions are exploratory and, for instance, it relates to experience and challenges managers encounter when implementing DDDM in their organizations.

All interviewees held managerial roles in their respective organizations. Similar to the survey, the interviewees were from various sectors (healthcare, manufacturing, technology and service) with different managerial experience. The authors professional network was used to reach out to the potential interviewees. Selected interviewees were sent formal invitations explaining the purpose of the study, expected time commitment, and confidentiality assurance.

Semi-structured interviews were conducted with 10 selected respondents shown in Table 1. Interviewees were chosen based on their roles related to data analysis, decision-making, and technology adaptation within their organizations. This selection ensured that a broad spectrum of perspectives from those intimately involved with DDDM processes were captured.

Interviews were initiated with two broad open-ended questions which focused on what participants understood of DDDM in their organization, then continued with more detailed questions. Each interview comprised of nine main questions and lasted between 30 to 45 minutes on Microsoft Teams. The interviews were recorded with the permission of the interviewees. After the interviews, the interviews were transcribed, and the output was placed in a spreadsheet and set up against each other.

Respondent	Position	Gender	Industry
R1	Innovation Sustainability manager	M	Healthcare
R2	Founder & CEO	M	Healthcare
R3	Regional Manager	F	Manufacturing
R4	CEO	M	Technology
R5	Director Global Supply Chain IT	M	Manufacturing
R6	CIO	M	Service
R7	Commercial Manager	M	Manufacturing
R8	Business Process Manager	M	Manufacturing
R9	Director, Consultant	M	Consultancy
R10	Principal Consultant	M	Consultancy

Table 1. List of Interviewees

This table showcases the diverse and experienced individuals whose insights form the backbone of our qualitative analysis. Their varied backgrounds provide a comprehensive view of the challenges and successes in implementing DDDM across different sectors.

Through this thorough and thoughtful interview process, invaluable insights were gained into the human side of DDDM, enriching our understanding and providing a strong foundation for our thesis.

It is important to note that the relatively small sample size—comprising ten interviewees and sixty survey respondents—may limit the generalizability and transferability of our findings in this thesis. Consequently, a larger sample size could have enhanced the validity of our research, particularly in the interview section.

3.3 Method of Analysis

3.3.1 Survey

To analyze the survey responses, quantitative data analysis techniques were used. Firstly, the survey dataset was reviewed to identify any errors such as missing responses or duplicates. The frequency and percentage of responses for each question were then calculated and pie charts/graphs generated for data visualization.

Descriptive statistics was used to summarize participants' familiarity with DDDM and AI technologies, perceptions of its importance, challenges in integrating data-driven approaches, perceptions of AI's potential impact on decision-making, challenges in integrating AI technologies, and recommendations for enhancing DDDM.

3.3.2 Interviews

To identify patterns and extremes throughout the interviews, the Gioia method was employed. This method is a useful strategy to develop theories and conceptions based on empirical data gathered from respondents (Gioia et al., 2013). This method was chosen for coding the interviews only because it provides a systematic approach to qualitative research, especially suited for exploring complex phenomena like DDDM. By categorizing data into first-order concepts, second-order themes, and aggregate dimensions, we ensured that the nuances and complexities of interview data are captured and clearly presented. The next step was to identify consistent patterns and outliers by providing a comprehensive understanding of the factors influencing DDDM. The method’s structured approach helped us in organizing the data systematically, making it easier to derive meaningful insights and actionable recommendations. Furthermore, the Gioia method emphasizes capturing the perspectives of different stakeholders. Therefore, it helped us to understand the multifaceted nature of DDDM and the challenges associated with its implementation.

Different themes extracted from our interviews by using the Gioia method is summarised in Table 2. This methodological approach enabled a deep, structured exploration of DDDM, highlighting both its positive impacts and challenges.

Themes	Understanding DDDM	Factors for Implementing DDDM	Traditional Decision-Making challenges	Impact of DDDM on Culture	Promoting DDDM & Challenges	Successful AI Use Cases
Patterns	Industry-wide recognition of DDDM significance. Leveraging data for efficiency, service, and strategy. Integration of analytics tools for informed decisions.	Organizational culture, leadership support, resource allocation vital for DDDM. Reliable data sources, literacy programs, interdepartmental collaboration key. Technological advancements like AI, analytics platforms aid DDDM.	Common challenges: reliance on intuition, limited data access, slow decision cycles. Addressing cultural barriers, change resistance, data reliability concerns crucial. Regulatory, security, resource constraints affect traditional decision-making.	Positive impacts of DDDM: increased efficiency, transparency, accountability. Recognition of organizational mindset shifts towards data-driven behaviours. Leadership's role in shaping decision-making culture and fostering data-driven mindset.	Common challenges in promoting DDDM: resistance to change, cultural barriers, data reliability concerns. Importance of leadership support, organizational culture, data literacy programs in driving DDDM adoption. Considerations: resource constraints, security, effective communication, stakeholder engagement.	Successful AI applications in healthcare, manufacturing and finance noted. AI improves decision-making, streamlines processes, generates actionable insights from large datasets. Challenges in AI adoption: data privacy, ethics, there is a need for human oversight.

Extremes	Advocacy for widespread adoption of DDDM). Recognition of challenges in understanding and implementing DDDM. Call for education and organizational support to address challenges.	Successful DDDM driven by strong leadership, strategic planning, organizational alignment. Challenges include cultural resistance, resource scarcity, technological limitations hindering DDDM.	Some emphasize limitations of traditional approaches, advocate DDDM shift. Others stress human judgment's continued relevance, suggest balanced approach.	Some noted improvements in decision quality, efficiency, employee empowerment with DDDM. Others highlighted challenges: cultural transformation, change resistance, ongoing leadership support for DDDM sustainability.	Successful strategies: targeted training programs, pilot projects, executive sponsorship for promoting DDDM. Challenges: overcoming resistance to change, building trust in data, aligning organizational priorities with DDDM objectives.	Transformative AI applications: improved organizational performance, customer experience, innovation. Concerns raised: biases, job displacement, unintended consequences, advocating cautious adoption.

Table 2. Patterns and extremes of the interviews based on the Gioia Method

Overall, while there were variations in perspectives and experiences across the interviews, common themes, challenges, and opportunities emerged, highlighting the complex nature of DDDM implementation and its impact on decision-making culture within organizations.

The Interview questions are listed in Appendix 7.2 and to ensure accuracy and that no data was overlooked, the interviews were transcribed by converting audio recordings into written text. We also familiarized ourselves with the content of each interview and took notes of our initial thoughts, impressions, or emerging themes. It was also ensured that the themes were distinct from one another and covered all aspects of the research question.

Considering the six themes, thematic analysis and quotations were used. In thematic analysis, how each theme related to the research questions were explored and patterns,

contradictions, and insights were determined. Direct quotes were also stated from a number of interviews to support the analysis and illustrate key points.

"Member Checking" was also conducted by sending the interview transcriptions to each interviewee for validation, ensuring that the interpretations accurately reflected their views. The findings from the interviews were additionally related to existing literature and triangulation was ensured by using multiple sources of data to cross-verify our findings. Lastly, our own potential biases (based on our own roles) were reflected in the research process.

3.4 Data Triangulation

Data triangulation in the context of AI and DDDM involves the use of multiple sources or methods to validate and enhance the understanding of research findings. By triangulating data from various perspectives, researchers can strengthen the credibility and reliability of their insights. In our thesis, we have used methodological triangulation which is using different methodologies (survey, interviews, and literature review) to approach the same topic (Alele & Malau-Aduli, 2023).

4. Results

In this chapter, we present our findings from the survey and interviews conducted. Our empirical research, combining survey data and in-depth interviews with managers across various industries, provides comprehensive insights into the promotion of DDDM within organizations. We identified the challenges they face, the benefits and opportunities presented by the adoption of AI technologies, and potential strategies to overcome barriers to DDDM.

4.1 Organizational characteristics

According to the survey results, 5/10 (50%) survey participants from very large organizations, 20/25 (80%) from large, 8/11 (72.7%) from medium and 9/14 (64.3%) from small believed that their organizations are very likely to increase AI investment over the next two to five years.

In our result, the lowest percentage among all organizations are very large ones, suggesting that these organizations may be more cautious or have already made significant AI investments. Large organizations representatives had the highest percentage, indicating that large organizations are the most bullish on AI investment. Respondents from medium sized organizations scored the second highest in willingness to invest in AI, suggesting that these companies are also quite optimistic about AI's potential. And finally, the small organizations while still a majority, their percentage is lower than that of large and medium-sized organizations, possibly due to resource constraints or different priorities.

Regarding industry type, the majority (80%) of respondents came from three key sectors: Manufacturing, Technology, Healthcare and Pharmaceuticals.

The survey results reveal significant insights into how different industries are approaching AI investment. The concentration of respondents in the above three key sectors- provides a focused lens through which we can examine industry-specific trends and attitudes towards AI adoption.

When it came to the extent of DDDM utilization within their organizations, 57% of respondents reported moderate, 23% low and the remaining 20% high. It is interesting note that a great majority of survey respondents found data and evidence very important (61%) or

moderately important (33%) when it comes to decision-making (Fig. 1). Therefore, we then asked the respondents about different decision-making approaches.

Figure 1. Survey participants' opinions on how important DDDM is in their organizations

4.2 Navigating decisions: Intuition vs. data-driven approaches in organizational choices

Some interviewees shared experiences of decisions made based on intuition or past experiences, rather than a data-driven approach. One example involved a project to optimize battery usage for energy companies. Despite positive stakeholder feedback, the project was halted after six months due to insufficient customer interest and concerns about the new employee's skills. The interviewee acknowledged that more market research might have saved the project, but they relied on intuition and past experiences instead.

In the healthcare sector, another interviewee mentioned that decisions are often made based on intuition, especially when experienced consultants diagnose diseases by gut feeling. Within the IT industry, interviewees highlighted challenges in making decisions about emerging technologies, particularly for manufacturing systems. They strive to be data-driven but face difficulties due to the lack of quantifiable data for new technologies. Decisions in these areas often rely on internal knowledge, judgment, intuition, and past experiences.

4.3 From gut feelings to data insights: Overcoming challenges in decision-making

In discussions about the challenges of relying on gut feelings for decision-making, interviewees highlighted the complexity and time-consuming nature of dealing with large data sets. In healthcare sector, traditional systems require doctors to spend significant time on administrative tasks and reviewing historical patient information, which limits efficiency. One interviewee noted the inherent limitations of non-data-driven approaches, emphasizing the risks and potential inaccuracies when decisions are not guided by data.

Human decision-making can be swayed by personal biases, preferences, and limited experiences, leading to less objective outcomes. This is particularly problematic in a rapidly changing world where up-to-date and accurate information is crucial. One healthcare project demonstrated that computers, with access to vast data, were more effective than individual doctors at diagnosing and treating patients, underscoring how using data could improve outcomes. Interviewees noted that traditional decision-making processes often lack transparency and objectivity, as personal biases and preconceived notions can influence decisions. Therefore, a shift is needed to reduce these biases by relying on data and analytics, promoting a more transparent and fair decision-making process.

4.4 DDDM and what it really means in an organization

In exploring our interviewees' perceptions of DDDM, it became clear that it is widely regarded as crucial for leveraging data to inform decision-making processes. This view was consistently echoed by all participants, highlighting DDDM's importance.

Several key factors emerged as priorities for effective DDDM. First, ensuring a common understanding of data collection and its purpose across the organization is essential. Data accuracy and quality are paramount. One respondent emphasized, *"The computer needs accurate and comprehensive information to generate reliable suggestions. So, it is crucial to base decisions on correct data."* This underscores the importance of data integrity in decision-making. Secondly, standardizing data collection processes and ensuring consistency in data definitions across different sites or departments is crucial. This enables scalability and effective utilization of data organization-wide, particularly in global companies.

Investing in employees' knowledge through training and education is also vital. This ensures employees can interpret and utilize data effectively in their decision-making processes. One respondent discussed the importance of embracing new technologies, such as Copilot, to enhance data usage efficiency. While acknowledging initial shortcomings, he expressed confidence in improvement over time. He noted that resisting such changes would leave organizations behind, emphasizing the need to adapt to new technology for long-term success. Another respondent mentioned, *"In our strategy, we consider a set of guidelines to focus on. This helps us give more attention and focus to the transition towards a data-driven culture. By following these guidelines, we can also allocate more resources to support this*

transition and ensure that we have the right people working on it." This highlights the strategic approach required to foster a data-driven culture.

Some of the interviewees gained a great deal in efficiency and quality of decisions from adopting DDDM in recent years. It was interesting to note that being more data driven made a number of interviewees from different sectors become more structured, resulting in a positive impact on their overall decision-making culture.

4.5 Assessing DDDM and its effectiveness in organizations

When asked to describe the level of DDDM in their organizations, only 20% answered high, 23% answered low and the majority of the respondents (57%) answered moderate (Tab. 3).

Level	Percentage
Low	23
Moderate	57
High	20

Table 3. Level of DDDM in survey respondents' organizations

When making decisions in their organizations, a great majority of survey respondents (75%) stated that they use both intuition (gut feelings) and a data analysis approach (Tab. 4).

Decision-making approach	Percentage
Trust my instinct/experience	1
Seek available data & analyze	24
Combinations of gut feelings & data analysis	75

Table 4. Approaches survey respondents take when making decisions in their organizations

Our survey results also show that availability of relevant data (43%) and complexity of the decision (33%) were the main factors respondents may choose to rely on gut feelings when making decisions within their organizations.

80% of the survey participants believed that their organization use a mixed approach (data-driven and intuitive), supported where one respondent said: *"We recognize the importance of both data-driven insights and intuitive judgment, especially in areas where data may be lacking".* Moreover, 56% of survey respondents thought that data-driven approaches are more effective and only 10% found gut feeling approach more effective (Tab. 5).

Respondents' views	Percentage
Gut feelings being more effective	10
Data-driven being more effective	56
Unsure or varies	34

Table 5. Survey respondents' perceptions of the efficiency of gut feelings vs. data-driven decision-making

Survey participants were asked about their satisfactions with their current tools and tech used for data analysis in their companies. Our results show that only 27% were satisfied, 56% neutral and the remaining 17% were dissatisfied (Tab. 6).

Respondents' views	Percentage
Dissatisfied	17
Neutral	56
Satisfied	27

Table 6. Survey respondents' overall satisfaction with current tools & technologies used for data analysis

Following the initial inquiry into decision-making, our survey presented participants with a multiple-choice question regarding the types of organizational systems employed. As anticipated, a high prevalence of adoption was observed across core systems, with the majority of respondents indicating the use of ERP, BI, Human Resource Management (HRM), and CRM systems in their organization (Fig. 2).

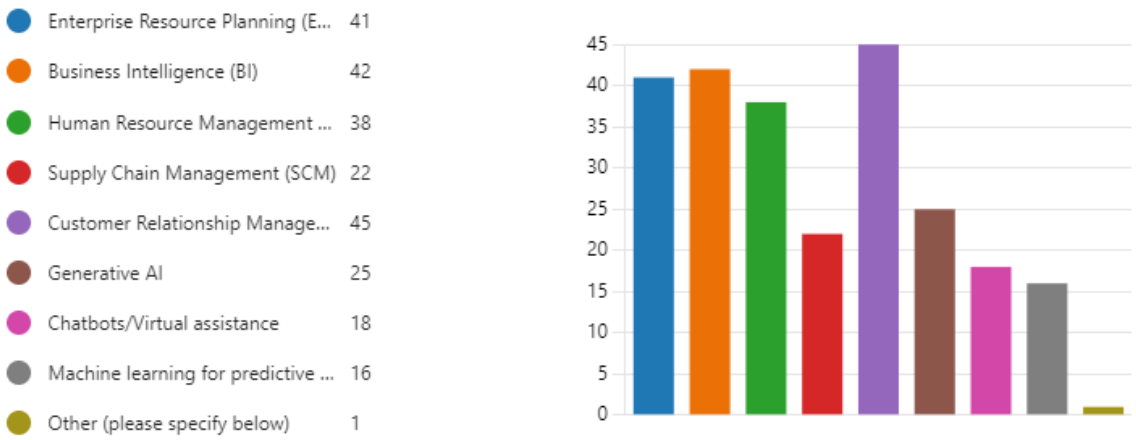

Figure 2. Adoption rates of core organizational systems among respondents (respondents could choose more than one option)

Our survey revealed a significant influence of organizational systems on decision-making. When queried regarding the type of systems utilized by their organizations and the perceived level of influence on decision-making, 90% of respondents indicated that these systems have a moderate to high level of influence and only 10% responded that these systems had a minimal influence on decision making.

4.6 Promoting DDDM

One of our respondents discussed the promotion of DDDM in their organization and continued with saying that DDDM is still a new concept for them, and traditional methods are often relied upon. He highlighted the ambiguity in defining DDDM, questioning whether generating detailed monthly reports for the Board of Directors constitutes a data-driven approach. Despite this uncertainty, he stressed the importance of continually evaluating and improving their approach to align with DDDM principles.

Another interviewee emphasized the value of DDDM, using market analysis to guide decisions such as adjusting the size of the sales team and continued how his organization promotes DDDM through checkpoints in the governance model that require data for decision-making, and by making tools and data accessible to everyone. This openness fosters a culture of DDDM, and technological decisions must consider data accessibility and integration to ensure effective use for decision-making.

4.7 Challenges and barriers to data driven initiatives

After discussing the promotion and benefits of increased transparency and traceability achieved by DDDM, interviewees noted several challenges in the decision-making process using data. One significant issue is the increased administrative burden due to the emphasis on data analysis. Accurate and comprehensive information is crucial for reliable decisions, with one interviewee emphasizing the importance of correct data and effective utilization of large data volumes. Another mentioned that even if DDDM is not explicitly discussed in every meeting, a governance model still guides key decisions related to budget, costs, IT architecture, and strategic initiatives.

Two interviewees observed that decisions not based on data often focus on people's needs or desires without prior data or analysis, indicating the challenge of fully implementing DDDM into organizations. Some interviewees suggested that excessive focus on data analysis could lead to inefficiencies and distract from essential decision-making factors. One emphasized the need for judgment to determine when extensive data analysis is necessary. Another noted the risk of self-bias, where decision-makers might have a predetermined outcome in mind, leading to biased decisions and potentially rendering data analysis unnecessary. Two interviewees warned of the risk of data manipulation or misinterpretation to support predetermined outcomes, underscoring the need for critical thinking and skepticism in data interpretation.

Here are the significant challenges and barriers to adopting data-driven initiatives within organizations, as supported by our survey and interview data:

- Lack of Skills or Expertise: 40 survey participants identified this as a major barrier. One interviewee noted, "*Our team lacks the necessary training to interpret and utilize data effectively, which hampers our ability to make data-driven decisions."*
- Data Quality Issues: Data quality issues were reported by 35 survey respondents as a significant challenge. As one interviewee mentioned, *"Inaccurate or incomplete data often leads to misguided decisions, making it difficult to rely on data-driven approaches."*
- Lack of Tech Infrastructure and User-Friendly Systems: 24 participants highlighted the absence of adequate technology infrastructure and user-friendly systems as a barrier. This point was echoed by one of our interviewees, who said, *"Our current IT*

infrastructure is outdated, and the systems we use are not user-friendly, which makes data analysis cumbersome."

- Lack of user-friendly systems: 20 of our respondents believed that not having access to user-friendly systems is a challenge in their organizations. This was echoed by one of the interviewees, who mentioned, *"One of the biggest challenges is the lack of user-friendly systems. The tools we have are not intuitive, and it takes a lot of time for our staff to learn how to use them effectively. This really slows down our decision-making processes and makes it hard to leverage the data we have."*
- Cost Considerations: 19 respondents identified cost as a challenge. An interviewee pointed out, *"The initial investment in technology and training for data-driven initiatives is high, and budget constraints often prevent us from moving forward."*

These challenges and barriers are summarized in Figure 3.

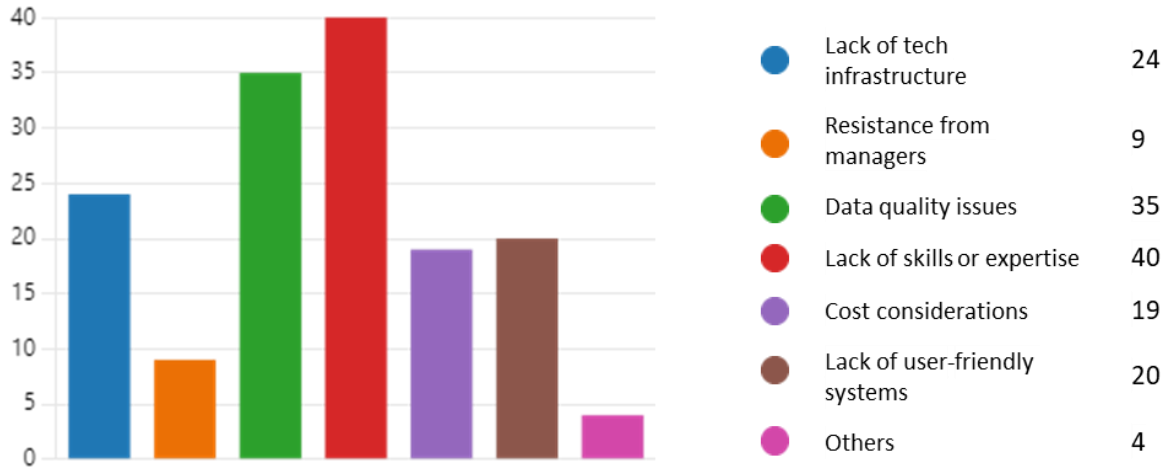

Figure 3. Main challenges faced by survey participants in adopting DDDM in their organizations (respondents could choose more than one option)

Cultural resistance additionally emerged as a common theme. Survey responses indicated a reluctance to change established practices, which was elaborated upon in interviews. As one of our respondents said: *"People are often resistant to change, especially when it comes to adopting new technologies or relying on data over intuition"*. This cultural barrier was noted as a significant challenge in fostering a data-driven culture. The survey data clearly indicated a surprisingly low DDDM culture among the respondents where only 13% responded that decisions are primarily based on data analysis and metrics (referred as data-driven in Tab.

6). The remaining participants believed that their overall view of decision-making culture is either mixed approach (80%) (using both intuition and data-driven) or solely dependent on intuition (7%) (Tab. 7).

Approach	Percentage
Data-driven	13
Intuitive	7
Mixed Approach	80

Table 7. Overall view of decision-making culture among survey respondents

4.8 How can AI help overcome challenges to DDDM initiative

Our survey results revealed a positive outlook on AI applications for competitiveness, with 56% of respondents believing AI has a significant impact on their companies' competitiveness (Fig. 4).

Figure 4. Survey participants' views on AI's future impact on their organizations' competitiveness

50% of respondents believed that training in AI technology is essential for leveraging AI in DDDM. Top-level support was important for 34% of respondents, while 28% highlighted the need for addressing ethical and privacy concerns.

Most respondents were optimistic about AI's potential to enhance DDDM, with 55% being very optimistic and 43.3% somewhat optimistic. However, challenges anticipated included lack of AI skills (73%), data privacy and security (62%), data quality (57%), resistance to change (52%), regulatory issues, ethical considerations, and high costs. (Fig. 5).

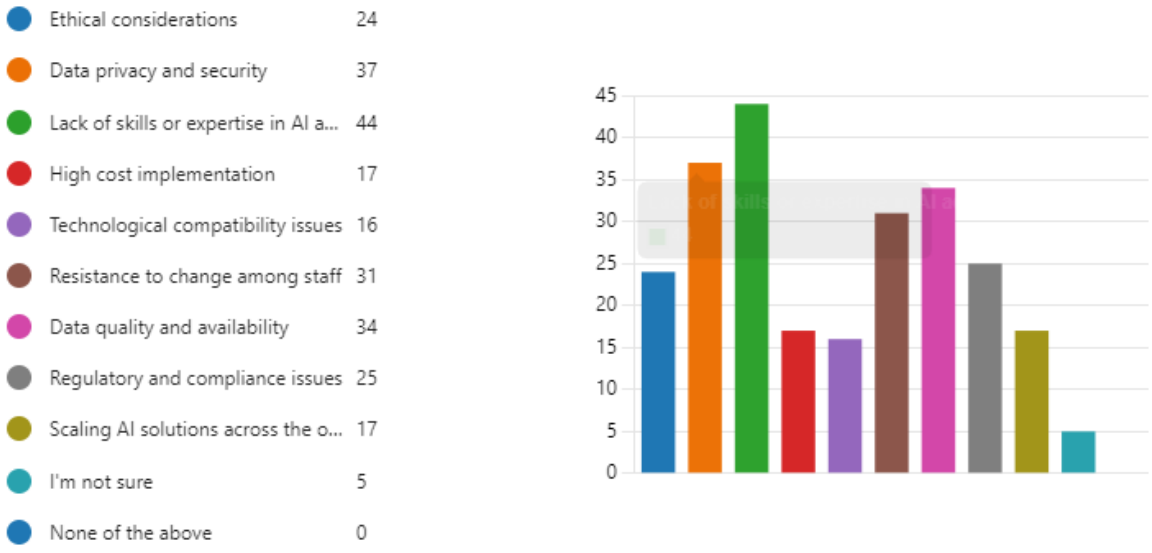

Figure 5. Anticipated challenges in integrating AI technologies for decision-making (respondents could choose more than one option)

Survey results show that respondents believe AI can enhance DDDM by automating data analysis for faster and more accurate decisions, identifying hidden trends and patterns, improving data visualization, and reporting, and enhancing predictive analytics for better forecasting and risk management (Tab. 8).

Respondents' views on AI enhancing DDDM	Percentage
Automating data analysis process	16
Predictive analytics for better forecasting	13
Improving decision-making speed & accuracy	15
Enhancing data visualization & reporting	14
Facilitationg personalized customer interactions	8
Identify trends & patterns not easily visible by humans	14
Enabling real time decision-making	9
Improving risk management	11
AI will not enhance DDDM for my organization	0

Table 8. Survey respondents' views on how AI could enhance DDDM in their organizations

Our survey results show that majority of our respondents were somewhat familiar (80%) with AI technologies and its potential in decision-making with 11% being very familiar (Tab. 9). This familiarity provided a solid foundation for the research and the follow-up question about respondents' experience with AI.

Respondents' familiarity	Percentage
Somewhat familiar	80
Very familiar	11
Not familiar at all	9

Table 9. Survey respondents' familiarity with AI technologies in decision-making

4.9 Interviewees' views and experiences on using AI applications

Interviewees from various organizations and sectors shared their experiences with AI applications, highlighting significant improvements in decision-making and organizational performance.

In the energy forecasting industry, AI has greatly enhanced forecasting models, shifting from manual identification of factors to utilizing a broader range of data without specifying parameters, improving capabilities and indispensability to customers. One respondent emphasized AI's broader impact within their company, noting that subsidiaries heavily using AI share their expertise, benefiting the entire group.

Specific benefits of AI integration mentioned include:

- Quality Monitoring: AI-enabled virtual quality sensors provide detailed quality assessments, enhancing efficiency in the production chain without physical sampling.
- Increased Efficiency: AI tools such as Copilot have shown promising results, potentially transforming how white-collar workers interact with information and increasing work process efficiency.
- Predictive Maintenance: AI-based solutions predict potential machinery failures, resulting in fewer breakdowns and improved operational efficiency and cost savings.
- Custom Forecasting: AI models have significantly improved forecasting capabilities, offering insights unattainable through traditional methods.

- Customer Acquisition: While not directly AI-driven, LinkedIn's technology, likely enhanced by AI algorithms, has streamlined customer searches and outreach, improving efficiency.

4.10 Themes, patterns, and extremes

The Gioia method used in our thesis was particularly useful for organizing and analyzing qualitative data, allowing for the identification of key themes and patterns, and offering a comprehensive view of the subject.

The findings reveal that there is a widespread recognition of the importance of DDDM across various industries. Organizations are leveraging data to enhance efficiency, improve service delivery, and make strategic decisions. The integration of analytics tools is essential for making informed decisions. There is strong advocacy for the adoption of DDDM, with some emphasizing the limitations of traditional approaches and advocating for a shift towards DDDM. Others stress the continued relevance of human judgment, suggesting a balanced approach.

Successful implementation of DDDM depends on several factors, including organizational culture, leadership support, resource allocation, and interdepartmental collaboration. Reliable data sources and data literacy programs are also crucial. Effective DDDM is driven by strong leadership, strategic planning, and organizational alignment. However, challenges such as cultural resistance, resource scarcity, and technological limitations can hinder implementation.

Traditional decision-making faces challenges like reliance on intuition, limited data access, and slow decision cycles. Overcoming cultural barriers and resistance to change is critical. There is an acknowledgment of the challenges in understanding and implementing DDDM, with calls for education and organizational support to address these issues.

DDDM positively impacts decision-making by increasing efficiency, transparency, and accountability. It fosters a shift towards data-driven behaviors within organizations. Leadership plays a crucial role in shaping the decision-making culture and fostering a data-driven mindset. While some note improvements in decision quality and employee empowerment with DDDM, others highlight ongoing challenges such as cultural transformation and resistance to change.

Promoting DDDM requires leadership support, organizational culture shifts, and data literacy programs. Effective communication and stakeholder engagement are also important. Successful strategies include targeted training programs, pilot projects, and executive sponsorship. Challenges include overcoming resistance to change, building trust in data, and aligning organizational priorities with DDDM objectives.

AI applications in healthcare, manufacturing, and finance demonstrate successful use cases of DDDM, improving decision-making and generating actionable insights from large datasets. While AI improves organizational performance and customer experience, concerns about biases, job displacement, and unintended consequences advocate for cautious adoption and the need for human oversight.

5. Discussion

The aim of this discussion is to explore how managers promote DDDM within their organizations and to answer the two research questions. By synthesizing insights from academic literature, our results (survey, and interviews), this chapter identifies the key strategies and practices that managers employ to foster a data-driven culture.

We highlight both the opportunities and challenges that managers face in driving the adoption of DDDM, providing an understanding of their pivotal role in transforming organizational decision-making processes.

According to our results, large and medium-sized organizations appear to be the most enthusiastic about increasing AI investment. Very large organizations show the least inclination to increase AI investment, which could be due to already having substantial AI infrastructure in place, facing more complex integration challenges, being more risk-averse due to their size and established processes. Small organizations show a moderate inclination towards increasing AI investment, which might reflect limited resources compared to larger counterparts, have a focus on other priorities for business growth and potentially seeing AI as less critical for their current operations. The overall trend suggests that mid-market companies (large and medium-sized) are positioning themselves to be at the forefront of AI adoption and investment in the coming years. This analysis highlights that company size does indeed have a significant impact on the likelihood of increasing AI investment. The data suggests that different sized organizations may have varying strategies, resources, and priorities when it comes to AI adoption and investment.

Manufacturing, technology, healthcare, and pharmaceuticals were the sectors most represented among the respondents. The predominance of these three sectors suggests a strong innovation culture across the respondents. These industries are often early adopters of new technologies, potentially skewing the overall results towards a more positive view of AI investment. To highlight this, the manufacturing industry for example has been identified as a significant adopter of AI technologies, particularly in areas such as process optimization, predictive maintenance, and quality control. These applications are driven by the need to enhance productivity and reduce operational costs (Hunter et al., 2018). The technology sector is also at the forefront of AI adoption, leveraging AI for product innovation, customer

experience enhancement, and data analytics. This sector's rapid technological advancements and competitive nature drive substantial AI investments (Babina et al., 2024). And lastly, AI is revolutionizing the healthcare and pharmaceuticals industry by improving diagnostic accuracy, accelerating drug discovery, and personalizing patient care. The potential for significant improvements in patient outcomes and operational efficiencies makes AI a critical investment area for these industries (Henriksson & Nyqvist, 2022).

The strong representation of these sectors in our results indicates a robust innovation culture. These industries are known for their early adoption of new technologies, which aligns with their positive outlook on AI investments. This trend is supported by the literature, which highlights the role of AI in driving innovation and competitive advantage across various sectors (Wamba-Taguimdje et al., 2020).

5.1 Promoting DDDM in organizations: The role of managers

As revealed in our results, managers hold a pivotal role in fostering DDDM within organizations, shaping a culture that values data and analytics in decision-making processes (Sandkuhl, 2019). Our findings align with existing literature, emphasizing the importance of aligning organizational processes with strategic goals, overcoming resistance to change, and creating a supportive environment for learning and adaptation (Sender, 1997).

Our data underscored the significance of implementing data literacy programs to bridge skill gaps and cultivate a data-literate workforce, which resonates with previous studies (Di Fiore, 2018). Advocacy for advanced analytics tools, as indicated in our results, is crucial for enhancing data analysis capabilities, contingent upon effective training of employees (Sandkuhl, 2019).

Our findings additionally echo the literature in emphasizing the need for building a robust data infrastructure to ensure data accessibility, reliability, and security for seamless integration into decision-making processes (McAfee et al., 2012; Davenport, 2014). Integrating data analysis into everyday business processes, as highlighted in our findings and existing literature, reinforces the importance of data in guiding decisions and optimizing organizational operations (Provost & Fawcett, 2013). Similarly, setting clear, data-driven performance metrics is essential for measuring success and facilitating informed adjustments (Marr, 2015).

Leadership by example, relying on data in decision-making, as observed in our results, inspires employees to follow suit, reinforcing studies that emphasize the normalization of data usage within organizations (Di Fiore, 2018). Creating an environment where data-driven ideas are encouraged and rewarded, as highlighted by our results and prior research, fosters collaboration and shared responsibility for DDDM (Davenport & Harris, 2007).

Promoting DDDM demands a multifaceted approach, as emphasized in our findings and literature, encompassing a supportive culture, data literacy programs, advocacy for advanced analytics tools, embedding data-driven practices, and leading by example (McAfee & Brynjolfsson, 2012). While our results align with much of the existing literature on promoting DDDM, some discrepancies exist, such as nuances in the effectiveness of specific strategies and their implementation challenges, warranting further exploration for a comprehensive understanding.

5.2 Opportunities and challenges in implementing DDDM

Organizations today are increasingly recognizing the transformative potential DDDM. From various surveys, interviews, and academic literature, a clear picture emerges of the opportunities and challenges that lie ahead in this journey.

Enhanced decision-making and organizational performance are notable benefits of DDDM. Our quantitative data indicated that data-driven approaches outperformed intuition, leading to more effective decision-making. The Interviewees reinforced this, highlighting how data enhances efficiency, customer service, and strategic planning across industries. These practical insights align with a study which found data-driven companies excel in financial and operational metrics (McAfee & Brynjolfsson, 2012b). This has been further emphasized where leveraging analytics has shown to foster a fact-based decision-making culture, boosting organizational performance (Watson, 2013).

Enhanced competitive advantage also emerges as a key opportunity, and survey participants noted a positive influence of systems like ERP, BI, and CRM on decision-making. Interviewees echoed this sentiment, stressing the importance of investing in data infrastructure and analytics tools for successful DDDM implementation. Our data has been supported by a study indicating that DDDM helps organizations identify market trends, understand customer preferences, and improve operational efficiencies. This collective understanding is reinforced

by findings of significant performance benefits for top-performing data-driven companies (McAfee & Brynjolfsson, 2012a).

Creating a Data-Driven Culture is another pivotal opportunity. Our results stressed the importance of a supportive organizational culture. Our data shows how leadership support and strategic resource allocation are critical for successful DDDM implementation. This emphasis is backed by the underlining of the role of analytics in fostering a culture that values fact-based decision-making (Watson, 2013). Furthermore, increased efficiency and productivity are compelling reasons to adopt DDDM. According to our results, the importance of data in supporting decision-making is critical. Moreover, organizations experienced improved efficiency and strategic planning by implementing DDDM. This is in line with previous studies showing that DDDM enables process streamlining, resource optimization, and overall operational efficiency. However, the path to becoming data-driven is not without obstacles. A recurring theme from our results and previous studies show that resistance from executives and management is a barrier. Additional barriers identified include cultural resistance and the challenge of building trust. The literature reflects this issue, with middle management resistance identified as a common challenge for an organization to become data-driven (McShea et al., 2016; Di Fiore, 2018).

Another major hurdle is the lack of skills and expertise. Our data show that a lack of skills and expertise is a significant challenge in implementing DDDM, where the need for education and organizational support was emphasized. This has previously been reported where data literacy and expertise are identified as critical challenges, underscoring the importance of building a skilled workforce (Frisk & Bannister, 2017).

Data quality and accessibility issues also pose significant challenges. Our results highlighted data quality as a major impediment and revealed concerns about data trustworthiness. This is in line with a previous study where they found that ensuring data quality and accessing relevant data are challenges organizations face in the process of becoming data-driven (Appelbaum et al., 2017).

Cost and resource constraints further complicate the implementation of DDDM. Cost considerations and challenges related to resource constraints and technological limitations were also highlighted in our results. This has been discussed in a study where they also found that the high costs of data infrastructure and analytics tools complicate the implementation of DDDM in organizations (Sangari & Razmi, 2015).

Change management and organizational culture were also critical challenges, indicated by our results that showed organizational culture and resistance to change as significant barriers. There was also an emphasis for the need for organizational alignment and strategies to overcome this resistance. This was also mentioned in a study where the importance of change management in overcoming these cultural barriers to successfully implement DDDM were highlighted (Kiron et al., 2013).

While many challenges and opportunities identified in our results aligned with academic literature, some discrepancies exist. For instance, data privacy and security were not prominently highlighted in our data but are significant concerns in the literature, especially with regulations like GDPR (Davenport and Bean, 2018). Similarly, trust and familiarity with analytics tools were discussed in the literature (McShea et al., 2016) but were not as explicitly mentioned in our results, which focused more on data quality and trust issues. The literature also discusses the benefits of decision support systems more specifically (Power, 2007), while our results tend to emphasize broader data and analytics tools.

In conclusion, the journey to implementing DDDM in organizations is paved with both significant opportunities and substantial challenges. Our results and literature collectively highlight the potential of DDDM to improve decision-making, enhance competitive advantage, foster a data-driven culture, and increase efficiency. However, overcoming resistance from management, addressing skills gaps, ensuring data quality, managing costs, and navigating organizational culture changes are critical to successfully realizing these benefits. By integrating practical insights from surveys and interviews with evidence-based research, organizations can better navigate the complexities of implementing DDDM and fully leverage its transformative potential.

5.3 The adoption of AI technologies enhances decision-making and presents challenges and opportunities in DDDM

The integration of AI technologies has revolutionized the way organizations make decisions. These technologies can analyze vast datasets quickly and accurately, uncovering patterns and insights that traditional methods might lack (Chui et al., 2018). This sentiment is echoed in our results, where participants highlighted AI's ability to automate data analysis, improve predictive analytics, enhance data visualization, and enable real-time decision-making. Our results recognized the transformative potential of AI, noting how it improves efficiency,

customer service, and strategic planning by leveraging sophisticated data analytics tools. This consistent recognition across multiple sources underscores the profound impact AI has on enhancing decision-making processes (Davenport & Ronanki, 2018).

One of the most significant benefits of AI is its ability to leverage predictive analytics. By analyzing historical data, AI technologies can forecast future trends, outcomes, and behaviors, enabling organizations to make proactive and strategic decisions. Our data underscored this capability, noting that AI enhances DDDM by enabling predictive analytics that inform more forward-looking decisions (Ransbotham et al., 2017). In addition, our results have shown the importance of predictive analytics in informing decision-making and enhancing strategic planning. This aligns with the literature, which highlights AI's role in providing predictive insights that support proactive decision-making and strategic initiatives (Davenport & Ronanki, 2018).

Despite its advantages, the adoption of AI technologies is not without challenges. The literature identifies several key issues, including data privacy, security concerns, the need for specialized AI skills and potential biases in AI algorithms (Smith, 2020; Johnson, 2019). These challenges were mirrored in our results, where lack of AI expertise, data privacy and security issues, high implementation costs, technological compatibility issues, resistance to change, cultural resistance, insufficient resources and data quality problems were emphasized. Additionally, the respondents emphasized the need for education and organizational support to bridge knowledge gaps and mitigate resistance, reflecting a comprehensive understanding of the multifaceted challenges associated with AI adoption.

While challenges exist, AI technologies also offer significant opportunities. The literature outlines several benefits, including the automation of routine decision-making processes, optimization of resource allocation, personalization of customer experiences, and competitive advantages through data-driven insights (Chui et al., 2018; Davenport & Ronanki, 2018). Our data echoed these points, believing AI could enhance decision-making by automating processes, improving decision-making speed, and enabling real-time insights.

Our data consistently recognized AI's role in improving decision-making, streamlining processes, and generating actionable insights. It further highlighted successful AI applications across industries such as healthcare, manufacturing, and finance, demonstrating the broad applicability and transformative potential of AI technologies.

Effective integration of AI with DDDM frameworks can streamline decision-making, improve prediction accuracy, and enable data-driven decisions at scale. The literature emphasizes the importance of aligning AI systems with organizational goals to ensure successful implementation (Bughin et al., 2017).

Our results suggested that training, addressing ethical and privacy concerns, and securing top-level support are crucial for aligning AI initiatives with organizational priorities.

Our respondents stressed the importance of leadership support, organizational alignment, and data literacy programs in driving DDDM adoption. They also noted the need for ongoing leadership involvement to sustain these initiatives, highlighting the critical role of leadership in fostering a data-driven culture.

A coherent analysis of the similarities and discrepancies between the survey, interview results, and literature reveals several key insights. All sources agree that AI significantly enhances decision-making by providing advanced analytics, predictive insights, and real-time data processing. They also consistently identify challenges such as data privacy, the need for specialized skills, resistance to change, and ensuring data quality and reliability. Opportunities highlighted across sources include the automation of processes, improved strategic planning, and competitive advantages through better decision-making (Ransbotham et al., 2017; Chui et al., 2018).

However, some inconsistencies exist. Interviews revealed a spectrum of opinions on the role of human judgment, with some advocating for a balanced approach integrating both traditional and AI-driven methods. This nuance is less evident in survey responses and literature, which tend to focus more on the superiority of AI-driven DDDM methods. Additionally, ethical considerations such as data privacy and algorithmic transparency were emphasized more prominently in the literature and survey responses than in interviews, where practical implementation challenges were more frequently discussed (Mittelstadt et al., 2016; Brock & von Wangenheim, 2019).

Overal, the adoption of AI technologies within organizations enhances decision-making processes by leveraging advanced analytics, predictive insights, and real-time data processing. Organizations face challenges related to data privacy, skill gaps, resistance to change, and ensuring data quality. However, opportunities lie in automating routine tasks, improving strategic planning, and gaining competitive advantages through data-driven insights. By aligning AI initiatives with organizational goals, fostering a supportive culture, and

providing ongoing leadership support, organizations can successfully integrate AI into their decision-making frameworks and fully harness the potential of DDDM (Davenport & Ronanki, 2018; Ransbotham et al., 2017).

The promotion of DDDM within organizations is a multifaceted task that requires strong leadership, strategic alignment, and a supportive culture. Managers are essential in fostering a data-driven environment by advocating for advanced analytics tools, implementing data literacy programs, and embedding data-driven practices into everyday operations. The challenges of resistance to change, skill gaps, and data quality issues must be addressed to realize the full potential of DDDM. According to Sandkuhl (2019), integrating AI and machine learning technologies can significantly enhance data analysis capabilities, which managers must ensure are available and that employees are trained to use effectively. Di Fiore (2018) notes that by leading by example, managers can help normalize the use of data across the organization. By effectively navigating these challenges and leveraging the opportunities presented by DDDM, managers can enhance decision-making processes, improve organizational performance, and maintain a competitive edge in their respective industries. Through this integrated approach, organizations can harness the transformative power of data to drive strategic initiatives and achieve long-term success.

5.4 Limitations of the study

Generalizability and Transferability: The relatively small sample size (ten interviewees and sixty survey respondents) could potentially limit the generalizability and transferability of our findings. Therefore, a larger sample size could have improved the validity of our research especially in the interview section.

Validity and Reliability: Conducting interviews via Microsoft Teams restricted non-verbal communication, which may have affected the depth of interactions and, consequently, the validity and reliability of the data. Future studies could utilize in-person interviews or high-quality video conferencing tools to improve these factors.

Credibility: The gender imbalance (90% men in interviews and 78% in survey) due to participant availability could have introduced bias, affecting the credibility of the results. Therefore, future research should aim for a more balanced and representative sample.

Methodological Alignment with Previous Research: Our methodology aligns with existing research on remote data collection but acknowledges the limitations inherent in this

approach. Linking to previous studies, our findings contribute to the ongoing discourse on remote research methods and their implications for data quality.

Despite these limitations, our thesis provides a solid foundation for future studies. By acknowledging these limitations, we can pave the way for more comprehensive research in the future.

5.5 Suggested future studies

As we conclude our exploration into DDDM and the adoption of AI in organizations, it becomes evident that there are promising avenues for future research that can further enrich our understanding and practical applications in this dynamic field.

One compelling direction for future studies lies in conducting long-term research to assess the enduring impact of DDDM on organizational performance. By tracking the evolution of decision-making processes over time, researchers can uncover valuable insights into the sustained benefits and challenges associated with data-driven strategies, as well as the evolving role of AI technologies in shaping organizational outcomes.

Expanding the research scope to encompass a diverse range of industries presents another intriguing opportunity for future investigations. By delving into sector-specific nuances and challenges, researchers can uncover industry-tailored best practices for implementing data-driven strategies and leveraging AI technologies effectively. Comparing the adoption trends and outcomes across different industries can offer valuable insights into the contextual factors that influence the success of data-driven initiatives.

Ethical considerations and governance frameworks surrounding DDDM and AI adoption represent a critical area for future exploration. Deepening our understanding of issues such as data privacy, algorithmic bias, and ethical decision-making practices can inform the development of robust governance mechanisms to ensure responsible AI deployment and ethical decision-making within organizations.

Furthermore, the integration of advanced analytical techniques, such as machine learning and predictive modelling, holds immense potential for enhancing decision-making processes. Future studies could investigate the application of these cutting-edge technologies in optimizing decision outcomes, improving strategic planning, and unlocking new opportunities for data-driven innovation.

Organizational culture and change management also emerge as key areas warranting further research attention. Understanding how organizational culture influences the adoption of data-driven practices and exploring effective change management strategies can help organizations navigate the cultural shifts required to embrace DDDM and AI technologies successfully.

Lastly, cross-cultural studies offer a fascinating avenue for exploring the impact of cultural differences on DDDM practices. By comparing organizational attitudes towards AI adoption and data utilization across diverse cultural contexts, researchers can uncover valuable insights into the cultural barriers and enablers that shape the implementation and effectiveness of data-driven strategies.

This narrative approach weaves together the potential future research directions into a cohesive story, highlighting the significance of each area and the collective impact they can have on advancing knowledge and practice in DDDM and AI adoption. In embracing these suggested future research directions, we pave the way for continued innovation and advancement in the realm of DDDM and AI adoption. By addressing these emerging challenges and opportunities, we can further empower organizations to harness the transformative potential of data and technology in driving strategic decision-making and competitive advantage.

In conclusion, this chapter has examined how managers promote DDDM within their organizations, identifying key strategies and practices that align with our survey and interview findings. Managers play a pivotal role in fostering a data-driven culture by aligning organizational processes with strategic goals, overcoming resistance to change, and creating a supportive learning environment. Implementing data literacy programs and advocating for advanced analytics tools are crucial steps, as is building robust data infrastructure to ensure data accessibility and reliability.

Promoting DDDM presents both opportunities and challenges. Enhanced decision-making, improved efficiency, and competitive advantage are significant benefits. However, organizations face challenges such as resistance to change, skill gaps, data quality issues, and resource constraints. Effective integration of AI technologies can further enhance decision-making processes through advanced analytics and real-time insights. Yet, this integration also

brings challenges, including data privacy concerns, the need for specialized AI skills, and potential biases in AI algorithms.

This study faced several limitations, including a relatively small sample size of ten interviewees and sixty survey respondents, which may limit the generalizability of our findings. The use of Microsoft Teams for interviews restricted non-verbal communication, potentially affecting the depth of interactions. Additionally, a gender imbalance among participants may have introduced bias, impacting the credibility of the results.

Future research could benefit from conducting longitudinal studies to assess the long-term impact of DDDM on organizational performance. Exploring industry-specific nuances and challenges across different sectors can yield tailored best practices for implementing data-driven strategies. Further investigation into ethical considerations and governance frameworks surrounding DDDM and AI adoption is essential. Studies should also examine organizational culture and change management strategies to understand their influence on DDDM adoption. Cross-cultural studies could provide insights into how cultural differences impact DDDM practices and AI adoption.

In summary, managers must adopt a multifaceted approach to promote DDDM, incorporating continuous leadership support, data literacy initiatives, and a supportive organizational culture. Addressing the challenges and leveraging the opportunities presented by both DDDM and AI technologies can enable organizations to fully harness their transformative potential, driving strategic initiatives and achieving long-term success.

6. Conclusion

Our investigation into DDDM and AI integration in organizations has yielded valuable insights from both our survey and interviews. The survey results highlighted a growing recognition of the significance of data-driven approaches and the potential impact of AI technologies on decision-making processes. However, they also revealed challenges in integrating these technologies, which align with existing literature on the subject.

The insights obtained from interviews with executives and managers further underscored the importance of fostering a data-driven culture to maintain a competitive edge. While there was a positive reception towards the benefits of DDDM, concerns regarding cultural and technological hurdles were also prevalent, echoing findings from prior research.

By comparing our survey and interview outcomes with existing literature, we have identified areas where our findings align and areas where they diverge. This comprehensive approach enhances our understanding of the practical implications of promoting data-driven strategies within organizations and lays the groundwork for future research endeavors aimed at advancing both knowledge and practice in this evolving field.

Looking ahead, future research endeavors could focus on conducting longitudinal studies to assess the enduring impact of data-driven strategies on organizational performance. Additionally, exploring industry-specific nuances and challenges across different sectors can yield tailored best practices for effectively implementing data-driven strategies. Moreover, a deeper exploration of ethical considerations and governance frameworks surrounding DDDM and AI adoption can inform the development of responsible deployment practices within organizations.

7. Appendix

7.1 Survey guide

Exploring Data-Driven Decision-Making and AI Adoption in Organizations

Welcome to our survey on DDDM and the adoption of artificial intelligence (AI) technologies in organizations. Your participation in this survey is valuable for understanding the current landscape of decision-making practices and technology adoption within various organizations.

This survey is designed to take approximately 9-14 minutes to complete. The insights you provide will contribute significantly to our understanding of this topic and will be a crucial part of a final master's thesis for our Executive Master of Business Administration (EMBA) program. Please rest assured that your responses will remain completely anonymous and confidential.

Thank you for taking the time to participate in this survey!

Andreas Berglund & Vahid Harandi

Background Information

1. Full name (optional)
2. Job title
3. E-mail (optional)
4. The country you are based
5. Gender

   Female

   Male
6. Age

   Under 25

   25-34

   35-44

   45-54

   55-64

   65 or older

7. Name of your company.
8. What industry are you in?

Technology: Includes software development, hardware manufacturing, and telecommunications.

Healthcare and Pharmaceuticals: Encompasses medical services, pharmaceuticals, biotechnology, and medical devices.

Financial Services: Includes banking, investment, insurance, and financial technology (fintech).

Energy and Utilities: Involves oil and gas exploration, renewable energy, electricity generation, and water utilities.

Manufacturing: Covers automotive, aerospace, consumer goods, and industrial equipment production.

Retail and Consumer Goods: Includes retail stores, e-commerce, consumer electronics, apparel, and fast-moving consumer goods (FMCG).

Construction and Real Estate: Involves construction services, property development, and real estate investment.

Transportation and Logistics: Encompasses airlines, shipping, railways, trucking, and logistics services.

Media and Entertainment: Includes broadcasting, film production, music, publishing, and digital media.

Food and Beverage: Encompasses food processing, agriculture, beverages, and restaurant chains.

Professional Services: This sector includes consulting firms, auditing firms, legal services, and other professional service providers that offer expertise in areas such as risk management, compliance, and assurance.

Other (please go to next and specify)

9. What is the size of your company (number of employees)?

Small (1-50 employees)

Medium (51-500 employees)

Large (501 to 5000 employees)

Very large (5001 employees or more)

10. Which functional areas do you have responsibility for within your organization? (Please select the one that best applies).

Finance and Accounting

Human Resources

Operations and Supply Chain

Sales and Marketing

Information Technology (IT)

Research and Development (R&D

Legal and Compliance

Customer Service and Support

Quality Assurance and Regulatory Affairs

Business Development

Engineering

Product Management

Strategic Planning and Management

All of the above (CEO, President, etc.)

Other (please go to next and specify)

11. How many years of experience do you have in managerial roles?

Less than 1 year

1-5 years

6-10 years

More than 10 years

Current State of Data-Driven Decision-Making

12. How would you describe the level of data-driven decision-making in your organization?

Low

Moderate

High

13. What do you think are the main challenges or barriers preventing your organization from adopting more data-driven decision-making practices? (select all that apply).

Lack of technology infrastructure

Resistance from executives/managers

Data quality issues

Lack of skills or expertise

Cost considerations

Lack of user-friendly systems

Other (please specify in next question)

14. In your opinion, how important is data and evidence in supporting decision-making within your organization?

Somewhat important

Moderately important

Very important

15. When faced with a decision, how do you typically approach it?

Trust my instincts and past experiences

Seek available data and analyze it thoroughly

Combine both gut feelings and data analysis

Other (please specify below)

16. What factors influence your reliance on gut feelings versus data-driven approaches?

Time constraints

Complexity of the decision

Availability of relevant data

Organizational culture

Other (please specify below)

17. How would you describe the overall culture of decision-making in your organization?

Data-Driven: Decisions are primarily based on data analysis and metrics.

Intuitive: Decisions rely largely on individual or collective intuition and experience.

Mixed Approach: Decisions are made through a combination of data-driven analysis and intuition.

18. How do you perceive the effectiveness of gut feelings versus data-driven approaches in achieving desired outcomes for important decisions?

Gut feelings are more effective

Data-driven approaches are more effective

Unsure or varies

Technology Impact "Before and After" Questions

19. Which of the following applications/systems does you organization use (select all that apply).

Enterprise Resource Planning (ERP)

Business Intelligence (BI)

Human Resource Management System (HRMS)

Supply Chain Management (SCM)

Customer Relationship Management (CRM)

Generative AI

Chatbots/Virtual assistance

Machine learning for predictive analysis

Other (please specify below)

20. To what extent do you believe these systems have influenced decision-making within your organization?

Highly influential; decisions are primarily data-driven.

Moderately influential; data is considered but not always the primary factor.

Minimally influential; decisions are still largely based on intuition or experience.

AI and Data-Driven Decision-Making

21. How familiar are you with artificial intelligence (AI) technologies and their potential applications in decision-making?

Not familiar at all

Somewhat familiar

Very familiar

22. In what ways do you believe AI could enhance data-driven decision-making in your organization? (select all that apply).

Automating data analysis processes

Predictive analytics for better forecasting

Improving decision-making speed and accuracy

Enhancing data visualization and reporting

Facilitating more personalized customer interactions

Identifying trends and patterns that are not easily visible to humans

Enabling real-time decision-making

Improving risk management

I don't think AI will enhance data-driven decision-making for my department in my organization

23. What challenges, if any, do you anticipate in integrating AI technologies for decision-making purposes? (select all that apply)

Ethical considerations

Data privacy and security

Lack of skills or expertise in AI adoption

High-cost implementation

Technological compatibility issues

Resistance to change among staff

Data quality and availability

Regulatory and compliance issues

Scaling AI solutions across the organization

I'm not sure

None of the above

Future Outlook and Recommendations

24. How optimistic are you about AI's potential to increase data-driven decision-making practices in your organization?

Very optimistic: I believe AI will significantly enhance our data-driven decision-making

Somewhat optimistic: I think AI will have a moderate impact on our data-driven decision making

Not optimistic: I do not believe AI will enhance our data-driven decision-making

25. What impact do you think AI will have on your organization's competitiveness in the future?

No impact

Moderate impact

Significant impact

26. What improvements or changes would you suggest to leverage AI for enhancing data-driven decision-making in your organization? (select all that apply).

Provide more training and education on AI technologies

Address ethical and privacy concerns associated with AI adoption

Encourage top-level support and leadership commitment to AI initiatives

I am not sure

Other (please specify below)

27. Overall, how satisfied are you with the current tools and technologies used for data analysis in your organization?

Dissatisfied

Neutral

Satisfied

28. How likely is your organization to increase its investment in AI over the next two to five years?

Unlikely

Neutral

Very likely

Survey closure

Thank you for participating in this survey. Your responses are crucial to our research on understanding the impact of Data-Driven Decision-Making and AI Adoption in Organizations. We appreciate your time and insights!

29. Are there any other comments or insights you would like to share with us regarding our survey? (optional)

7.2 Interview guide

Presentation and introduction:

The interview starts with a short presentation from the interviewer explaining the interview process.

It follows up with exchanging names, titles and organizations.

And continues with a short description of Executive MBA and our thesis.

Before we start, we made sure it is Ok to record this interview for the purpose of our thesis.

Background:

- Name, role, organization, and key responsibilities within their roles.

Introductory questions:

- What is your understanding as a manager of data driven decision making in your organization?
- If an organisation is implementing a data driven culture or trying to transition towards DDDM, what factors do you think they should focus on?

Different types of decision makings:

- Can you describe a specific instance where decisions were made based on intuition, or past experiences rather than data driven approach?
- What are/were the main challenges or limitations associated with the traditional decision-making approach that relied less on data and analytics?
- Can you share a notable example where data analysis led to a significant improvement in decision outcomes or organizational performance?
- How do you promote Data-Driven Decision Making in your organization, and what challenges have you faced with existing technology and cultural resistance?
- How has the adoption of DDDM influenced the decision-making culture within your organization, and what changes have you observed in terms of decision quality and efficiency?

Benefits of AI Adoption:

- After integrating AI technologies, what benefits/advantages have you experienced in your organization? (This question is only for managers using AI in their organizations).
- Can you highlight a successful use case where AI applications have provided valuable insights or recommendations that were previously unachievable through traditional methods?

Closing

- Thanked the participants for their time.
- Do you have any additional comments to share with us on our thesis?
- Is there anything that you wished we have asked you during this interview and you would like to share with us?

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