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Faculty of Business Economics

Master of Management

Master's thesis

Data literacy and Data competence for effective decision-making: Qualitative study on top management in companies in Belgium

Janet Biodun-Bello

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Data Science

SUPERVISOR :
Prof. dr. Benoit DEPAIRE

MENTOR :
De heer Toon JOUCK

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2024

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PREFACE

This thesis marks the completion of my Master’s in Management with a specialization in Data Science at Hasselt University. My research delves into the levels of data literacy and competency among top management in Belgian companies, particularly in making informed decisions.

I have often heard that top executives rarely utilize data in their decision-making processes and frequently need more knowledge about data, implying a significant gap in data literacy and data competency. It intrigued me, given that we live in a data-driven world where making decisions backed by data offers numerous advantages. Thus, I embarked on this research to investigate the extent of data literacy and competency among these top managers and identify the barriers preventing them from becoming data-savvy in today's data-centric environment. The research is limited to top management in companies in Belgium due to time constraints.

My professional and personal support throughout this journey made this dissertation possible. I want to recognize and thank the individuals who contributed to its completion.

First and foremost, I am profoundly grateful to God Almighty for granting me the strength and courage to face and overcome the most challenging obstacles.

I sincerely thank my supervisor, mentor, Dr. Toon Jouck, and Prof. Dr. Benoit Depaire for their patience, valuable feedback, constant encouragement, invaluable guidance, and tremendous support throughout this research. Their support was instrumental in shaping this thesis and navigating the complexity of the subject matter. Their unwavering support motivated me to complete this work, and I am deeply grateful for their dedication and hard work in assisting me throughout this journey.

I could not have completed this dissertation without the unwavering support of my family and Kieran Clarke. Their unconditional love, wisdom, and understanding have been vital to my success.

I also want to express my heartfelt thanks to Ms. Hermans for her significant contributions and insightful recommendations. I sincerely appreciate your steadfast support throughout this journey.

Lastly, I am immensely thankful to the ten participants of this study. Their time and valuable contributions were essential to the qualitative aspect of this research, and without them, this study would not have been possible.

Summary

Problem Statement

Data is crucial for navigating today's organizational complexities. Data Literacy involves comprehending and effectively utilizing data for decision-making (Mandinach & Gummer, 2013), while Data Competency refers to proficiency in areas such as AI, algorithms, and machine learning (MyABCM, 2022). A significant challenge for organizations is ensuring top management maintains proficiency in both areas. Research indicates that many top managers rely on intuition rather than data analytics due to insufficient training, often making decisions based on ideology rather than facts (Rossi, 2017). A data-competent leader is influential, driving better decisions, improved communication, reduced turnover, and enhanced customer experiences (Kraemer, 2022). Furthermore, leaders who blend data-driven insights with intuition are more effective (Brown, 2023).

Research Objectives and Research Questions

While researchers have explored the importance of data literacy and data competency across various groups, they have notably overlooked why top leadership often needs to utilize or adopt these skills more. Moreover, no research measures data literacy and data competency, specifically among top management in companies, particularly in Belgium. This study aims to fill this gap by assessing the present levels of data literacy and data competency among top management in Belgium and identifying the specific challenges they encounter in adopting data-driven decision-making. It addresses two primary research questions: The level of data literacy and competency among top Belgian management and the barriers hindering their adoption and effective use of data literacy and competency in decision-making processes. By answering these questions, the study seeks to provide valuable insights into improving data-driven decision-making at the highest levels of corporate leadership.

Research Methodology

The study employed an exploratory approach, utilizing qualitative methods, primarily interviews and literature reviews, to gather data from diverse participants across various industries. Data collection involved online and face-to-face semi-structured interviews, facilitating in-depth discussions. The literature review aims to identify existing theories, concepts, and gaps in the literature related to this research topic and to develop a thorough understanding of the value added by data literacy and data competencies, the various skills involved, and the strategies for creating a data-driven organization. The literature review covered various sources, including academic articles, journals, e-books, and reputable websites. We used thematic coding to identify and categorize key themes, ensuring a structured interpretation of the data (Medelyan, 2024).

Findings

The study's findings reveal several insights, showing that top management frequently uses data to identify issues and achieve positive business outcomes, demonstrating high data literacy. It aligns with existing definitions of data literacy, encompassing understanding and effectively utilizing data for decision-making. Mandinach and Gummer (2013) define data literacy as the ability to recognize, gather, organize, analyze, summarize, and rank data, as well as to formulate hypotheses, identify problems, interpret data, and plan, execute, and oversee actions.

This study also contradicts previous research that suggests leaders often distrust data due to their reliance on traditional decision-making methods (Brown, 2023). Instead, it found that top management trusts data, verifying it mainly due to concerns about data quality rather than an inherent preference for traditional methods.

Another study suggested that while leaders often highlight their leadership and strategic skills, many need more proficiency in data analytics and sometimes make decisions based on ideology rather than evidence (Rossi, 2017). However, this study partially challenges that view. While participants' data competency levels varied, and some needed to be fully data competent, the idea that leaders rely solely on intuition and ignore data does not hold. Leaders frequently use data in their decision-making processes and do not rely only on their intuitions.

The study also found that top managers' familiarity with data literacy and data competency varied, often influenced by their educational backgrounds and training. Those with advanced degrees in economics, engineering, and business administration exhibited a higher understanding and application of data literacy skills. It aligns with literature that underscores the importance of education in developing data competencies. Specifically, it suggests that leaders should implement data literacy training initiatives to support data and analytics strategies and address

the current skills gap. This approach can foster a culture where enhancing data competency and literacy is integral to the organization (Gartner, 2021).

Overall, the findings suggest that top management recognizes the importance of data in decision-making and demonstrates a high level of data literacy. It represents a shift towards greater trust and reliance on data among contemporary leaders, contrasting with some earlier research.

As seen above, top management must improve their data literacy and competency. However, several barriers prevent top management from achieving advanced data literacy and competency levels. Lack of time to learn and develop data skills is one of the significant barriers. Unfamiliarity with digital tools and needing formal training to help with data literacy development. Rapid changes in technology make it challenging to maintain proficiency. Issues related to data management and structuring impede the effective use of data. A lack of interest in becoming proficient in data literacy is also a barrier.

In addition, other barriers mentioned were organizational culture, resource allocation, and trust in data. There is a gradual shift towards a data-driven culture within organizations, with data increasingly utilized in some areas across various departments. However, reliance on traditional misutilization of data in some regions persists. The advancement and application of data-driven practices vary significantly, often depending on the individual manager's approach. The allocation of resources towards improving data needs to be more consistent. Some companies provide no resources for training and development, while others have recently initiated efforts to enhance data skills among top management. Most top management highly trusts data but ensures its accuracy through verification methods. Participants reported varying confidence levels in data, with some expressing high trust and others remaining cautious.

Recommendations

This study recommends systematic assessments, comprehensive training programs, and a cultural shift towards valuing data insights. Regular and systematic evaluations are essential for accurately measuring data literacy and competency levels. Organizations should develop and adopt standardized assessment tools to evaluate primary and advanced data skills. Regular assessments will help identify skill gaps and inform targeted training programs.

Comprehensive training programs are necessary to bridge the gap between foundational knowledge and advanced data competencies. Organizations should invest in training that covers advanced data analytics tools and techniques, offering workshops, online courses, and certifications to encourage continuous learning. A cultural shift towards data-driven decision-making is critical for integrating data literacy into everyday business practices. Organizations should foster a culture that values data by embedding literacy into organizational values and practices. Encouraging leaders to use data in their decision-making processes and recognizing data-driven initiatives will promote this shift. Adequate resource allocation is crucial for developing data literacy and competency. Organizations should invest in the latest technology, provide access to relevant data sources, and ensure ongoing support for data-related projects. Budgeting for continuous professional development in data analytics for top management is essential.

Limitations

While this study provides valuable insights into the data literacy and data competency of top management in Belgian companies, it has several limitations. The small sample size of just 10 participants may not adequately represent the diversity across various industries and organizations, making it difficult to generalize the findings. Additionally, the study relied solely on self-assessed knowledge from interview responses of these participants rather than employing systematic measurement tools or practical tests, which limited the ability to accurately quantify data skills and offer a complete view of data proficiency. Additionally, the reliance on interviews may introduce bias, as participants might overstate their understanding or usage of data tools.

Future Research

Future research should include a broader and more diverse sample of senior management from various industries to generalize findings on data literacy better. Objective measuring methods or longitudinal studies could provide a more accurate assessment of data proficiency and how it evolves. Additionally, exploring variations in data competency across countries, cultures, and different data tools would offer valuable global insights into data-driven decision-making.

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Chapter 1: INTRODUCTION

PROBLEM STATEMENT

In today's data-driven society, data experts do not just need to understand and use data. A foundational level of data literacy and competency is essential for everyone, including leaders, to navigate the complexities of modern organizations (Martin, 2023).

Data Literacy involves understanding and effectively using data for decision-making. It includes recognizing, gathering, organizing, analyzing, summarizing, and ranking data. Additionally, it entails skills in formulating hypotheses, identifying issues, interpreting data, and planning, executing, and overseeing actions (Mandinach & Gummer, 2013).

Data Competency refers to proficiency in areas such as Artificial Intelligence (AI), algorithms, programming systems, Machine Learning, query languages, and various technologies (MyABCM, 2022).

A significant challenge for organizations is ensuring top management's data literacy and data competency proficiency. Research indicates that many top managers rely on gut feelings for decision-making and depend on data scientists for processed information due to their lack of formal training or experience in data analytics (Rossi, 2017). Moreover, while many leaders pride themselves on their leadership and strategic abilities, a substantial portion lacks proficiency in data analytics. Alarmingly, several leaders have made decisions based solely on ideology, disregarding facts and evidence (Rossi, 2017). This thesis underscores the importance of integrating data-driven insights with ideological considerations to enhance decision-making. A critical challenge is encouraging leaders to embrace analytical insights and relinquish some degree of autonomy (Brown, 2023).

There are numerous benefits to having data-competent and data-literate leaders. Data literacy and data competency among leaders are vital as they contribute to improved decision-making, enhanced communication and negotiation skills, reduced employee turnover, and better customer experiences (Kraemer, 2022). Leaders play an essential role in fostering a culture of data literacy within their organizations by acting as advocates and exemplars (Fernandez, 2023). Trusting data as a guide and knowing when to evaluate results critically are essential modern leadership skills. Leaders must develop a deep understanding of data to make wise decisions and promote an environment of data trust throughout the company. Consequently, leaders combining intuition with data-driven insights are more effective and influential (Brown, 2023).

1.1 RESEARCH OBJECTIVES AND QUESTIONS.

In this research, we are interested in data literacy and data competency for effective decision-making among top management. This emphasis is due to top management's crucial role in steering the organizations through the seamless adoption of technologies and data-driven decision-making processes. Adequate data literacy among leaders ensures they can establish a straightforward narrative for data literacy, highlight its business value, and embed a data-driven mindset throughout the organization (Panetta, 2021). In addition, our interest is further driven by existing research suggesting that top management often bases their decisions on intuition alone.

The Gap in Existing Research

Although researchers have examined the importance of data literacy and competency across various groups, they often overlook why top leadership frequently underutilizes or fails to adopt these skills. Additionally, no research measures data literacy and data competency, specifically among top management in companies, particularly in Belgium.

Significance of the Research

Therefore, this research aims to address gaps in the existing literature and contribute valuable insights to the current body of knowledge in the following areas:

- The current level of data literacy and competency among top management in Belgium.
- The specific challenges and barriers faced by top management in adopting data-driven decision-making.

By focusing on top management in Belgium, this research aims to generate valuable knowledge that can inform strategies to enhance data literacy and data competency, ultimately fostering a data-driven culture within organizations and helping to improve the organization's performance.

Research questions

The study will address two main research questions to shed light on these issues.

1. How data literate and data competent are the top management in companies in Belgium?
2. What are the main barriers preventing top management in companies in Belgium from adopting and effectively using data literacy and data competencies in decision-making processes?

1.2 RESEARCH METHODOLOGY

This thesis will employ qualitative research methods to answer the research questions, beginning with a literature review to analyze existing studies on data literacy and data competencies. This literature review aims to identify existing definitions and understand the impact and importance of data literacy and data competencies within organizations with a focus on top management. The second research method is an interview with a sample of top managers from various industries in Belgium. It will use semi-structured questions to encourage in-depth discussions to understand how data literate and competent these participants are and identify any barriers to making data-driven decisions.

The strategy for finding resources on data literacy and data competencies includes searching academic articles, journals, e-books, and reputable websites. To conduct this search, I used specific search terms such as 'data literacy definitions,' 'data competencies in the workplace,' 'importance of data literacy,' and 'data literacy among top management.' Additionally, I consulted key databases like Google Scholar and the University of Hasselt database to find relevant academic articles and journals. For e-books, I focused on library catalogs and online platforms. Reputable websites, including industry blogs and government publications, were also explored to gather up-to-date information and insights from the field. Chapter 3 of this study provides a detailed explanation of the interview methodology.

1.3 LIMITATIONS OF THE STUDY

While this study provides valuable insights into the data literacy and data competency of top management in Belgian companies, it has several limitations. The small sample size of just 10 participants may not adequately represent the diversity across various industries and organizations, making it difficult to generalize the findings. Additionally, the study relied solely on self-assessed knowledge from interview responses of these participants rather than employing systematic measurement tools or practical tests, which limited the ability to accurately quantify data skills and offer a complete view of data proficiency. Additionally, the reliance on interviews may introduce bias, as participants might overstate their understanding or usage of data tools.

Chapter 2: LITERATURE REVIEW

This chapter reviewed the existing research on data literacy and data competencies. It discusses how data literacy and data competencies are defined. A specific focus on top management is applied to see if there are existing research findings on data literacy and data competencies among top management. The chapter also distinguishes between data literacy and data competency, noting their complementary roles in effectively leveraging data. Finally, it addresses how to measure data literacy and data competency and identifies barriers to achieving these skills in organizations. It provides a foundation for assessing these competencies among top managers in Belgian companies.

2.1 DATA

Data refers to factual information, including measurements or statistics, that serves as a foundation for reasoning, discussion, or calculation (M.Banik, 2020).

2.1.1 KEY DATA NEEDED BY TOP MANAGEMENT

Top management in businesses prioritizes several types of data. According to Provost (2013), these data are customer behavior, marketing campaign performance, operations, competitor analysis, and financial data.

2.1.2 IMPORTANCE OF DATA TO TOP MANAGEMENT

Data is essential to top management, and they gain many benefits from it. These benefits are listed below:

- **Gaining Behavioral Insights:** At the core of every successful business is the commitment to understanding and satisfying customer needs, which is critical for gaining trust and loyalty. By utilizing demographic, geographic, and behavioral data, companies can enhance their understanding of their customers and better meet their specific requirements. Businesses heavily invest in customer analytics to examine patterns such as customer churn, which helps them refine their offerings or make necessary strategic changes (pykes, 2022).
- **Enhance processes:** Data enables business leaders to enhance their understanding and optimize processes, minimizing resource wastage. Through analyzing data and applying business process analytics, leaders gain a comprehensive overview that identifies process inefficiencies, barriers, or failures and can help refine performance processes (pykes, 2022).
- **Deeper Insight:** A clear understanding of the current position is essential to make informed strategic decisions. Business leaders must understand how various parts of their organization perform relative to key objectives and targets. Accurate data is crucial for obtaining precise insights into this performance (pykes, 2022).

2.1.3 THE DATA-INFORMATION-KNOWLEDGE-WISDOM PYRAMID

The DIKW pyramid serves as a conceptual model for understanding the transformation from mere data to actionable insights, offering a structure to evaluate the significance and practicality of data. Within this model, each tier is foundational for the next, emphasizing the necessity of progressing through all four stages to support data-informed decision-making (Cotton, 2023).

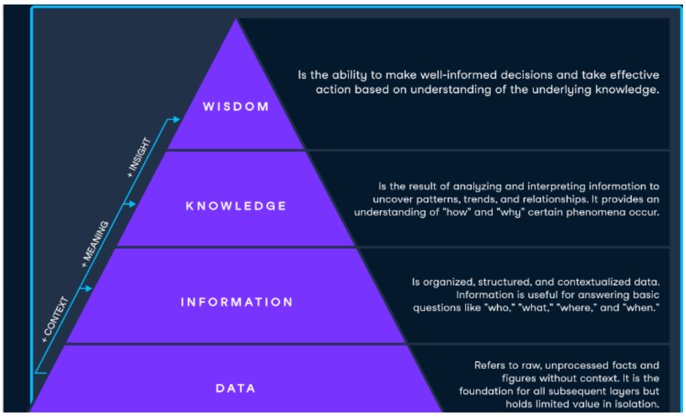


Figure 1: DIKW PYRAMID

- **Wisdom:** At the pinnacle, wisdom represents the capacity to apply well-judged decisions and actions grounded in a deep knowledge comprehension.
- **Knowledge:** Knowledge emerges from the thorough examination and interpretation of information, revealing patterns, trends, and connections that furnish insights into the "how" and "why" behind observed events.
- **Information:** Information is data that has been organized, structured, and given context, rendering it capable of addressing fundamental queries such as "who," "what," "where," and "when."
- **Data:** Data, the base layer, consists of unprocessed, context-free facts and figures, forming the essential groundwork for all other levels, yet by itself, it offers minimal intrinsic value.s (Cotton, 2023).

The DIKW Pyramid is both a model and metaphor, illustrating the progression from data to wisdom and paralleling the journey from data literacy to data competency. According to Cotton (2023), this framework emphasizes the necessity of a robust foundation in data literacy as a prerequisite for advancing to higher levels of data competency. This development is crucial for enabling effective decision-making and strategic actions grounded in profound insights derived from data analysis.

2.2 DATA LITERACY

After explaining what data is, the next step is to dive into what data literacy is. There are different definitions of data literacy, and the authors have different definitions below.

According to Wolff et al. (2016), data literacy involves posing and addressing real-world inquiries using both extensive and limited datasets through investigation while acknowledging the ethical implications of data usage. It relies on fundamental practical and innovative abilities, with the capacity to enhance expertise in specialized data management skills based on objectives. These skills encompass the aptitude to choose, refine, examine, illustrate, assess, and understand data and the capability to convey narratives derived from data and integrate data within a design framework.

According to Ridsdale (2015), Data literacy is the skills to gather, oversee, assess, and utilize information responsibly.

According to Herzog (2019), Data literacy is the capacity to comprehend, articulate, and convey data within a particular context, demonstrating comprehension of data origins and structures, analytical methodologies, and applied techniques while also being able to articulate the application of use cases and the positive effect on business values.

According to Sternkopf and Mueller (2018), data literacy is an ongoing process of learning that fosters the skills to recognize, comprehend, interpret, generate, convey, and process information fragments (data) to cultivate understanding and the capacity to engage actively in our community.

According to Mandinach and Gummer (2013), data literacy is about grasping and utilizing data efficiently for decision-making, recognizing, gathering, arranging, analyzing, condensing, and ranking data, as being skilled in formulating hypotheses, pinpointing issues, interpreting the data, and establishing, planning, executing, and overseeing courses of action.

In summary, all these definitions emphasize that data literacy involves the technical skills to collect, manage, analyze, and interpret data and the ability to apply these skills responsibly within various contexts. It includes understanding the ethical implications of data usage, the ability to communicate insights effectively, and the capacity to integrate data into decision-making and design frameworks.

This study will refer to this definition because of its specificity and comprehensiveness. Data literacy is about grasping and utilizing data efficiently for decision-making, recognizing, gathering, arranging, analyzing, condensing, and ranking data, also being skilled in formulating hypotheses, pinpointing issues, interpreting the data, and establishing, planning, executing, and overseeing courses of action (Mandinach, Gummer , 2013).

In addition, given that data literacy may be considered relatively new compared to other literacy domains, it is becoming more widely acknowledged as an emerging field across academic disciplines apart from information systems and strategic management. The past decade has witnessed a significant surge in publications, indicating growing interest and attention towards this topic (Ongena, 2023).

The graph illustrates the annual count of information systems (IS) publications contributing to data literacy (Ongena, 2023).

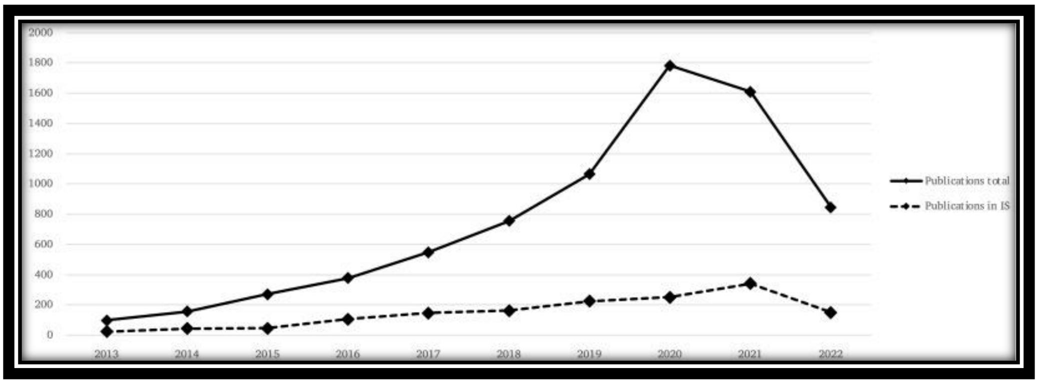


Figure 2: Data literacy publication.

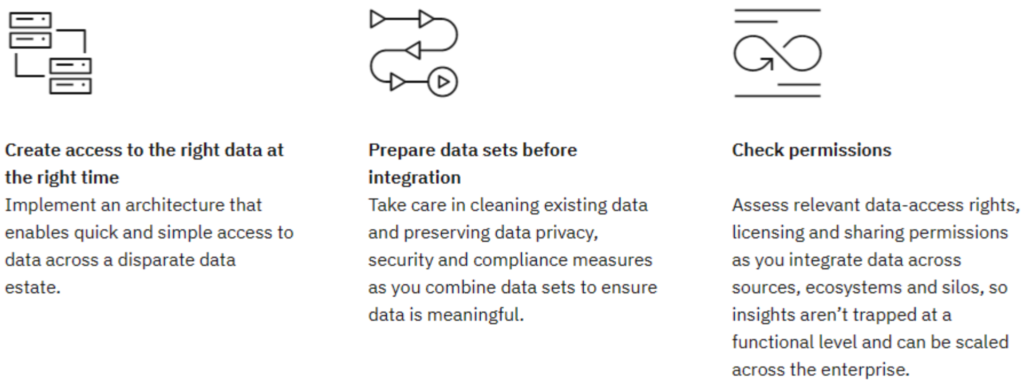
2.2.1 DATA LITERACY: The Core of Cultivating a Data-Driven Organisation Culture

Organizations are increasingly focusing on democratizing data and enabling all employees to access, interpret, and use data. This shift creates significant opportunities but requires equipping employees with the necessary skills. Despite investments in data tools, many organizations neglect the critical need for data literacy. It is essential for empowering staff to make informed decisions and drive innovation. Organizations must support it at all levels to effectively integrate data literacy, question existing practices, and foster a data-driven mindset. It involves measuring current data literacy levels, developing training programs, and regularly reassessing and adapting them. A successful data literacy program ensures that data-driven decision-making becomes a shared responsibility across the organization, leading to enhanced performance and innovation (Estelmb, 2022).

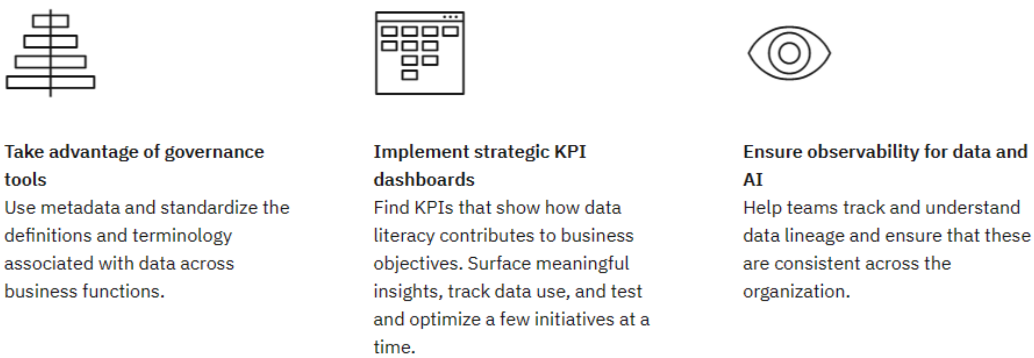
Furthermore, the leadership team is crucial in establishing a data-driven culture. To transition from a non-data-driven mindset, leaders must consistently emphasize the importance of data. This cultural shift should be initiated from the top levels of the organization. It underscores that top managers need to be data literate (Gaonkar, 2023). It also explains that this research focuses on assessing the data literacy and data competency of top managers in Belgium, given their crucial role in fostering a data-driven culture.

Leaders can instigate this cultural transformation and cultivate data literacy and curiosity among their teams through several methods:

- **Make data access widely available throughout the organization:** While many view data science training programs as the initial step towards cultivating a data-driven culture within an organization, the true beginning lies in enhancing the accessibility of data (Mehdi Charafeddine,Jennifer Kirkwood,, 2023).



- **Arrange data straightforwardly and transparently:** After setting up a framework for controlled data access, it is vital to guide decision-makers through understanding data flow across the pipeline (Mehdi Charafeddine,Jennifer Kirkwood,, 2023).



- **Teach data citizens responsible analysis and how to implement AI-driven actions from data insights.**

Data literacy programs empower organizations to understand, interpret, and apply data (particularly model-generated data) for improved decision-making processes (Mehdi Charafeddine,Jennifer Kirkwood,, 2023).

Teach people to tell data stories

Ensure professionals at all levels of the organization can use data visualization and storytelling techniques best suited to their strategic business objectives, and root this training in a communication effectiveness curriculum.

Design training to solve for everyday problems

Be sure your education programs reflect the real-world needs of different roles and connect data to the day-to-day value stakeholders.

Assess skills and close gaps.

Recruit hires with technical certifications or P-TECH program degrees to close skills gaps. Use dashboards that define metrics and KPIs to track how your organization is evolving to be more data-driven.

- **Foster data leaders with a compassionate approach:**

Leaders must actively listen to their teams to pinpoint specific data literacy skills to enhance business outcomes and implement a focused training program (Mehdi Charafeddine,Jennifer Kirkwood,, 2023).

Create C-suite partnerships

Take a use-case-first approach that reinforces the value of data literacy for cross-organizational leaders and gets senior stakeholder buy-in.

Provide the opportunity for feedback

Encourage open conversations at every level and include diverse perspectives to generate better outcomes. Continuously clarify the value that data can deliver back to the organization.

Model data literacy skills

Model ideal behavior, like not taking data at face value and challenging teams on data insights that raise questions. Encourage teams to network in and outside the organization so diverse perspectives are represented in all aspects of work.

2.2.2 IMPORTANCE OF DATA LITERACY IN ORGANIZATIONS

As highlighted in the previous section, data literacy is crucial for cultivating a data-driven culture. This section will delve deeper into the additional benefits that data literacy brings to organizations.

Data literacy empowers every member of an organization to accurately identify essential questions, collect relevant data, and link various data points to uncover actionable insights for the business. It also ensures that employees know how to handle and apply data ethically and comply with regulations. Enhancing data literacy across an organization can improve customer service, cost reductions, profit growth, more effective risk management, optimized resource utilization, a more robust data-driven culture, and improved data governance (Atlan, 2023).

Key advantages of fostering data literacy include:

- **Better Decision-making:** Equips individuals and organizations with the analytical skills necessary to make informed choices (Atlan, 2023).
- **Enhanced Productivity:** Boosts analytics and visualization capabilities, directly influencing operational efficiency. It can help resolve problems faster, potentially increasing sales and production while reducing costs and mitigating risks (Atlan, 2023).
- **Reputation and Innovation:** Data literacy can enhance a company's reputation by benefiting employees and customers. It also encourages innovation, positioning companies to capitalize on new opportunities and technologies ahead of competitors (Atlan, 2023).
- **Improved Communication:** Employees with a good understanding of data can articulate complex analyses clearly and succinctly, fostering better collaboration and efficiency within teams (Atlan, 2023).

Given the significant role of data literacy in improving decision-making and enhancing productivity, it is crucial to investigate the main barriers preventing top management in companies in Belgium from adopting and effectively using data literacy and data competency in their decision-making processes.

2.2.3 HOW TO MEASURE DATA LITERACY IN ORGANISATIONS

As seen above, one of the ways to establish a data-driven culture is to measure the data- literacy levels in the organizations. Companies should start measuring data literacy by considering the following questions (Gartner, 2021):

- How many individuals in the organization can understand statistical methods like correlation or computing averages?
- How many leaders can develop a business strategy supported by solid, precise, and pertinent data?
- How many managers possess the skills to articulate clearly the outcomes generated by their systems or procedures?
- How many data scientists can communicate the results produced by their machine-learning models?
- To what extent do the clients truly grasp and value the data insights?

The questions identified in the existing literature are essential for this thesis, as questions 1, 3, and 5 will be utilized during interviews to evaluate data literacy and data competency among top management in Belgian companies.

2.2.4 OPTIMAL STRATEGIES FOR TEACHING DATA LITERACY

As organizations face the challenges posed by growing data volumes, technological advancements, and an increasing gap in data literacy, there is a pressing need to devise strategies to enhance data literacy. This gap, characterized by a disconnect between the acknowledged importance of data and the actual proficiency in data literacy, mainly affects non-technical data literacy skills. Such skills, which are notably in short supply, encompass making decisions based on data, understanding business data sources, and communicating, presenting, and interpreting data effectively. (wendy Pothier and Patricia Condon, 2023)

To achieve the ambitious goals of Data and Analytics (D&A) strategies, which involve effectively leveraging organizational data and extracting valuable insights, Chief Data Officers (CDOs) should initiate data literacy training programs to address the existing skills gap. This approach can foster a culture where the enhancement of Data competency capabilities and the enrichment of data literacy become integral to the organization's culture (Gartner, 2021). The below strategies are different strategies used in teaching data literacy :

In any educational context focused on data literacy, the first strategy is to clearly articulate the advantages of data and data skills right from the start. This aspect is especially crucial for learners at the midpoint of their careers, as they are more likely to dedicate their scarce resources of time and effort when they perceive a direct benefit to their community, industry, family, or other areas of personal importance (Chantel Ridsale, James Rothwell).

The second strategy, module-based learning, enables learners to reach educational milestones progressively and methodically. This approach, characterized by successive or iterative learning, allows for the incremental building of knowledge, prioritizing understanding and application over memorization or strict adherence to guidelines. This method simplifies grasping new concepts by starting with more straightforward tasks and gradually advancing to more complex ones, boosting students' confidence in their capabilities (Chantel Ridsale, James Rothwell).

The third strategy, project-based learning, is an effective method to apply a progressive learning strategy. Engaging in projects that involve comprehensive research and possess real-world relevance strengthens the linkage between theoretical knowledge and practical application. This format also allows evaluators to evaluate skills in a practical context rather than through conventional methods. Incorporating real-world data that aligns with students' interests within an appealing framework enhances the educational experience, going beyond mere data analysis. This engagement with data promotes creativity, deepens learning, and increases the potential for ongoing education. (Chantel Ridsale, James Rothwell). In addition, It is suggested that having students gather their data for analysis can deepen their understanding, as it turns them into active participants in the data collection process. However, this approach typically involves small-scale data, which does not offer experience with more extensive, externally sourced datasets. Modern data collection tools like sensors could be introduced into educational settings to bridge this gap. These devices enable students to collect substantial volumes of data efficiently, serving as an intermediary step between gathering personal data and analyzing large-scale datasets from external sources. This method could provide a more comprehensive learning experience in data handling and analysis (wolff, Gooch, Montaner, Rashid, Kortuem, 2016).

2.2.5 BARRIERS PREVENTING ORGANISATIONS FROM BEING DATA LITERATE

No existing literature specifically addresses the barriers preventing top management from becoming data literate and data competent. Therefore, the barriers mentioned below will be explored during the interviews to determine if they are also challenges faced by top management. It will help answer the second research question of this thesis.

According to Gohari (2024), the following are the barriers preventing organizations from being data literate:

Lack of Data Skills and Knowledge: One significant obstacle to data literacy is employees' insufficient data skills and knowledge. Many organizations may lack the necessary in-house expertise or offer adequate training and development opportunities for employees to enhance their data skills.

Siloed Data: Another frequent barrier to data literacy is siloed data. This situation arises when different departments or teams collect, analyze, and store data separately, making it challenging to share and collaborate on data-driven insights.

Poor Data Quality: Organizations often face issues with data quality, such as incomplete or inaccurate data, which can diminish the credibility of data-driven insights and reduce trust in the data.

Resistance to Change: Some employees may resist change and be reluctant to adopt new tools, processes, or working methods. This resistance can be particularly problematic for data-driven decision-making, which often requires a shift in mindset and approach.

Allocation of resources: Lastly, the allocation of resources, such as a budget for training or coaching, can be a barrier to data literacy and data competency. Organizations may find investing in the necessary technology, tools, and training to build a data-literate and competent workforce is challenging.

Organization culture: According to Marr (2021), one significant barrier to improving data literacy within an organization is its culture. Leaders must demonstrate a data-first mindset by using data in meetings, product pitches, and decision-making processes. If leaders do not emphasize the importance of data, employees are unlikely to prioritize a data-driven approach themselves.

2.3 DATA COMPETENCY

Data competency pertains to a trait that encompasses understanding in areas such as Artificial Intelligence (AI), algorithms, programming systems, Machine Learning, query languages, and various technologies. In addition, data competency is closely linked to fields like Big Data and Business Intelligence, where professionals known as data scientists play a critical role (MyABCM, 2022). These experts gather and analyze valuable information that significantly influences managerial decision-making processes (MyABCM, 2022). Data competencies include (Chantel Ridsale, James Rothwell):

- **Data Analysis:** This entails the capability to formulate and address various inquiries through data examination, which includes crafting an analytical framework, employing suitable statistical methods and tools, and interpreting and contrasting the findings with existing research.
- **Data Awareness:** Involves understanding the essence of data, including its various forms, and grasping data-related concepts and terminologies.
- **Data Cleaning:** Encompasses the expertise to assess data cleanliness and employ effective methodologies and tools to rectify issues, ensuring data is primed for analysis.
- **Data Discovery:** The ability to efficiently search for, identify, and access necessary data from diverse sources to meet an organization's requirements.
- **Data Ethics:** Responsible data acquisition, utilization, interpretation, and sharing require an ethical understanding that acknowledges legal and ethical considerations such as biases and privacy concerns.
- **Data Exploration:** Involves using various methods and tools to examine data contents, applying techniques like summary statistics and visualization to identify patterns and relationships within the data.
- **Data Gathering:** The skill to collect data, both simple and complex, to fulfill specific needs, potentially through survey execution or sourcing from administrative, satellite, or social media data.
- **Data Interpretation:** The ability to comprehend tables, charts, and graphs, recognize significant points, and synthesize information from related sources for a coherent understanding.
- **Data Management and Organization:** Entails skills to navigate, access, organize, protect, and store data efficiently within internal and external systems according to organizational needs.
- **Data Modeling:** Requires applying sophisticated statistical and analytical methods (e.g., regression, machine learning) for data exploration and constructing models to discover data relationships and make predictions.
- **Data Visualization:** The capability to generate insightful tables, charts, and graphics for data representation, assessing their effectiveness in conveying the intended message accurately without misinterpretation.
- **Evaluating Data Quality:** Involves critically examining data sources to verify their suitability for organizational needs, identifying and correcting errors or discrepancies, and ensuring compliance with quality standards and policies.
- **Evaluating Decisions Based on Data:** The proficiency to appraise various data sources and evidence for informed decision-making, including assessing policy and program effectiveness.
- **Evidence-Based Decision-Making:** The competence to leverage data in supporting decisions and policy formulation emphasizes critical data analysis, question formulation, dataset identification, prioritization of information, and evaluation of potential solutions.
- **Storytelling:** Articulating significant statistical findings involves tailoring the presentation to the audience's familiarity with the topic, setting the context, and choosing the most effective visual aids to enhance comprehension and engagement.
- **Metadata Creation and Utilization:** Involves the capability to generate and utilize metadata, which serves as critical documentation providing the necessary context, definitions, and descriptions to facilitate accurate data interpretation and usage.
- **Data Stewardship:** Encompasses the responsibilities and skills needed for effective data management. It includes ensuring the data's quality, availability, and compliance with relevant policies, directives, and regulations to maintain its suitability.
- **Data Tool Proficiency:** The ability to competently use and understand specialized software, tools, and processes is essential for the collection, organization, analysis, visualization, and management of data.

Among the various data competencies, a select few are fundamental to top management. These key competencies, along with the reasons for their importance, are outlined below:

According to Schmidt et al. (2023), these data competencies are:

- **Data analysis and interpretation skills:** Analytical and numerical thinking skills are essential for a data-driven approach. Leaders must possess robust analytical abilities, including data interpretation and pattern recognition skills, to effectively tackle data-related challenges. These interpretation skills enable leaders to analyze the data, discern patterns, derive conclusions, and understand the outcomes and their implications for the business.
- **Storytelling and data visualization:** Storytelling is a crucial strategy for leaders, enabling them to frame data in narratives that support their decisions. Leaders must tailor these stories to their audience's background, using emotional and intellectual connections to communicate effectively. For instance, they might emphasize management principles to other leaders or focus on numerical details with data scientists. By simplifying complex data and presenting it clearly, leaders can convey their insights persuasively, combining strong verbal and non-verbal skills to resonate with diverse audiences. Data-driven leaders must confidently discuss data with stakeholders to build trust and support their decisions.
- **Data tool proficiency:** They need a thorough understanding of the data collection process, statistical methods, and the technical infrastructure, including Data Analytics tools and software. Knowledge in these areas helps them appreciate how data is gathered, processed, and analyzed, enabling informed conversations. By demonstrating expertise and understanding data management challenges, leaders establish credibility with upper management and technical teams.
- **Data awareness:** Leaders must possess sufficient knowledge to prevent manipulation by those more proficient with data. Understanding how experiments are designed, how data is collected and analyzed, and identifying potential errors in calculations or shortcomings in the technical infrastructure is essential. Being well-informed enables leaders to ask critical questions and ensure the integrity of the data processes.

2.4 DIFFERENCES AND SIMILARITIES BETWEEN DATA LITERACY AND DATA COMPETENCY

Data competence is a more thorough understanding that allows for intelligent analysis and strategic use of data in professional situations (MyABCM, 2022). Data literacy is the first step toward data competency (Panetta, 2021). Both are essential for companies to use data as a resource, but the scope and depth of application and understanding vary.

2.4.1 SIMILARITIES

- Understanding data, including accessing, analyzing, and using it effectively, is a prerequisite for data literacy and data competency. They play a crucial role in empowering people to engage meaningfully with data.
- Using data to back their findings and plans, people who are either data literate or data competent may help improve organizational decision-making.

2.4.2 Differences

While data literacy involves the basic skills necessary to understand and utilize data, data competency requires more in-depth technical proficiency, including the ability to work with advanced data technologies and methodologies.

Chapter 3: Methodological Framework

This chapter provides a detailed overview of the methodological approach framework employed in the interviews, focusing on an exploratory approach to understanding data literacy and data competence among top management in Belgian companies. For data analysis, we used thematic coding to systematically identify and categorize key themes, ensuring a structured and rigorous interpretation of the qualitative data.

3.1 RESEARCH CONTEXT AND METHODOLOGY APPROACH

Exploratory research is an investigative approach employed at the initial stages of a research project, particularly when there is minimal or no existing information on a specific subject. This dynamic and flexible approach aims to gain insights, uncover trends, and generate initial hypotheses. It seeks to answer questions like "What is happening?", "Why is this happening?" and "How is this happening?". Methods commonly employed in exploratory research include interviews, case studies, observations, surveys, and literature reviews (Voxco, 2021).

The purpose of the interview in this research is to explore the depth of understanding, skills, knowledge application, and experiences of top management regarding data literacy and data competence and to gain in-depth insights into challenges preventing top management in companies in Belgium from being data literate and data competent. We based some open-ended questions used to measure data literacy and data competencies among top management in Belgian companies on existing research detailed in section 2.2.3 on measuring data literacy in organizations.

Furthermore, this study selected a diverse sample of 10 participants representing various industries, genders, company sizes, and management roles to gain more comprehensive insights. We employed a convenience sampling method, leveraging personal connections and social media to recruit these diverse participants. Additionally, we used snowball sampling to obtain more participants through referrals from the initial group. Due to time constraints and the availability of participants, we used these two sampling methods.

To ensure confidentiality, as requested by some interviewees, we will anonymize participants' names and replace them with IDs in the respondent table below.

Table 1: Respondents table

Sector	Participants Positions	Company Size	ID	Sex	Duration
Pharmaceutical	Senior Principal Engineer	Small (5-100 employees)	A1	F	31 mins
Food	Owner	Mid-Size (100-1000 employees)	A2	M	30 mins
Manufacturing	Global Director of Strategic Marketing & Innovation	Large (1000 and above)	A3	F	40 mins
Finance	Chief Finance Officer	Large (1000 and above)	A4	F	30 mins
Investment	Owner	Mid-Size (100-1000 employees)	A5	M	40 mins
Recruitment	Owner	Small (5-100 employees)	A6	M	30 mins
R&D	Chief Scientific Officer	Large (1000 and above)	A7	F	40 mins
Technology	Owner	Small (5-100 employees)	A8	M	30 mins
Pharmaceutical	Chief Data and Analytics officer	Large (1000 and above)	A9	M	30min
R&D	Director of R&D	Large (1000 and above)	A10	M	30min

3.2 DATA COLLECTION

The progression of technology has made online interviews a more viable option, with systems becoming increasingly seamless and continuously improving (NSTR, 2024). Some interviews were conducted using Google Meet and Teams due to the geographical distance of some respondents. Consequently, we considered online meetings to save time and reduce costs. While face-to-face interviews allow for the observation of body language and non-verbal behavior, online interviews also yield results that are equally credible and valid (NSTR, 2024).

In addition to interview data, secondary data, such as literature reviews, were utilized throughout the data collection process. We conducted semi-structured interviews and used an open approach to gain comprehensive insights from each respondent. Respondents were encouraged to share their concepts and perspectives while staying aligned with the questions. The interview began with icebreaker questions to ease the tension, followed by social demographic questions to gather relevant information about the respondents' positions and sectors. After this initial phase, I delved into more detailed questions to obtain relevant information from the participants. The study divides the questions into four clusters, with two clusters based on the research questions and sub-questions within each cluster to explore the topic in greater depth. Lastly, the research questions were sent to the participants beforehand, allowing them to read and prepare for the interviews.

3.3 DATA ANALYSIS

Before analyzing the data, it is essential to transcribe the audio recordings from the interviews. This transcription process allows the data to be processed, organized, and interpreted effectively (Delve, 2024). Qualitative data analysis involves various methods of reading and interpreting the data to uncover observations, trends, and insights that answer the research questions or contribute to a qualitative research dissertation (Quirkos, 2023).

3.3.1 Analysis Techniques:

The first step in qualitative data analysis is thoroughly understanding the data sources. It requires repeatedly reading the data until the researcher identifies common concepts, issues, or topics across the corpus (Quirkos, 2023). One widely used approach for this is coding. Coding is a qualitative data analysis strategy where parts of the data are assigned descriptive labels (Medelyan, 2024). It allows the researcher to identify related content throughout the data. Coding is part of thematic analysis, which extracts themes from the text by examining word and sentence structures (Medelyan, 2024). Thematic analysis entails an active process of reflexivity, where the researcher's subjective experience plays a central role in meaning-making from the data (Delve, 2024).

3.3.2 Importance of Coding:

Coding qualitative data simplifies the interpretation of responses. Researchers can better analyze and summarise survey results by assigning codes to words and phrases in each response (Medelyan, 2024). In this study, we use the top-down method called deductive coding. We create a codebook based on our original collection of codes, which may stem from our research questions, an established framework, or an existing theory. We then review the information and match quotes to codes (Delve, 2024).

3.3.3 Data Analysis Process for this study:

The data analysis process in this study comprises the following steps:

Step 1: Familiarization with the Data

To achieve a comprehensive understanding of the content of the transcribed interviews, we began by reading through the transcripts multiple times. We focused on getting an overall sense of the themes and topics discussed during the initial reading. In subsequent readings, we paid closer attention to specific details, recurring themes, and notable quotes. This process facilitated immersion in the data, leading to a deeper understanding of the participants' perspectives.

Step 2: Development of a Coding Framework

Next, we developed a structured set of codes derived from the research questions and objectives. To do this, we first identified key themes based on the research questions, pinpointing the main themes or categories relevant to the study. We then created an initial list of codes representing these themes, ensuring each code was concise and clearly defined.

Step 3: Application of Codes to the Data

With a refined set of codes, we categorized and organized the data by applying the codes to specific quotes and passages. We segmented the transcribed interviews into manageable segments, such as sentences, paragraphs, or key quotes. We then matched each segment to one or more codes that best represented its content. Annex 2 contains the transcripts from the interview.

Step 4: Summarization of Quotes

We paraphrased each quote in more straightforward terms to simplify and summarize each coded quote while capturing its essence. It involved rewriting each quote to retain its original meaning but in a more concise manner. We carefully checked each summary to ensure it accurately reflected the intent and content of the original quote. We documented the original quote, assigned code(s), and the summarized version for easy reference.

Below is a coding tree table that illustrates this process.

Table 2: Coding table

Step 1	Step 2	Step 3	Step 4
RQ1: How data literate and data competent are top management in companies in Belgium?	Understanding Data Literacy and Data Competency.	"Data literacy to be able to understand data, create data insights that you can use in decision making, and competency to transform that into actions" (A3)	Interpretation of data
		"It's the knowledge of handling data to understand what data is, how you can report data." (A5)	Handling Data
		"Knowing where to find the information that you're looking for and competency is then really for me really how you can do searches in those databases and find what you need". (A1)	Searching for data
		"it would be like how well you understand data and how well you use this data in order to achieve business goals". (A4)	Leveraging data
RQ2: What are the main barriers preventing top management in companies in Belgium from adopting and effectively using data literacy and data competencies in decision-making processes?	Educational Background	"I have a masters in Economics and Business administration" (A1O)	Educated
		"When I was educated I was not aware of these systems " (A1)	Uninformed
		"My engineering background give me valuable insights into data literacy and competencies." (A2)	Proficient
		"My education in HR management covered the importance of GDPR " (A6)	Knowledgeable
	Assessment Methods	"We don't have a systematic way of measuring." (A3)	Unmeasured
		"I don't think it's being done". (A4)	Uncertain
		"no, we don't measure it." (A5)	Unmeasured
		"No. Not that I know of." (A1)	unaware
	Skill Levels	"Excel and Tableau on not more than medium" (A1)	The average level in Excel and Tableau
		"I can use Excel at an average level" (A3)	The average level in Excel
		"We only use Excel. I can open it, type numbers, and do basic computations, but my staff handles the rest" (A4)	Basic level of Excel
		"I am most comfortable with Excel." (A5)	Proficient in Excel
	Knowledge Application	"I use it on a frequent basis, I use data to support my decision making". (A6)	Frequent
		"I use it normally weekly or monthly" (A5)	Periodic
		"It is a common practice, and it is a day-to-day practice to look into the data to make the decision." (A8)	Daily
	Challenges in adoption	" Lack of training and unfamiliarity with digitalization" (A3)	Training
		" I hate analyzing and I just want the result" (A4)	Lack of willpower
		" keeping up with the latest trends" (A6)	Changes in technology trends
	Organisational Culture (data usage in companies)	"People use data everyday, every week for marketing, sales, finance" (A5)	Frequent
		" The culture of data is pretty good, we use it for evaluating clinical studies" (A1)	Good
		" Data is there but it is not capitalized on" (A7)	Underutilized
		" Culture of data is limited" (A8)	Limited
	Resources Allocation	" No resources allocation" (A8)	None
		" No for last two or three years but we decided to start doing that now" (A5)	Planned
		" They provide some training but not on one to one basis" (A7)	Partial
	Trust In Data	" I don't have high trust in data provided to me " (A5)	Low
		" I trust the sources I get the data from" (A1)	High
		" It depends on the data quality " (A7)	Conditional
		" I trust it 80% of the time" (A8)	Mostly

Chapter 4: FINDINGS

After thoroughly analyzing the existing research, this chapter will delve deeper into the findings from the interviews. We will specifically explore the data literacy and data competence levels of top management in Belgian companies. Additionally, we will identify and examine the barriers that hinder their ability to enhance their data literacy and competence.

The interviews conducted for this study offer a valuable source of qualitative data, capturing the insights of top management from various Belgian companies regarding data literacy and competency. Through a thematic analysis of these interviews, the findings shed light on the current levels of data literacy and competency among top managers. Additionally, the analysis identifies vital barriers that hinder these executives from achieving higher data literacy and competency levels.

Below, we will present the findings for each of the research questions. The annex after Chapter 8 contains these research questions. Additionally, each research question's findings are summarized with a comprehensive overview, accompanied by graphs to represent and highlight the key results visually.

4.1 RQ1: How data literate and data competent are top management in companies in Belgium?

Before delving into the specifics of our research findings, we have prepared a table and graph to summarize the categories to which the 10 participants belong based on their data literacy and data competencies across various dimensions. This overview provides a clear snapshot of the results. The table classifies participants into High, Average, or Low categories.

Details about the rankings for different dimensions and the number of ratings on the graph:

Data Literacy and Data Competency Definition:

High: Participants used terminology closely aligned with research definitions of data literacy and data competency.

Average: Participants mentioned relevant terminology but failed to explain the concept of data competency thoroughly.

Low: Participants were unable to provide accurate definitions.

Educational Background:

High: Participants possess a solid educational background that significantly contributes to their data literacy and competency.

Average: Participants have limited formal education in data literacy and competency but have received internal training to improve these skills.

Low: Participants lack educational background and training supporting data literacy and competency.

Assessment Methods:

High: The company dedicates substantial effort to measuring data literacy and competency within the organization.

Average: Assessment practices vary depending on the use case and specific questions.

Low: The company does not measure data literacy and competency.

Skills Levels:

High: Participants demonstrate high proficiency with both advanced tools (e.g., Python, SQL, SPSS) and basic statistical tools (e.g., Excel), using them daily along with strong statistical knowledge.

Average: Participants are more proficient with basic tools like Excel, using them more frequently than advanced tools.

Low: Participants are only comfortable with Excel and use it infrequently.

Knowledge Application:

High: Participants incorporate data into every decision they make.

Average: Participants incorporate data into decision-making, but the extent depends on the nature of the decision.

Low: Participants do not use data in their decision-making.

Balancing Data-Driven and Intuitive Decision-Making:

High: Participants rely on data and experience and balance both well.

Low: Participants rely solely on personal experience for decision-making.

Table 3: Summary of Data Literacy and Data Competency of the Participants

Participants	Data Literacy and Data Competency Definition	Educational Background (Data related)	Assessment Methods	Skill Levels (data competency)	Knowledge Application (data literacy)	Balancing Data-driven and Intuitive Decision Making
A1	Average	Average	Low	Average	High	High
A2	High	High	Low	High	High	High
A3	Average	High	Low	Low	Average	High
A4	Average	Low	Low	Low	High	-
A5	Average	High	Low	Low	High	High
A6	Average	High	Low	Low	High	High
A7	High	High	Average	High	High	High
A8	Average	High	Average	High	High	High
A9	High	High	Low	High	High	High
A10	Average	High	Low	High	High	High
Summary	High = 3 Average = 7 Low = 0	High = 8 Average = 1 Low = 1	High = 0 Average = 2 Low = 8	High = 5 Average = 1 Low = 4	High = 9 Average = 1 Low = 0	High = 9 Average = 0 Low = 0

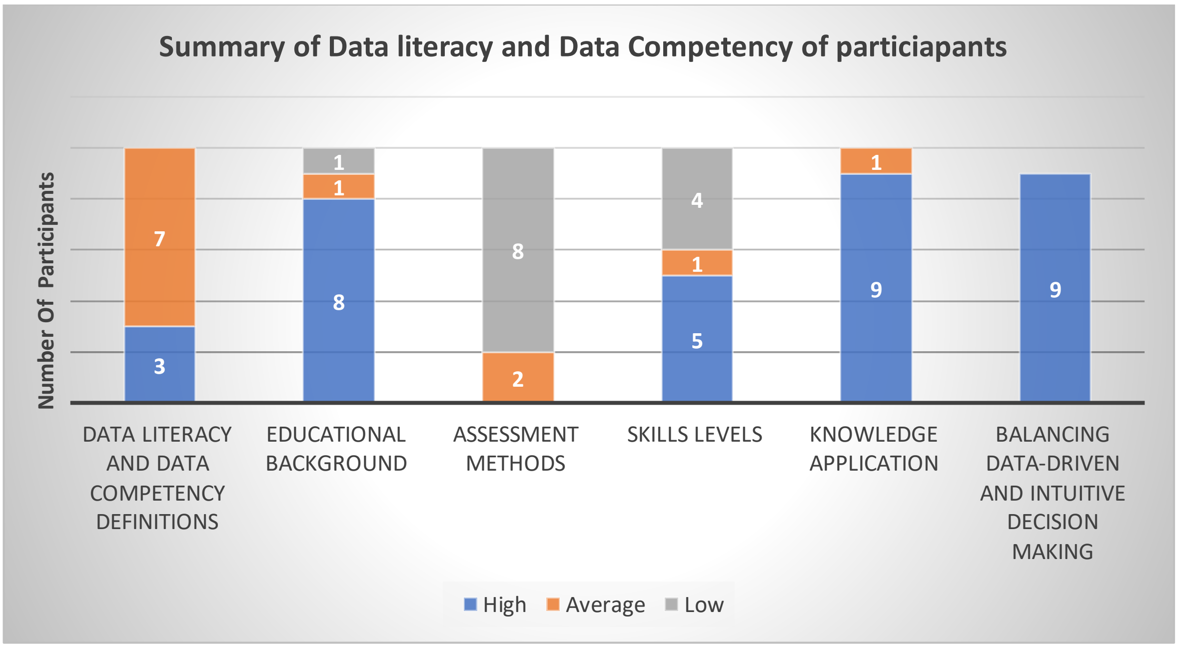


Figure 3 Summary of Data Literacy and Data Competency of the Participants

4.1.1 Understanding of Data Literacy and Competency:

This section aimed to determine if the participants understand data literacy and data competency. The participants had different perspectives on what data literacy and data competency mean. For instance, many interviewees defined data literacy as the ability to locate, interpret, and utilize data for decision-making purposes. Data Competency is a broader concept involving skills to perform searches, analyze datasets, and extract meaningful insights. They highlighted that data competency extends beyond mere understanding, involving the capability to perform searches, analyze datasets, and extract meaningful insights. According to A3, “Data literacy is the ability to understand data, create data insights that you use in decision making, and competencies means being able to transform that into actions.” One of the interviewees also describes it as " the knowledge of handling data to what data is, what you can do with it, how you can manage data, how you can report data” (A5).

In addition, A2 said, “Data literacy is the ability to understand data, its types, importance, and the underlying systems required to gather and store data, and data competency is the ability to derive meaningful results from analyzing and manipulating data.”

Moreover, after defining data literacy and data competency, there was also an additional question to understand the participant's familiarity with data analysis. The findings show that these top managers are very familiar with it through education or experience.

Educational backgrounds: Participant A3 mentioned, “I would say quite familiar because I come from the study fields where data is used; the data is centered around both economics and engineering.”

Personal Experiences: A6 shared, “In my previous job at STDM, I analyzed financial statements and verified the accuracy of reported data, and as a recruiter, I handle sensitive personal information and ensure its proper use and confidentiality.” A7 stated, “Yes. So, regarding data analysis and interpretation, I work in pharmaceutics, which is about developing medicines for children. So, we do lots of experimental studies, where we do the data analysis”.

Conclusion These various definitions demonstrate that some top managers comprehend the concepts of data literacy and data competency because they use terminology that aligns with the definitions of data literacy and data competency in this research.

4.1.2 Educational Background:

This section seeks to explore how the varying educational backgrounds of participants influence their data literacy and competence.

The respondents' educational backgrounds were diverse, and some had advanced degrees in sciences, engineering, and business administration, contributing to their knowledge and skills in data literacy and competency. Some participants mentioned how their educational background helped them be more knowledgeable. A2 highlighted the benefits of an engineering background: “My engineering background helps greatly. We took advanced mathematics in university, which paved the way for data literacy and competencies. Also, A9 emphasized the importance of advanced studies “So, yeah, in my master's and my PhD, I did a lot of data interpretation, calibrations of models, the capability of handling data, interpreting data, that is really, yeah, was more developed”.

Moreover, A3 discussed the combined influence of economics and engineering education: “My educational background strongly supports my understanding of data literacy and competency. My studies in economics helped me understand how people make choices and consumer behavior. In my engineering education, I studied topics like risk management, probability, and scenario analysis, which aid in predicting future outcomes”.

Nonetheless, two participants stated they had no education, which contributed to their data literacy and competency. They relied on colleagues, self-learning, and work experience to build these abilities. One respondent noted, "When I was educated, I was not aware of these systems, and I think they did not even exist, now I just ask my colleagues who I know have probably done more analysis which systems to look and how to do it. And then I try myself and then I discuss it with colleagues because I don't think I am super competent” (A1). A4 admitted that their marketing degree provided minimal preparation “Honestly, very little because I graduated with a marketing degree, mostly” (A4).

Conclusion: The educational background is crucial in determining data literacy and competency among participants. Those with advanced degrees in fields emphasizing data analysis, such as engineering and sciences, generally exhibit higher proficiency. Their formal education provides a foundation that facilitates their understanding and application of data literacy and data competency concepts.

4.1.3 Assessment Methods:

This section assesses whether different companies evaluate data literacy and data competency among their top management. Given this study's aim to understand the level of data literacy and data competency among top executives, it is essential to determine if companies measure these skills within their leadership teams. This assessment will help identify how seriously companies take data literacy and data competency at the highest levels.

Lack of Systematic Assessment

A significant finding from the study is the consensus among participants that their organizations lack systematic methods to assess data literacy and competency. Most top managers reported that their companies do not have formal processes to measure these skills. The following responses illustrate this sentiment:

"No, I don't think we really assess that data literacy top management" (A8).

"No, we don't measure it" (A5).

"I don't think it's being done; we don't measure it" (A4).

"No, I think it's a good question. But I think we don't have a systematic way of measuring" (A3).

The pervasive lack of formal assessment methods indicates a potential area for improvement in organizational practices. Additionally, these findings might explain the scarcity of existing research on the levels of data literacy and data competency among top management, as companies do not prioritize this aspect.

Situational Assessments

Despite the lack of systematic assessment, some participants mentioned that their companies evaluate data literacy and competency among top management, but this depends on specific situations. Two participants articulated this conditional approach, noting that assessment practices vary based on the type of use case and the nature of the question at hand:

"That is very hard to say. It really depends on the type of use case and the type of question at hand" (A8). " This is measured based on the amount of data we put in the company's open source projects" (A7).

4.1.4 Skill Levels:

This section aims to analyze data competency levels among top management comprehensively. The interview process assessed their familiarity with various analytics tools such as Excel, SQL, Tableau, Python, and PowerBI. It also evaluated the frequency of usage of these tools and their statistical knowledge.

Proficiency in Basic Analytics Tools:

The proficiency levels in using data analysis tools varied widely among the interviewees. Many interviewees expressed comfort with basic tools like Excel, indicating that it is common among top management. However, their proficiency and usage frequency varied significantly:

Basic Proficiency: Some participants demonstrated only basic proficiency. For example, one participant (A4) mentioned, "We've only used Excel and I use it every day, but I can open it, type numbers, and do basic computations. The rest, my staff will do." This indicates regular use but limited proficiency.

Moderate Proficiency: Another participant (A3) stated, "I would say I'm an average-plus user and I use Excel every week." This suggests a moderate level of comfort with the tool.

High Proficiency: A participant (A6) rated their proficiency as "7 out of 10," indicating a higher comfort level compared to others but still not expert-level.

Use of Basic Analytics Tools:

Furthermore, participants primarily use Excel for basic and intermediate functions, such as performing simple sums, averages, subtractions, and creating pivot tables. However, some instances involve utilizing more advanced features. Notably, participants mentioned using Excel for data visualization and analysis.

One participant explained, "We tend to use Excel for data visualization to create plots and bar charts" (A7). Another participant shared that Excel is essential when unexpected results appear in pharmaceutical data, stating, "You start using Excel when you encounter unexpected results in the pharma data. By inputting all the data into Excel, you can analyze and visualize it to understand what is happening. For instance, I previously used Excel to analyze and visualize the permeation rate of packaging materials" (A1).

Others highlighted Excel's utility in specific tasks: "I used the pivot table in Excel" (A3) and "I can do basic computations like sum, average, and subtractions" (A4).

Proficiency in Advanced Analytics Tools:

Six interviewees expressed comfort with more advanced analytical tools like Tableau, SQL, and Python. The proficiency levels in these tools also showed considerable variation:

Moderate Proficiency in Tableau: One participant (A1) mentioned, "Excel and Tableau on not more than medium," indicating a moderate level of proficiency with Tableau.

Advanced Proficiency in SQL and Python: A participant (A2) rated themselves "4 out of 5" in using SQL and Python, suggesting a more advanced skill level. Another participant (A10) stated, "Weekly, as we make reports and design experiments regularly, but don't consider myself a statistical expert," indicating regular use with moderate proficiency. A8 also mentioned that they use SQL, Python, Power BI, and Excel daily, “ SQL, Python, Power BI, and Excel is what I use daily.”

Use of Advanced Analytics Tools:

Two of the participants provided a detailed explanation of their use of advanced analytics tools. They mentioned, "I had access to run queries, so I used SQL and Snowflake. I retrieved all the data, transformed it, and manipulated it for my purposes. Then, I performed modeling and created visualizations using Python."(A9). Also, A7 mentioned that “I am very familiar with and frequently use statistical data analysis tools, including SQL for database development, SPSS, Minitab, and Excel for daily tasks. Although I am interested in learning Python, I haven't used it yet. Additionally, we use open-source software like Visio for data presentation. On a daily basis, I primarily rely on statistical software and Excel”.

Statistical Knowledge:

This interview revealed varying levels of statistical knowledge among top management:

A1 demonstrated demonstrated a solid understanding of basic statistical concepts. She explained, "Correlation is when there is a connection between two things, but causation means one causes the other. For example, there is a correlation between low education levels and voting for the extreme right, but it does not mean low education causes that behavior." Although she understands the concepts, A1 relies on colleagues for statistical expertise: "I go to my colleague and ask him because he is the statistical expert of the team." In addition, A2 exhibited a firm grasp of statistical terminology and application. He stated, "Probability is the likelihood that an event would happen. Standard deviation measures how far a dataset is spread from its mean. Regression approximates a single line to predict outcomes." Lastly, A4 showed a basic understanding: "Correlation means there is a direct link, and causation means one thing causes another."

In conclusion, the proficiency levels in using data analysis tools among interviewees varied widely. Many are comfortable with basic tools like Excel, primarily for simple computations and visualizations. Some have moderate proficiency, employing features like pivot tables regularly. A few demonstrated advanced skills with tools such as SQL and Python, which are used for complex data manipulation and analysis. Statistical knowledge also varied, with some participants having a solid understanding of concepts like probability and regression while others relied on colleagues for expertise.

Excel is the most commonly used tool, with varying degrees of proficiency and application among top management. While top management is generally familiar with basic data analysis tools, a notable gap exists in the usage and proficiency of more advanced analytics tools. It indicates an area for potential skill development to enhance data-driven decision-making capabilities.

4.1.5 Knowledge Application:

After analyzing their skill levels in data competency, this section will continue to assess their data literacy level. It involves evaluating their understanding of data and integrating these insights from data into their regular decision-making process. We will look for examples of times when they identified significant problems using data on positive outcomes.

Assessment Areas:

Frequency of Data Integration in Decision-Making:

Data insights are integrated into the decision-making process regularly, ranging from daily to monthly, depending on the complexity of the task and the data's relevance to the decision at hand, “Very often depends a bit on the type of decision that I am making”(A3). one participant also mentioned using data to match candidates to job vacancies daily “Daily, we match candidates to companies based on updated data about job vacancies and company requirements, making decisions accordingly” (A6).

Also, other participants mentioned that it is a common practice for them to look into data for decision-making:

“I think so, it is a common practice, and it is a day-to-day practice to look into the data to decide because that kind of helps us decide on the next set of experiments we would be doing” (A7).

“We do it frequently. It is normal to hear” (A8).

They also gave an example of strategic decisions they made based on data. Participants provided examples such as using company data to plan cash flow, identifying impurities in formulations, and deciding between in-house manufacturing and outsourcing based on market research. As stated by A8, “CRM, the finance dashboards, the cash flow planning. That is all data”.

Another participant also mentioned, "In a recent project, I integrated two distinct data sets, A and B, which independently influenced the product outcome by combining their impacts to develop a comprehensive strategy. This approach allowed for more effective decision-making and outcome control by limiting variables from both data sets” (A9).

Problem Identification:

Significant problems identified using data include duplicate or outdated information, frequent machine malfunctions affecting production yields, and identifying impurities in formulations. Solutions involved data cleaning, root cause analysis, and process improvements at supplier ends.

“Identifying an impurity, conducting a DOE, and implementing process improvements at the supplier's end”(A10).

“A significant problem was identified in our production line where the yield was consistently below the expected target. Analyzing the production data, we noticed a pattern indicating that a specific machine frequently malfunctioned. We conducted a root cause analysis, pinpointed the faulty component, and replaced it. Post-replacement data showed a marked improvement in yield, meeting our targets consistently” (A2).

Positive Business Outcomes Influenced by Data Literacy:

Data literacy has positively influenced business outcomes by improving recruitment processes, getting funding, enhancing production efficiency, and ensuring effective strategic investments.

“We were deciding on a major investment in new technology. We conducted a data analysis of our current production metrics and potential improvements and demonstrated the ROI of the investment. This data-driven approach led to the approval of the investment, which subsequently resulted in a 20% increase in production efficiency” (A2).

“We used user statistics and feedback to demonstrate the impact and utility of our database to funders, which helped secure additional funding for its expansion. This data-driven approach showed how effectively the database served its users and justified further investment for future growth” (A7).

Conclusion: The participants demonstrate high data literacy, seamlessly integrating data insights into their regular decision-making processes. They frequently use data to inform daily tasks, strategic decisions, and problem identification, leveraging data for positive business outcomes. Data integration in decision-making occurs regularly, with frequency varying from daily to monthly based on task complexity and data relevance. Participants highlighted the daily use of data for matching job candidates to vacancies and emphasized the common practice of relying on data for various decisions. Examples include strategic decisions involving cash flow planning and manufacturing choices, where combined data sets lead to more effective outcomes. Identified problems using data, including duplicate information and machine malfunctions, addressed through data cleaning and root cause analysis. Data literacy has led to positive business outcomes, such as improved recruitment, securing funding, and enhancing production efficiency through data-driven investment decisions.

Note: It is important to note that participants stating they base their decisions on data does not necessarily mean that they interpret or use the data correctly all the time.

4.1.6 Balancing Data-Driven and Intuitive Decision-Making:

The aim is to verify whether top management predominantly relies on intuition, as suggested in the existing research referenced in the problem statement. To explore this, we asked participants how they balance data-driven and intuitive decision-making.

Participants emphasized the importance of striking a balance between these approaches. They highlighted that while data provides a solid foundation for making informed decisions, intuition plays a crucial role in contexts where data may be incomplete or ambiguous. This blend ensures that decisions are both evidence-based and adaptable to unforeseen circumstances.

A9 highlighted that he relies on data 70-80% of the time and intuition for the remaining 20-30%, stating, "70-80% of the time, I choose data directly. For the other 30%, I use intuition."

A5 asserted the necessity of combining both approaches: "I always do both. I never rely solely on data. When I get data, I am always critical." A8 discussed using data as a foundation: "We use the data as a basis to make an informed decision and then add our experience to that." A10 emphasized the need to consider the data's statistical significance and practical relevance.

A3 provided a detailed example: "To balance growth, we analyzed data to understand our customer base, focusing on small customers and order volumes, particularly in regions like Africa and the Middle East. By identifying areas where local partners could better serve these customers, we used data and strategic insights, combined with my intuition and knowledge, to advocate for a more centralized approach. It ensured scale and efficiency while explaining the benefits of reducing fragmentation and optimizing partner networks."

Another participant explained the role of intuition when data is incomplete: “Ah, very interesting, balance data-driven decisions. So yeah, sometimes it is like the data definitely helps us to see what it is, but in terms of the situations where we are yet to collect the data, the existing data does show the positive kind of outcomes, but we don't know whether we should be going in that way or not. So that's where our intuition or experience helps. So I use 60% data and 40% experience”(A7).

Conclusion: Participants emphasized the importance of balancing data and intuition in decision-making, noting that data provides a solid foundation while intuition is crucial when data is incomplete or ambiguous. This blend ensures that decisions are evidence-based and adaptable to unforeseen circumstances. For instance, A9 uses data 70-80% of the time and intuition for the rest, while A5 and A8 advocate for combining both approaches critically. A3 and A7 highlighted using data to inform decisions and leveraging intuition and experience when data is lacking, ensuring practical relevance and strategic insights. In addition, according to Brown (2023), leaders who combine intuition with data-driven insights are more effective and influential. Based on the findings above, these participants combine intuition and data-driven insights.

4.1.7 Summary of RQ1: The findings on how data literate and data competent top management are in companies in Belgium.

The participants demonstrate a solid understanding of data literacy and competency, particularly those with relevant educational backgrounds. Their data skills vary, with basic tools like Excel being commonly used for tasks such as sums, averages, subtractions, pivot tables, data visualization, and analysis, including creating plots, bar charts, and analyzing pharmaceutical data. However, proficiency with advanced tools like SQL and Python is mixed. Despite regular integration of data into decision-making, which positively impacts business outcomes like production efficiency and funding acquisition, there is a notable lack of formal assessment methods within organizations. Managers effectively balance data-driven decisions with intuition, though there is potential for further development in advanced skills and systematic assessments.

4.2 RQ2: What are the main barriers preventing top management in companies in Belgium from adopting and effectively using data literacy and data competencies in decision-making processes?

Before diving into the details of the second research findings, we chose to create two tables and corresponding graphs that summarize the challenges participants face in achieving proficiency in data literacy and competency. The first table and graph capture the challenges explicitly stated by the participants. The second set represents challenges identified in existing research, as discussed in Chapter 2, Section 2.2.5. This comparison aims to determine whether these challenges align with the barriers hindering top management in Belgium. Table 4 categorizes these challenges into High, Average, or Low rankings.

Below are the tables and graphs that visualize these findings.

Table 1 and Graph 1:

Table 4: Challenges in adoption table 1

Challenges	Time constraints	Lack of training	Changes in technology trends	Data management challenges	Lack of willpower
Participants	3	5	3	1	1

Note: Some participants have answered multiple challenges.

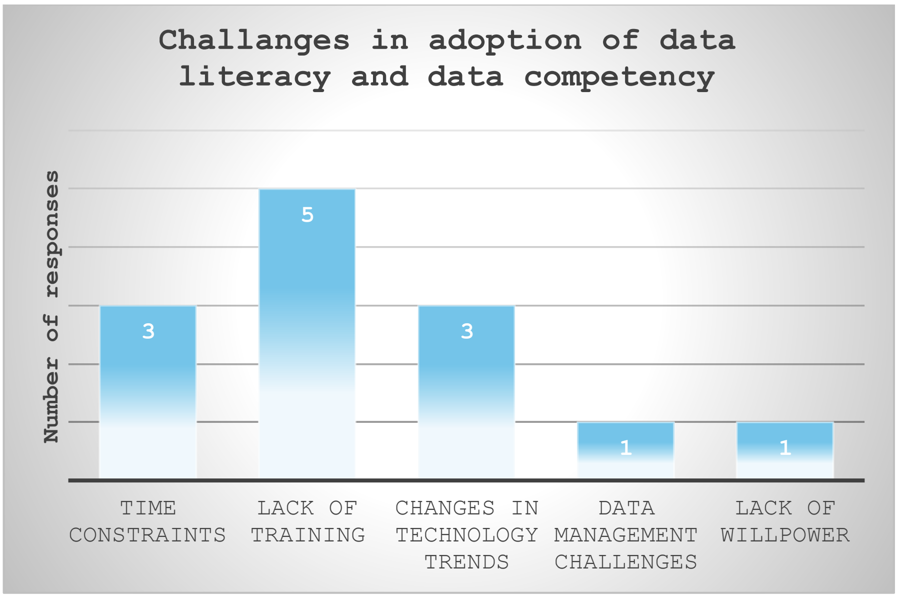


Figure 4: challenges in adoption graph 1

Table 2 and graph 2:

Details about the rankings for different dimensions and the number of ratings of the graphs and tables below:

Organizational Culture:

High: Good data culture in the company

Average: Still in the process of improving data culture in the organization.

Low: No data culture.

N/A: No Answer / Participant does not know.

Resources Allocation:

High: Lots of investments ensure top management are data literate and competent.

Average: Still in the process of making sure the top management is data literate and data competent.

Low: No investments in making sure top managements are data literate and data competent.

N/A: No Answer / Participant has no knowledge.

Table 5: Challenges in adoption

Participant	Organizational culture	Resource allocation
A1	High	Average
A2	Average	N/A
A3	Average	Low
A4	N/A	N/A
A5	High	Low
A6	High	Average
A7	Average	Average
A8	High	N/A
A9	Low	Low
A10	Average	High
Summary	High =4 Average =4 Low = 1	High = 1 Average = 3 Low = 3

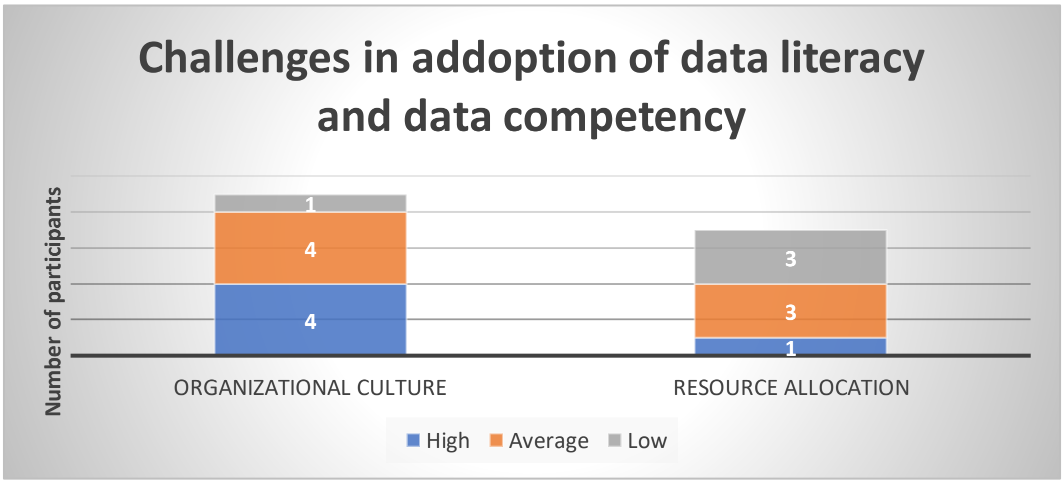


Figure 5: Challenges in adoption graph 2

4.2.1 Challenges in Adoption:

As observed, the participants are data literate, but their levels of data literacy vary, and their data competency is generally low, with only a few individuals possessing low to advanced data competency. Therefore, this section identifies the barriers preventing top management from achieving advanced levels of data literacy and competency.

Participants identified several key barriers to adopting and effectively utilizing data literacy and data competency, including:

Time Constraints:

Time constraints emerged as the predominant barrier to enhancing data literacy and competency. Participants frequently cited a lack of time as a significant barrier to learning and applying new data skills:

"My main barrier is time; I simply do not have the time to learn all this kind of software" (A5).

"Time is the biggest challenge for me" (A2).

"I think the biggest challenge is finding time" (A8).

Lack of Training:

Inadequate training and unfamiliarity with digital tools were also significant obstacles. One participant highlighted the need for more comprehensive training programs:

"I never had any courses in data analysis, which is a shame because it is essential in both finance and science today" (A1).

"A lack of training within my company is a barrier to effectively using data. Although we have made progress with Power BI, more advanced training would enable me to work faster, more efficiently, and more professionally" (A3)

Changes in Technology Trends:

The swift evolution of technology and IT knowledge poses a challenge to maintaining data competency. Participants noted the difficulties in staying current with new technologies:

"Learning advanced tools like Python and keeping up with the latest data analysis technologies can be challenging" (A6).

"Keeping up to date with trends in data science, especially with emerging AI and machine learning technologies, is essential but demanding" (A7).

"The rapid evolution of AI and sophisticated statistical tools requires continuous learning" (A10).

Data Management Challenges:

The report also highlighted challenges related to data management. Participants indicated areas where they feel they need to improve their skills in data structuring and management:

"From a database perspective, there is room for growth. While I can consume and work with data, improving my skills in structuring data is necessary" (A9).

"It is important to stay updated with the latest data science trends and technologies. The emergence of new AI and machine learning technologies underscores the need for continuous learning through online courses" (A7).

Lack of Willpower:

Finally, the analysis identified a lack of willpower to develop data literacy skills as a barrier.

"I dislike analyzing data and just want the results without engaging in the process" (A4).

Conclusion: The barriers to advancing data literacy and data competency mentioned by the participants are complex, encompassing time constraints, insufficient training, rapid technological changes, data management challenges, and a lack of willpower.

Furthermore, as discussed in Chapter 1, Section 2.2.6, additional barriers can hinder top management from achieving proficiency in data literacy. In the following section, the aim is to examine If the barriers mentioned in the existing research are also part of the barrier hindering the top management in Belgium from being proficient in data literacy. So, we examine the extent of these barriers within the companies where the participants are employed. A significant presence of these barriers would suggest they might contribute to the lack of data competency and literacy among top management.

Data-Driven Culture:

The significance of cultivating a data-driven culture is documented in existing research, especially in Chapter 2, Section 2.2.1. Furthermore, Section 2.2.6 highlights that organizations without a data-driven culture may struggle to attain high levels of data literacy. This section investigates the data culture within the organizations where the study participants work, exploring whether it might be a barrier to achieving proficiency in data literacy and data competency.

The findings from this interview indicate a gradual shift towards a data-driven culture within the organization. While data is increasingly utilized across various departments and recognized by top management, there remains a reliance on traditional methods and underutilization in some areas. The advancement and application of data-driven practices vary significantly, often depending on the individual manager's approach.

One participant said, "Our organization is gradually becoming more data-driven, but there is still a reliance on traditional methods in some areas" (A2). Another interviewee noted, "I think it is pretty good. We use data for financial aspects and evaluating our clinical studies" (A1). However, a participant shared a different perspective: "Data is there, but it is not capitalized on" (A7).

One interviewee highlighted a mixed experience: "The basics are well in order. We have a good rhythm for looking at commercial data, so I feel confident in that area. We also have good insights into managing operations. However, when it comes to more advanced data, especially related to customers and their needs, it's more mixed. The level of advancement in this area depends significantly on the individual manager" (A3).

Another participant affirmed that people use data daily, stating, "People use data every day, every week, in marketing, finance, and sales" (A5). Furthermore, participants highlighted top management's growing emphasis on data: "It's getting more data-driven, with top management presentations increasingly focusing on data and trends" (A9). Despite this, another participant summarized a sense of limitation: "It's limited, let's say" (A6).

Resources Allocation:

The allocation of resources for enhancing data literacy is notably inconsistent across organizations, with some entities reporting minimal or no investment in training and development in this area, as reflected by statements such as, "No, I think you probably get a bit of like no from everyone" (A3), and, "I cannot really say" and "No, I do not think so" (A2, A9), which highlight a general lack of commitment. However, recent improvements are observed in some organizations, where new initiatives have been introduced to enhance data literacy, as evidenced by the comment, "In the last two or three years, we did not focus on this, but a decision was made two months ago to increase resources in this area" (A5), and, "As a small company, we allocate resources as needed, such as investing in job tools for better data management" (A6), indicating targeted efforts to address the gap. Additionally, while some resources are allocated, they are not always explicitly focused on data literacy, with feedback such as, "They do offer some training, though it might not be specifically focused on data literacy. It would be beneficial if they could provide more hands-on workshops and practical sessions to help people better understand and apply these skills" (A7), suggesting a need for more tailored programs. Financial constraints further complicate resource allocation, as highlighted by the observation, "Resources, along with informed decisions given the limited resources we have. We do not have the money for these tools. So, financial constraints are a challenge here as well" (A8), emphasizing the difficulty in securing adequate funding for comprehensive data literacy initiatives.

4.2.2 Summary of RQ2: The findings of the main barriers preventing top management from adopting and effectively using data literacy and data competencies in the decision-making process

The participants mentioned the several barriers they face to achieving advanced levels of data literacy and competency. Time constraints are a significant issue, with many executives citing a lack of time to learn and apply data skills. Lack of training and unfamiliarity with digital tools also pose substantial challenges, as many have not received formal education in data analysis. The rapid changes in technology trends make it difficult for executives to stay proficient with the latest tools and techniques. Data management challenges and structural issues within organizations hinder their ability to use data effectively. A participant also stated a lack of interest in becoming proficient in data literacy. Data-driven culture and inconsistent resource allocation for training also contribute to these challenges.

Chapter 5: DISCUSSIONS

Comparison of Literature Review and Interview Findings. It is important to note that the interview findings are based on interviews with the 10 participants, where we evaluated their self-assessed knowledge based on their responses rather than through practical tests.

The findings of this study reveal that top management frequently utilizes data to pinpoint issues and achieve positive business outcomes, indicating a high level of data literacy among them. It aligns with existing definitions of data literacy, encompassing the ability to grasp and efficiently utilize data for decision-making. According to Mandinach and Gummer (2013), data literacy involves recognizing, gathering, organizing, analyzing, summarizing, and ranking data, formulating hypotheses, identifying problems, interpreting data, and establishing, planning, executing, and overseeing courses of action.

Interestingly, contrary to existing research, which suggests that leaders often struggle to fully trust data due to their reliance on traditional decision-making methods (Brown, 2023), the findings of this study indicate that top management has a high level of trust in data. They verify data primarily due to concerns about data quality rather than an inherent preference for traditional methods.

Another study highlighted that while leaders often boast about their leadership and strategic abilities, a significant portion lacks proficiency in data analytics. It also noted that some leaders judge based on ideology, disregarding facts and evidence (Rossi, 2017). However, the findings partially contradict this. While it is true that the level of data competency varied among participants, and some were not fully data-competent, the assertion that leaders rely solely on gut feelings and ignore data was not supported. On the contrary, the study found that leaders frequently use data in decision-making and do not rely solely on intuition.

Top managers demonstrated varying levels of familiarity with data literacy and competency, often shaped by their educational backgrounds and training. Participants with advanced degrees in economics, engineering, and business administration displayed a higher understanding and application of data literacy skills. It aligns with the literature emphasizing the importance of education in developing data competencies. Specifically, the literature advises Chief Data Officers (CDOs) to initiate data literacy training initiatives to meet the high aspirations of data and analytics strategies and bridge the current skills deficit. This approach can foster a culture where the enhancement of data competency capabilities and the enrichment of data literacy become integral to the organization's culture (Gartner, 2021).

In conclusion, the study finds that top management generally shows a firm trust in the effective use of data, contrasting with some research suggesting a reliance on traditional methods. While data competency varies among leaders, especially by educational background, they integrate data into decision-making rather than relying solely on intuition. It underscores the need for continued data literacy training to support data-driven decision-making and align with modern analytics strategies.

Chapter 6: CONCLUSION

This study assessed the data literacy and data competency levels among top management in Belgian companies, revealing a detailed view of both advancements and ongoing challenges. Results show that while executives demonstrate a high level of data literacy and effectively use data insights for decision-making, they encounter significant obstacles in fully utilizing advanced data competencies. Executives are proficient at integrating data with their intuitive judgment for daily operations, strategic decisions, and problem-solving, highlighting their skill in leveraging data for beneficial business outcomes while still valuing experience. However, a notable gap exists despite their strong data literacy. Top executives often struggle with advanced analytics tools. The educational background significantly influences these competencies, with those holding advanced degrees in fields like economics, engineering, and business administration generally having better data literacy.

Nevertheless, even among these individuals, there is a heavy reliance on essential tools such as Excel and limited use of more advanced platforms like SQL, Tableau, and Python. It indicates that while foundational data skills are present, there is a pressing need to enhance these abilities to exploit data-driven decision-making fully. The study also highlights a lack of systematic assessment methods within organizations for measuring data literacy and competency among senior management. Several key barriers to effectively embracing and utilizing data literacy were identified, including time constraints due to the demands of executive roles and the fast pace of technological change, which makes it challenging for leaders to keep up with new data tools and techniques.

Moreover, the study identified a notable shortage of formal training opportunities, with participant expressing a strong desire for more accessible and relevant educational resources to enhance their data literacy. Some leaders also lack the commitment to adopting data-driven approaches, which hinder data literacy and data competency. Data management challenges, including issues with data collection, storage, and analysis, also present significant obstacles. Another critical barrier is the inconsistency in fostering a data-driven culture across organizations. While data utilization is increasingly recognized at the executive level and across various departments, traditional methods persist in some areas, leading to uneven advancement in data-driven practices. The allocation of resources for data literacy initiatives also varies widely across organizations, with some demonstrating a solid commitment and others exhibiting minimal engagement, often due to financial constraints.

Recommendations

To enhance data literacy and data competency among top management, implement systematic assessments to regularly measure skills, develop standardized tools such as competency-based evaluations or data literacy scales for evaluating both basic and advanced data skills, and use results to guide training programs. Invest in comprehensive training on advanced data analytics tools and techniques, making it accessible and tailored to management's needs. Promote a data-driven culture by embedding data literacy into organizational values, encouraging data use in decision-making, and fostering collaboration to break down data silos. Allocate sufficient resources for technology, training, and support to ensure continuous improvement and professional development in data analytics.

Limitations

This study offers valuable insights into data literacy and competency among top management in Belgian companies but has several limitations. The small sample size of 10 participants may not represent the diversity across different industries, making generalization difficult. It relied on self-assessed knowledge from interviews rather than systematic measurement tools or practical tests, limiting the accuracy of data skill quantification. Additionally, interview-based assessments may introduce bias, as participants might exaggerate their data capabilities.

Future Research

- Future research might include a broader and more diversified sample of senior management from different industries and organizational sizes. It would allow us to generalize the findings further and understand how data literacy and skill differ across industries.
- Instead of relying exclusively on self-evaluations, future research may use objective measuring methods or practical examinations to assess data literacy and proficiency. It would offer a more accurate representation of the participant's skills and enable a thorough investigation of their data competency.

- Future research can be a longitudinal study, which might help us understand how data literacy and competency vary over time, particularly in response to changes in technology, training, or corporate culture.
- Research might look at how data literacy and data competency in top management vary between countries or cultural contexts, offering a broader global perspective on the problem.
- Future research might look at the link between the use of various data tools and the skill levels of top management, determining which technologies are most suited to enhance data-driven decision-making.

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APPENDICES

Appendice 1: Interview Questions

Introduction:

I am Janet Biodun-Bello, and I am currently studying at Uhasselt, majoring in Master of Management - Data Science. My research topic is "Data Literacy and Data Competence for Effective Decision-Making: A Qualitative Study on Top Management in Companies in Belgium."

According to research, leaders often struggle to fully trust data when making decisions due to their innate expertise in traditional decision-making methods (Brown, 2023). They utilize their gut feelings to make judgments and rely on data scientists to offer "processed information" because they lack formal training or experience in these areas (Rossi, 2017).

This research aims to understand the main barriers preventing top management from adopting and effectively using data literacy and data competencies in decision-making processes and how these competencies can be measured among top management.

This interview will be conducted for approximately 30 minutes, and you are free to avoid any questions that make you feel uncomfortable. There are no right or wrong answers.

Cluster 1: Socia-demographic data

- What is your name?
- What is your education?
- What is your job title?
- Where do you work?
- What country are you from?

Cluster 2: Measuring Data Literacy and Data Competencies Among Top Management

Understanding Data Literacy and Competency:

- How would you define data literacy and data competency in your own words?
- Can you describe your familiarity with data analysis and interpretation?

Educational Background:

- How does your educational background support your understanding of data literacy and competencies?
- How does any training you did recently support your understanding of data literacy and competencies?
    - What additional educational opportunities would you find beneficial?

Assessment Methods:

- What methods or tools does your organization currently use to assess data literacy among top management?
    - How effective do you find these methods in accurately measuring your data skills?

Skill Levels:

- Which data analytics tools and software are you most comfortable with e.g SQL, Python, power BI, Excel, and Tableau?
- How frequently do you use data analysis tools and software in your daily activities?
    - How would you rate your proficiency in using these data analytics tools and software?
    - Can you describe a specific project where you applied one of these tools or software to extract information and visualize data?
- Do you know statistical concepts?
    - Can you explain the difference between correlation and causation with an example?
    - Can you explain statistical terms like probability, standard deviation, and regression?
    - How do you decide which statistical method to use for a particular data set?
- How do you ensure the data you use is accurate and reliable?

Knowledge Application:

- How often do you integrate data insights into your regular decision-making process?
    - Can you provide an example of a time when you utilized data to make a strategic decision?
- Describe a time when you identified a significant problem using data. What steps did you take to resolve it?
- Have you ever had to convince a stakeholder to change their perspective based on your data analysis? How did you do it?
    - Can you describe a specific instance where data literacy positively influenced a business outcome?
    - Can you provide an example of a successful data-driven presentation you gave?
- How do you personally advocate for and model data-driven decision-making in your role?
- How do you balance data-driven decisions with intuitive decision-making?

Cluster 3: Barriers to Adopting and Effectively Using Data Literacy and Competencies

Challenges in Adoption:

- Can you identify any specific skills or knowledge gaps that make it challenging for you to become proficient in data literacy?
- Are there any tools or technologies related to data that you find challenging to use or understand?
- Have you encountered any organizational resistance or cultural factors that hinder your ability to adopt data literacy?
- Do you think any structural or policy-related barriers within your organization affect the development of your data competencies?
- Are there any other challenges or barriers that hinder you from being proficient in data literacy and data competencies?

Organizational Culture:

- How would you describe the culture of data use within your organization?
- What steps do you think are necessary to foster a more data-driven culture?

Resource Allocation:

- Do you think your organization allocates sufficient resources toward improving data literacy among top management? Why or why not?
- What additional resources or support would help you better utilize data in your role?

Trust in Data:

- How much do you trust the data provided to you for decision-making?
    - What factors influence this trust?
- Can you share an experience where data quality issues impacted your decision-making process?

Role of Data Scientists:

- To what extent do you rely on data scientists for processed information?
- How do you ensure that you understand and can act on the insights provided by data scientists?

Cluster 4: Additional questions

Client Understanding:

- To what extent do your clients truly grasp and value the data insights you provide them?

Future Outlook:

- How do you see the role of data literacy and competencies evolving in top management over the next five years?
    - What future challenges and opportunities do you anticipate in this area?

Thank you for giving me the opportunity to interview you for my research. Your insights and answers are valuable to this research.

Appendice 2: Transcript

These interviews were transcribed by me and have been edited for clarity and conciseness. To ensure accuracy, I carefully reviewed the audio files multiple times during the transcription process.

A1

Measuring Data Literacy and Data Competencies Among Top Management

Understanding Data Literacy and Competency:

- **How would you define data literacy and data competency in your own words?**

I think it's that you know where to find things or where to find the information that you're looking for, that there are different systems and that at least you are aware of it. And then competency is then really, for me, really how you can do searches in those databases and find what you need. I mean, not what you think you should find, but you know, have the right questions, ask the right questions. Yeah, yeah, that's great. That's basically the summary of data literacy.

- **Can you describe your familiarity with data analysis and interpretation?**

I think a little bit about the area that I work in. So, yeah, in the pharmaceutical industry and analyzing trends in the projects that I'm working on and interpreting them. But I don't think that I am a big data analyzer or data scientist, not at all. I think when I know the subject, I know where to look and how to do it, but yeah.

Educational Background:

- **So how does the educational background support your understanding of data literacy and data competencies?**

When I was educated, I was not aware of these systems and I think they didn't even exist, these online systems that came later, I'm afraid. So at the time, yeah, it was a long effort to look everything up and to combine it to get something useful out of it.

- **And so then recently, do you have any training about data literacy or data competency?**

I just, yeah, I ask with my colleagues and who I know are probably, yeah, have done more analysis that way, where to look things and which systems to look and how to do it. And then I try myself and then I discuss it with colleagues because I don't think I am super competent. I'm already happy that I know where to look and what to look for.

And then I always like to discuss with other people the findings and if the questions were right, yeah. That's great. That's a step in data analysis.

Assessment Methods:

- **So what method or tools does your organization currently use to access data literacy among top management?**

No. Not that I know of.

Skill Levels:

- **So which data analytics tools and software are you most comfortable with?**

Excel and Tableau we use. You can put a lot of things in Excel and do some analysis. Tableau we use for our financial planning.

So yeah, I use it to put data in it but I don't really use Tableau to retrieve data. I am more looking into some, what is it called? Pharma. Pharma data? Yeah, pharma data.

It's more really to get scientific information about new products or about clinical data, those kinds of things, not financial data. Because of this, I think it's more like finance and so. we use them for any type of data.

- **How frequently do you use data analysis tools and software in your daily activities?**

it's not frequent. Not on a project, yeah, yeah, yeah. Or when I want to get a larger overview what is the competition doing or are there already other products on the market which look a little bit similar.

- **How would you rate yourself when it comes to your expertise with these tools?**

Not more than medium.

Tableau, less. Excel, I can find my way a bit, yes.

- **So can you describe a specific project where you applied one of these tools or software to extract information and visualize data?**

You think, oh, I do this, and this will come out. And then when it's unexpected, then you start, yeah, filling in all the data in Excel and looking at it to check what happens. So yeah, for example, I did in the past for permeation rate of packaging materials.

And then, yeah, if you fill in all the data of all the details of the package, you can, yeah, visualize the data. And that helps you in see, ah, yeah, you can see a common theme or maybe two different groups or so, then you see that, yeah. That's good.

- **So do you have knowledge of statistical concepts like correlation, causation, or probability, standard deviation, regression?**

Yeah, correlation is when there is a, yeah, a correlation between two things, but that doesn't, a causation is that one is the result of the other. Yes. For example, there's a correlation between low education levels and voting for extreme right.

Probability is sort of the likelihood that something will happen. And the standard deviation is then sort of how, how the chance, the width of the probability, if you want.

And regression is actually, yeah, when you say that it's the relation of a variable, of an independent variable with different other variables that may be dependent. So, you can see with the regression of these other variables dependent on that, yes or no. So great.

Yeah, you do. But I don't know how statistical, I have a colleague. That's my statistical expert.

Yeah, but you know these terminologies and that's where we start from. I know and I understand it when they tell me, but I go, we often use box plots and stuff like that. We visualize it, but I am not really sure.

- **So how do you decide which statistical method to use for a particular data set?** I go to my colleague and ask him. And he's a statistical expert of the team.

Do you accept it or do you just ignore it?

No, if I ask, I accept it.

- **How do you ensure the data you use is accurate and reliable?**

Ah, yeah, well, because the data are in my company, the data are actually achieved or reached by following certain procedures. So if you cannot, yeah, that I'm talking about internal data, of course. External data, yeah. That's why we work with certain search engines, like Science Direct and Pharma, what is it, Pharmaceutics or so. There are a couple of search engines and the information in there always comes from, yeah, how do you say that? Peer-reviewed sources.

And is it because these sources, they've been verified? Is that what you're talking about? Yeah, we can access them, yes. So they are J&J, yeah. There is somewhere a department who looks at, yeah, the trustworthy sources also to get our science.

Knowledge Application:

- **So how often do you integrate data insight into your regular decision-making process?**

For example, we use or we develop devices to put the drug that we develop in the body to administer it. And then we always, before we bring that to the market, we do usability studies, human factor studies, we call it.

And sometimes these humans, you think that you have really a perfect device and then it comes back and the data show that the users do not understand it, misuse it, they don't do accurate administration or so. And so, yeah, that happens more often than you can imagine. And then when you get- And so then, yeah, so you do the usability study and then, so it's actually with people who would normally either patients or healthcare providers who would administer and then they give all the feedback and then we change the device, we have to.

So, yeah, we change, we modify the project as it goes based on the feedback and the failures that we see. So, yes. And that's good, that's good.

But that's also, yeah, you use statistics for that too. But it's, yeah. Yeah, the probability that that's gonna work on this.

Yeah, yeah, yeah. But it's, yeah, it's usually, like, they say that if you, even only with eight users, using a device, you can find more than 90% of the mistakes people will make. So you don't need more than that.

Thousands of people. No, you don't need thousands of people. You take eight people and you can find.

And then later at the end, maybe you want a bigger group, but yeah, you can find most of the things with a small sample. Yeah, yeah, that's true.

- **So describe a time when you identified a significant problem using data?**

Oh, well, yeah, once with the devices. So we saw really a major problem. And then, yeah, we had to, we went to the supplier of the device.

And together, yeah, we discussed the issues. And then he modified the design.

- **Have you ever had to convince a stakeholder to change their perspective based on your analysis?** And how did you do that?

I think probably I am lucky because most of the people that I'm working with directly are science-based, but yeah. So often you can convince people, but they keep coming back, yeah. Yeah.

And you think you've convinced them. So yes, I think the only thing you can really do is making, yeah, making the case, showing the data, but also maybe make a story around it. So yeah, tell the story of what's happened, not just the graphs and the figures.

- **Can you describe a specific instance where data literacy positively influenced a business outcome in your company?**

Maybe you got insight from a data and then you're able to increase your revenue or you're able to get more customers. Yeah, but I'm not in that kind of business.

It's more with us, it's more like on the science and then you would go for, you would modify the project or so, for example, you developed a kind of a tablet for children and then you do some tests on acceptability with children and then you find that they can't swallow it because it sticks in the throat or so. And then you have to go back and modify the design of your tablet or maybe go for a powder or so, which is easier for the kids, something. This is more the area that I work in.

- **How do you balance data-driven decisions with intuitive decision-making?**

Oh, yeah, it's always based on data, yeah.

Barriers to Adopting and Effectively Using Data Literacy and Competencies

Challenges in Adoption:

- **can you identify any specific skills or knowledge gaps that make it challenging for you to become proficient in data literacy?**

Yeah, well, I don't think I ever had a course in data. Analysis or even like, you know, the ground layer. That was not part of the education I had. And that's really a shame because a lot of science these days, I think also, and in the past it was only about finance, but I think now science is also based on that. So much is happening around the globe and yeah, you cannot keep track by reading one or two or three papers even.

I miss it, I don't think I have enough knowledge, but even new masters or engineers are so fresh from university. They don't know that either.

They don't know that. It's only by doing that you learn. And that's a really a gap, I think.

In my education, but in certainly of the new generation. No, they just put a different distance between them, you'd go engineering. We have people that study data.

Yeah, and I think as an engineer, as a scientist, you have to know how to do that too, for different reasons and in different. Yeah, yeah, that's true. Are there any tools or technologies related to data that you find difficult to use or understand? Ah, statistics. And to know which to use for what, which. Yeah, but you asked that, which method to use for what. I know, and then my colleague explains to me.

- **Have you ever encountered any organizational resistance or cultural factors that hinder you and that hinder your ability to adopt data literacy?**

Oh, I think, yeah. I think experienced people can be young or old, but people with a certain experience, they may be adverse to using data and they base themselves on their experience, I think. So that's what you notice.

And then you have this hearsay, because in one project this happens and then they extrapolate it to all other projects. We are struggling in the team at the moment. And then even with all the examples that you show, no, and this happened in that project for this and this reason, they extrapolate it to all future projects and they want you to do something, but there is nothing to do, because that was a very specific case and it's limited to there.

So, yeah, and experience versus data.

So if I understood you correctly on this question, the resistance is mainly based on people who already have experience.

So they do things based on their experience rather than changing their perspective or doing something to it, okay.

- **Do you think there are any structural or policy-related barriers within your organization that affect the development of your data competency**?

No, I don't think it's structural, but it's not policy-related, but sometimes political.

Yes, like always. Okay, are there other challenges or barriers that hinder you from being proficient in data?

Time. I think I would like to dig into that, but there's never time.

Organizational Culture:

- **How would you describe the culture of data use within your organization?**

I think it's pretty good. Yeah, because it's necessary, yeah. I think, of course, we use it for the financial aspect, but also for the results, for the evaluation of our clinical studies.

It's all about data science. It's, I think, only some time. And also, yeah, on developing, we are now setting up models to develop new medicines.

So yeah, I think it's very much focused on that because you can do a lot, you can evaluate a lot more and focused when you use data science. So yeah, I think the organization as such is really interested in that.

- **what step do you think are necessary to foster a more data-driven culture?**

I don't think everyone in the organization is fully on board or really gets it, especially some of the more practical teams, like the local engineers on the line. They've got to focus on keeping things running, so it's tough for them to take a step back and analyze where problems might be coming from. They just don't have the time. I think what they really need is some training or mentorship, just more support overall. So yeah, I guess we should be looking at allocating more resources towards that.

Resource Allocation:

- **Do you think your organization allocates sufficient resources towards improving data literacy among the top management?** Why or why not?

Yeah, for some things, yes, and for some things, maybe not. Some things we, like we, we are in science and here, yeah, I know I can check with colleagues where to go, what to do, but then there's a lot of focus on the financial aspect and we have to fill this in and fill that in, but I never know how these data are treated and, you know, it would help and it would give a bit, yeah, more purpose if you understand better exactly what they do with it and that's sort of like a black hole you're dumping in.

- **So what additional resources or supports would help you better utilize data in your role?**

Some more explanation would be helpful, like I mentioned before, about what's going to happen with this data when it's sent out. But they never really do that because it's all tied up with company secrets or ownership, so they keep it under wraps. But sometimes it feels like we're just giving information without getting anything in return. It's like, you know, we're just dealing with 'the accountants,' and we don't really understand the purpose behind what we're doing.

Trust in Data:

- **how much do you trust the data provided to you for decision-making?**

Because I get them from the right sources. If I don't do that, then I don't know where to start. True, yeah, yeah.

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- **So can you share an experience where data quality issues impacted your decision-making process? Maybe we start first. Have you ever had a data quality issues?**

Sometimes you have to look for the correlation between factors and to evaluate.

Sometimes you see a correlation, but you don't always know what the cause is. That's not always a reason for the data quality, but maybe it's insufficient data or maybe we asked the wrong question. So, we have done the wrong tests to get the right answers.

Role of Data Scientists:

- **So to what extent do you rely on data scientists for this process information?**

Yeah, I know in the past I've done a project, but that, yeah, and we provided data and they did the analysis.

Additional questions

- **How do you see the role of data literacy and competency?**

It will keep evolving because of the increase in Big data.

A2

Measuring Data Literacy and Data Competencies Among Top Management

Understanding Data Literacy and Competency:

- How would you define data literacy and data competency in your own words?

Data literacy is the ability to understand data, its types, importance and the underlying systems requires to gather and store data. Data competency is the ability to derive meaningful results from analysing and manipulating data.

- Can you describe your familiarity with data analysis and interpretation?

We use data analytics for various goals. For example, we use machine learning algorithms to simulate demand, to predict performance and to project sales or profit. In engineering, data analysis is important to constrain tolerances in production, minimize waste and maximize efficiency.

Educational Background:

- How does your educational background support your understanding of data literacy and competencies?

My engineering background helps greatly. We took advanced mathematics in uni which paved the way for data literacy and competencies. Also, engineering thinking and logical thinking is a great asset for analyzing and understanding data. Additionally, MoM DS bridged the gap between mathematics and engineering with business.

- How does any training you did recently support your understanding of data literacy and competencies?

I took an online course in data science using python. It helped me understand data transformation, data cleaning, data analysis techniques.

  - What additional educational opportunities would you find beneficial?

Apart from technical training, Qualitative training is essential. In order to understand and benefit from data analysis results and to produce actionable goals.

Assessment Methods:

- What methods or tools does your organization currently use to assess data literacy among top management?

Currently we don't have a specialized test or assessment for data literacy in top management. But our time consists of engineers and technical people who are well established in the domain.

  - How effective do you find these methods in accurately measuring your data skills?

Skill Levels:

- Which data analytics tools and software are you most comfortable with e.g SQL, Python, power BI, Excel, and Tableau?

Python and SQL

- How frequently do you use data analysis tools and software in your daily activities? Almost daily. Varying from engineering analysis to business intelligence tasks.

  - How would you rate your proficiency in using this data analytics tools and software? 4/5

- Can you describe a specific project where you applied one of these tools or software to extract information and visualise data?

Doing a business study for a client. We designed an automation solution for a food production business and recorded data from the machines which was used to simulate performance over 5 years and to produce a cost benefit study.

- Do you have knowledge of statistical concepts? Yes
    - Can you explain the difference between correlation and causation with an example? Correlation is when two datasets exhibit similar patterns. Causation is when one dataset affects the other and causes it to behave in a certain way.
    - Can you explain statistical terms like probability, standard deviation, and regression? Probablity is the likelihood that an event would happen. Standard deviation is how far a dataset is spread far from its mean or average. Regression is an approximation to a single line.
    - How do you decide which statistical method to use for a particular data set? Most applications require similar statistical methods. However, depending on the application. For example, a prediction problem would require regression tools, a classification problem requires other ML tools like random forests.
- How do you ensure the data you use is accurate and reliable? By testing over and over until the results make sense.

Knowledge Application:

- How often do you integrate data insights into your regular decision-making process? During the design process. Most of our designs are based on proven mathematical background.
    - Can you provide an example of a time when you utilized data to make a strategic decision? When deciding what type of company we were gonna be, we did a market research and crunched the data. We were deciding between manufacturing in house or outsourcing. After studying the market we found out that outsourcing would make more sense at the beginning with a plan to manufacture in house after a certain capacity.
- Describe a time when you identified a significant problem using data. What steps did you take to resolve it?

A significant problem was identified in our production line where the yield was consistently below the expected target. By analyzing the production data, we noticed a pattern indicating a specific machine was frequently malfunctioning. We conducted a root cause analysis, pinpointed the faulty component, and replaced it. Post-replacement data showed a marked improvement in yield, meeting our targets consistently.

- Have you ever had to convince a stakeholder to change their perspective based on your data analysis? How did you do it?

As I am the key decision maker, I don't really need to convince/change anyone's perspective.

- Can you describe a specific instance where data literacy positively influenced a business outcome?

We were deciding on a major investment in new technology. We conducted a data analysis of our current production metrics and potential improvements, and we were able to demonstrate the ROI of the investment. This data-driven approach led to the approval of the investment, which subsequently resulted in a 20% increase in production efficiency.

- Can you provide an example of a successful data-driven presentation you've given?

- How do you personally advocate for and model data-driven decision-making in your role?

I always ensure my decisions and recommendations are backed by data. I regularly share data insights during meetings, encourage team members to use data in their analyses, and offer to teach them data tools and techniques.

- How do you balance data-driven decisions with intuitive decision-making?

While I rely heavily on data for making decisions, I also consider my industry experience and intuition, especially in situations where data may be limited or inconclusive.

Cluster 3: Barriers to Adopting and Effectively Using Data Literacy and Competencies

Challenges in Adoption:

- Can you identify any specific skills or knowledge gaps that make it challenging for you to become proficient in data literacy?

Time?

- Are there any tools or technologies related to data that you find difficult to use or understand?

Not really, as long as you put time and effort into learning it, you can understand it.

- Have you encountered any organizational resistance or cultural factors that hinder your ability to adopt data literacy?

Perhaps from those who find it difficult to understand or use it.

- Do you think there are any structural or policy-related barriers within your organization that affect the development of your data competencies?

Lack of a formalized data literacy program

- Are there any other challenges or barriers that hinders you from being proficient in data literacy and data competencies?

Just time.

Organizational Culture:

- How would you describe the culture of data use within your organization?

Our organization is gradually becoming more data-driven, but there is still a reliance on traditional methods in some areas.

- What steps do you think are necessary to foster a more data-driven culture?

Providing regular training/education

Resource Allocation:

- Do you think your organization allocates sufficient resources towards improving data literacy among top management? Why or why not?

I can't really say.

- What additional resources or support would help you better utilize data in your role?

Time management so we can train further.

Trust in Data:

- How much do you trust the data provided to you for decision-making?

I generally trust the data, but I always verify it through cross-checking and validation.

- What factors influence this trust?

Data quality, source reliability, and consistency of results.

- Can you share an experience where data quality issues impacted your decision-making process?

We once faced issues with inaccurate sales data due to a reporting error, which led to incorrect forecasting and overproduction.

Role of Data Scientists:

- To what extent do you rely on data scientists for processed information?

I rely on them for complex analyses and insights.

- How do you ensure that you understand and can act on the insights provided by data scientists?

Communication and making sure I know what their methods are.

Cluster 4: Additional questions

Client Understanding:

- To what extent do your clients truly grasp and value the data insights you provide them?

Future Outlook:

- How do you see the role of data literacy and competencies evolving in top management over the next five years?

Data literacy and competencies will become increasingly critical as businesses rely more on data-driven strategies. Businesses will need to continuously update their skills to stay competitive.

  - What future challenges and opportunities do you anticipate in this area?

Keeping up with rapidly evolving technologies and ensuring data privacy and security. Opportunities lie in leveraging advanced analytics for strategic advantage and innovation.

Thank you for giving me the opportunity to interview you for my research. Your insights and answers are valuable to this research.

A3

Measuring Data Literacy and Data Competencies Among Top Management

Understanding Data Literacy and Competency:

- **So the first thing is, do you have an idea what data literacy or data competency means?**

I probably don't have a Wikipedia description for that, but.

Data literally to be to be able to. Understand data. Create data insights that you can use in decision making and competencies, then competency to transform that into actions.

Yeah. Amazing. Yeah, that's just that's just a simple definition. Thank you for that.

- **And can you also describe your familiarity with data analysis and interpretation?**

I would say quite familiar because I come from the study fields where data is.

At the central the data central both in economics and engineering. So yes, my study background supports that and also in business decisions and in the areas where I work and and like in every area, I think data is is very important.

Yeah, yeah. So you're familiar with interpreting data and analysing it. OK, that's great.

Educational Background:

- **how does your educational background support your understanding of data literacy and data competency?**

My study fields really support my decision-making. For example, in economics, I learned about how people make choices and their preferences, which helps me understand customer behaviour. In engineering, I studied risk management, using probability and analysis to predict potential outcomes. I also learned to use business data to understand how companies make decisions and how effective those decisions are, which helps predict future decisions. It's a very data-driven approach

- **And do you have any training recently that support your understanding of data literacy competencies like, do you have any training that relates to data or anything recently**?

Not enough, I would say that my only training comes from our own finance team because we have lately developed more reports.

So margin report, customer reports product portfolio reporting. So my only training is that they're guiding me on how can I myself philtre and create views from our power BI, but it's very operational training but not no training really more like big data.

- **So what training would you find beneficial like? Would you really find really that you benefit from if you had to get the training on ?**

I'm still getting familiar with our company's specific data and terminology. While it seems straightforward when others show it to me, I struggle when trying to use it on my own. It would be really helpful to have a resource like a Wikipedia for our internal data definitions. Additionally, I've worked with digital data but I'm interested in learning more about big data and how advanced companies are using it. I think exploring this could also inspire our leadership team.

Assessment Methods:

- **That's nice. OK, So what methods or tools does your organisation currently use to access data literacy among top management?**

We’ve developed a system called One Data, which centralizes a lot of our data using Power BI for reporting. We also purchase market studies and use external sources like Euro Monitor and Mintel to gain insights into competitors and market trends. Additionally, we conduct an annual 360 study where we ask our global sales and marketing teams for information on competitor activities. However, we don’t yet have advanced digital methods for tracking customer behavior and needs, though it's something we plan to develop.

Regarding how leaders understand and access this data, we don’t have a systematic way to measure their data literacy. It’s a bit disorganized; there’s no formal onboarding process for data access and training. I’ve had to navigate this on my own, and we don't currently measure how well top leaders grasp the data.

Skill Levels:

- **Which data analytics tools and software are you most comfortable with?**

I’m not a programmer, so I’m not directly using SQL or Python, but I understand what they do. I’m familiar with tools like Power BI, Excel, and Tableau. I’ve used Power BI, and while I appreciate its capabilities and how it can simplify tasks, I’m not very comfortable with it. I tend to use it on a need-to basis and wish I could be more self-sufficient for in-depth analysis, but I struggle with finding time to get better at it.

Excel is another story, I will say I’m an average-plus user. I’m comfortable with it, including using pivot tables, and manage quite well with it.

- **how frequently do you use these tools and software on a daily activities?**

Not on a daily, not every day, but every week.

Excel I use every day for something, yeah.

- **can you describe a projects where you applied one of these tools? I think power BI and excel.**

Yes, I use Power BI to visualize data, particularly for a project on improving our product portfolio management. We focus on both creating new products and assessing the health of our current portfolio to make decisions about what to phase out. I’m leveraging practices from another business unit that handles this well.

For deeper analysis, I use Excel in addition to Power BI. I start with basic reports in Power BI and then export data to Excel for more detailed analysis.

- **Do you have knowledge of statistical concepts?**

Yes, I understand the difference between correlation and causation. For example, if there's a positive correlation between a person's age and the need for certain support tools, it means that as age increases, the need for these tools also increases, but it doesn’t mean that age causes this need.

I’m familiar with statistical terms like probability, standard deviation, and regression, though I use these methods less frequently now. My focus is more on qualitative observations, such as analyzing differences in how different regions or leaders use data. I notice that those who are more data-driven tend to perform better, but I don't always apply formal statistical methods to these observations.

To ensure data accuracy and reliability, I rely on the data provided by our business units.

- **So how do you make sure on your own that these data are accurate and reliable?**

To ensure data accuracy and reliability, I sometimes spot-check and validate information by reaching out directly to the business units or finance to confirm that reports are correct and that I understand them properly. This approach helps me ensure that the data I'm working with is accurate.

Knowledge Application:

how often do you use data insights like the insights you get from data? How often do you?

The use of data in my decision-making varies depending on the type of decision. For major decisions related to products and customers, data is essential for me. However, I also incorporate qualitative information alongside quantitative data. As a leader, I often need to make decisions even when I don't have full insights, so I use data to support my decisions but also rely on intuition and other qualitative factors.

- **Can you provide an example of a time when you utilized data to make a strategic decision?**

For example, when choosing between two CRM systems, I look at numerical data like license costs and functionality. But I also collect qualitative data by reaching out to companies with experience using these systems to understand their pros and cons. This combination of data helps shape my decision, even though it might not be perfect. I use both quantitative and qualitative information to make well-informed decisions and justify them, especially when navigating complex internal politics.

- **So describe a time where you identify a significant problem using data?**

A significant issue we faced with using data was during the rollout of customer portals at Azelis. We discovered that the best-performing portal had a different organizational approach behind it, with a clear strategic management plan. Analyzing the data showed that effective management and organization were crucial for success, not just the implementation of the portal itself. The data revealed that differences in customer logins and portal usage were tied to how the local teams managed and organized their processes. This was a major revelation, demonstrating that success with new tools requires proper organization and strategy, rather than just launching something new and expecting it to work.

- **You ever had to convince a stakeholder to change your perspective based on your data analysis?**

I don't know what would be a good example here?

Change completely like change perspective based on data analysis.

I don't have a perfect example.

- **And can you also describe a specific instance where data literacy possibly influences a business outcome**?

Yes, data analysis has positively influenced business outcomes. For example, in a previous project, we discovered that managing various customer payment terms was creating unnecessary complexity and additional work. By making this data visible and showing the impact on operations, we were able to standardize payment terms, which improved efficiency and reduced administrative effort.

- **How do you personally advocate for data-driven decision making in your role?**

Yes, I advocate for more data-driven decision-making in my current role. For instance, with managing our product portfolio, I emphasize the need for data to guide decisions. I also use data to identify and address inefficiencies in our business processes. For example, I found that creating an asset code for a new product took one month, whereas it should be done in a week. By highlighting these delays and the unclear roles and communication involved, I aim to improve our processes and make more informed business decisions. This approach helps in clarifying responsibilities and enhancing overall efficiency.

- **How do you balance data driven decisions with intuitive decision-making?**

I'm currently supporting a project focused on managing distribution for one of our regions. Data plays a crucial role here: first, to highlight the number of small customers we're directly managing and whether it's efficient for us to handle them directly from afar, such as in Africa or the Middle East. By analyzing this data, we can assess if we should partner with local distributors who have a better regional presence. I'm also using data to understand the effectiveness of our current distributors. For example, analyzing the volumes and performance of these partners helps in deciding whether to consolidate or expand our distributor network. It’s essential to communicate the importance of scale and reduce fragmentation to enhance efficiency. This involves not only having accurate data but also explaining its implications to stakeholders to make informed decisions.

Barriers to Adopting and Effectively Using Data Literacy and Competencies

Challenges in Adoption:

- **Can you identify any special skills or knowledge gaps that make it challenging for you to become proficient in data literacy?**

One barrier to effectively using data is the lack of training within the company. Although we’ve made progress with Power BI, having more advanced training would help me work faster, more efficiently, and more professionally.

- **I think you already answered this one because the next question is if there are any tools or technology related to data that you find difficult to use or understand?**

I think your power BI.

- **have you encountered any organisation, resistance or cultural factors that hinder you enter your ability to adopt?**

Another barrier is the fixed mindset and departmental silos. In my current business, there was historically less demand than capacity, which made it easy to be complacent. Now, with increased competition, there's a need to shift to a more customer-focused mindset.

Additionally, some people are reluctant to adopt new technologies due to unfamiliarity and disbelief in their value. They prefer sticking to established methods and may not fully invest in or embrace digitalization efforts.

- **So do you think there any structure, structural or policy related barrier within your organisation that affect the development of your data competency? Like, is there a policy?**

No.

Organizational Culture:.

- **So how would you describe the culture of data usage within your organisation?**

Our basics for handling commercial data are solid, and we have good insights into managing operations. However, when it comes to more advanced data, like understanding customer needs, it varies. Our approach is more dependent on individual managers and their level of expertise.

- **what steps do you think are necessary to foster a more data-driven culture so to encourage more data, different culture?**

To enhance our data-driven culture, we should focus on internal stimulation and knowledge sharing. Prioritizing this topic in global leadership meetings and showcasing how data informs decision-making can be more effective than hiring external consultants. Using our own examples and practices to demonstrate the value of data is a powerful approach.

Resource Allocation:

- **Do you think your organisation allocates sufficient resources towards improving data literacy among top management?**

No, I I think probably you get a bit of like no from everyone. So no, I don't think it's enough.

- **What additional resources or support would would help you better utilise data in your role?**

BI and training resources.

Trust in Data:

- **And so now we talk about trust in data. How much do you trust the data provided to you for decision making?**

I would say that quite I trust quite much.

I know the people that are dealing with a lot of the data creation, so I think I don't have a big mistrust. I know that system can sometimes be manipulated that people don't use the system the same way. So we have to be critical about the.

The the outcomes, but overall, I would say that quite I trust quite my trust is quite good.

- **And also an additional question, how much do you trust the insights you get from data?**

Depends on the data source.

- **Can you also, have you ever have an experience with data quality issues that impacted your decision making process?**

Yes. I'm trying to remember because I thought I have had issues. Yes, so there has been. Yeah, I don't have again, like a perfect example, but yes, they have. Of course. I think, yes, I have had issues.

Role of Data Scientists:

- **To what extent do you rely on data sciences or processed information?**

Yes.

- **And how do you ensure that you understand and can act on the insight provided by the data analysts?**

By first of all, asking them that I understand what they're doing, what they that they have done, and then like I discussed earlier. I then used my network then to validate.

Thank you so much for your time. I really appreciate it and.

A4

Cluster 2: Measuring Data Literacy and Data Competencies Among Top Management

- **How would you define data literacy and data competency in your own words?**

Just taking it, my understanding of it, it would be like how well you understand data and how well you use this data in order to achieve business goals."

- **Can you describe your familiarity with data analysis and interpretation?**

Well, in my role, most of the data that I look at are financial data."

- **How does your educational background support your understanding of data literacy and competencies?**

Honestly, very little because I graduated with a marketing degree, mostly."

- **What methods or tools does your organization currently use to assess data literacy among top management?**

I don't think it's being done. It's not being done? You don't measure it? Yeah, we don't measure it.

- **Which data analytics tools and software are you most comfortable with e.g SQL, Python, Power BI, Excel, and Tableau?**

So what data analysis tools and software are you most comfortable with? So I'm going to mention some software just to give us like SQL, Python, Power BI, Excel, Tableau. Which one of these have you used before and are you comfortable with? We've only used Excel, but is SAP a part of it?

- **How frequently do you use data analysis tools and software in your daily activities?**

And how frequently do you use data analysis tool and software in your daily activity? So you say you only use Excel. How often do you use this? Every day.

- **How would you rate your proficiency in using these data analytics tools and software?**

Can you describe the specific, how would you rate your proficiency in using this Excel? Me? I can open it. I can type numbers. I can do basic computations. But the rest, my staff will do it.

- **Do you have knowledge of statistical concepts?**

I just want to know your knowledge of statistical concepts. Can you explain the difference between correlation and causation? Yeah. Correlation is there's a direct link. Causation is there's, you know, it might not be the cause.

- **How do you ensure the data you use is accurate and reliable?**

How do you ensure the data you use, the data provided to you in this case, is accurate and reliable? Okay. So for me, I always start with the raw data.

Cluster 3: Barriers to Adopting and Effectively Using Data Literacy and Competencies

- **Can you identify any specific skills or knowledge gaps that make it challenging for you to become proficient in data literacy?**

Yeah, for me, I hate doing it. I hate analyzing it. I just want the results already.

- **Are there any tools or technologies related to data that you find difficult to use or understand?**

Now with ChatGPT, no.

- **Have you encountered any organizational resistance or cultural factors that hinder your ability to adopt data literacy?**

Yeah. Like I said, my boss is not, he's not data driven.

- **Do you think there are any structural or policy-related barriers within your organization that affect the development of your data competencies?**

Yes. Like I mentioned, we don't have, there's SOP in place, but at the end of the day, they just do whatever they feel like.

Cluster 4: Additional questions

1. **How do you see the role of data literacy and competencies evolving in top management over the next five years?**

It's going to be with the rise of AI and all that everyone's going to be using.

A5

Cluster 2: Measuring Data Literacy and Data Competencies Among Top Management

Understanding Data Literacy and Competency:

- **How would you define data literacy and data competency in your own words?**
    - It's the knowledge of handling data to what data is, what you can do with it, how you can manage data, how you can report data. How you can, yeah.
- **Can you describe your familiarity with data analysis and interpretation?**
    - I have had statistics during my education. And I, so basic knowledge of statistics, I know because I'm a commercial engineer. And during my, so what I am using is management by statistics, management by data.

Educational Background:

- **How does your educational background support your understanding of data literacy and competencies?**

You get to have a good knowledge about statistics. It's 30, 40 years ago. So it's a bit far away. But it's just to have good insights. It's just that you, for instance, thinking in terms of probability, all these things that for me is that familiar.

- **How does any training you did recently support your understanding of data literacy and competencies?**
    - Recently, I didn't have had trainings. Last training, that was a long time ago. You mentioned the management by statistics. Yes, but that's 20 years ago
- **What additional educational opportunities would you find beneficial?**

I never did it because I had my people around me know the technical part of Power BI and SQL and all these things.

Assessment Methods:

- **What methods or tools does your organization currently use to assess data literacy among top management?**

No. Okay. But people working in my company, no, we don't measure it. It's just an opportunistic way. So we have to do something.

- **How effective do you find these methods in accurately measuring your data skills?**

But after they're done learning, how do you know, like they actually grasp what they learned or. But the results, if I ask some reports or something like that, yeah, then I cannot get the reports. Okay. Then indirectly.

Skill Levels:

- **Which data analytics tools and software are you most comfortable with?**

Excel.

How would you rate your proficiency in using these data analytics tools and software?

I use more data to manage people, basically. Yes. **Do you have knowledge of statistical concepts?**

Yes.

- **Can you explain the difference between correlation and causation with an example?**
    - Correlation is that there's a relationship between two factors. If one goes up, then you know that the other one all goes up or down, but it's always the same. But you don't know really why. It's like that. And the causation is that there's a cause from one factor to another one. It's a cause.

- **Can you explain statistical terms like probability, standard deviation, and regression?**

Probability is of course, let's say you have a 95% probability, then you know for this 5% that's possible that it's noticed. If you're the higher probability you want, then your survey has to be more in depth or bigger survey to get more probability. And deviation, standard deviation is that the bigger the standard deviation is, the more distance that certain things are to the average.

- **How do you ensure the data you use is accurate and reliable?**

Well, checking with reality.

Knowledge Application:

- **How often do you integrate data insights into your regular decision-making process?**

Normally weekly or monthly.

- **Can you provide an example of a time when you utilized data to make a strategic decision?**

So when you are giving the data from your employees, how do you know that this data is accurate and reliable? Well, checking with reality. Empirical

Describe a time when you identified a significant problem using data. What steps did you take to resolve it?

Well, for instance, in my administration, I had the data. I asked to make data for all the different things that administration did.

- **Have you ever had to convince a stakeholder to change their perspective based on your data analysis? How did you do it?**

Have you ever had to convince a stakeholder to change your perspective based on your data analysis? How do you do it? Change what? So like you have like your stakeholders, like your. Yeah, for instance, that was that example that I gave.

- **Can you describe a specific instance where data literacy positively influenced a business outcome?**

Not explicitly mentioned but inferred from various responses about using data for decision-making and management.

- **Can you provide an example of a successful data-driven presentation you've given?**

Not explicitly mentioned in the transcript.

- **How do you personally advocate for and model data-driven decision-making in your role?**
    - By showing them the results of having that data and what they can do with that one.
- **How do you balance data-driven decisions with intuitive decision-making?**
    - I always do both. And never do only data on data. Always when I get data, I'm always critical. Always critical.

Cluster 3: Barriers to Adopting and Effectively Using Data Literacy and Competencies

Challenges in Adoption:

- **Can you identify any specific skills or knowledge gaps that make it challenging for you to become proficient in data literacy?**

For me, it's all this kind of software. For me, it's that I don't have the time to learn it. So my main barrier is time.

- **Are there any tools or technologies related to data that you find difficult to use or understand?**

No, it's just the software and for the rest, I think most of the things I understand.

- **Have you encountered any organizational resistance or cultural factors that hinder your ability to adopt data literacy?**

Sales, because they know that data controls them, but for the rest, no.

- **Do you think there are any structural or policy-related barriers within your organization that affect the development of your data competencies?**

It's pure opportunistic in our company. Some people say, yeah, you are responsible for reporting, so you do the training, and you're not responsible, you don't do training.

- **Are there any other challenges or barriers that hinders you from being proficient in data literacy and data competencies?**

No. Apart from time? Okay. Time, yeah, time always.

Organizational Culture:

- **How would you describe the culture of data use within your organization?**

People use data every day, every week, marketing, finance, and sales, all of them.

- **What steps do you think are necessary to foster a more data-driven culture?**

I think maybe basic training from something, reporting models, for instance.

Resource Allocation:

- **Do you think your organization allocates sufficient resources towards improving data literacy among top management? Why or why not?**

By the last two or three years, not. But now we decided to, that decision two months ago, my executive assistant was already good at reporting, will have more time to do so.

- **What additional resources or support would help you better utilize data in your role?**

I think that person will have more time. So, it's especially that time.

Trust in Data:

- **How much do you trust the data provided to you for decision-making?**

I don't have high trust. You have also data that's fraud. Because you have a lot of false data.

Some data trust more than other data. But if data is incorrect because somebody changed data or fraud, then it happens. I have always been critical.

Role of Data Scientists:

- **To what extent do you rely on data scientists for processed information?**

I get each week my reporting.

- **How do you ensure that you understand and can act on the insights provided by data scientists?**

And when they bring the data to you, do you understand, and you can act on insights based on this data yourself? Yeah. When I don't understand, I don't want to have it.

A6

Understanding Data Literacy and Competency:

How would you define data literacy and data competency in your own words? A: Data literacy involves managing, reading, storing, and analyzing data, understanding its importance, and being aware of regulations like GDPR. Data competency includes being up to date on when and how to use data effectively.

Can you describe your familiarity with data analysis and interpretation? A: In my previous job at STDM, I analyzed financial statements and verified the accuracy of reported data. As a recruiter, I handle sensitive personal information and ensure its proper use and confidentiality.

Educational Background:

How does your educational background support your understanding of data literacy and competencies? My education in HR management covered the importance of GDPR and the legalities of data storage. It emphasized the need to delete or provide data upon request and the penalties for data misuse.

What additional educational opportunities would you find beneficial? A: Staying updated on laws and best practices, and learning about new tools like applicant tracking systems to safely store and manage data, would be beneficial.

Skill Levels:

Which data analytics tools and software are you most comfortable with (e.g., SQL, Python, Power BI, Excel, Tableau)?

I mostly use Google Sheets and Excel.

How frequently do you use data analysis tools and software in your daily activities? Daily. I always have Excel sheets open for various tasks.

How would you rate your proficiency in using these data analytics tools and software?
I would rate myself 7 out of 10 in using Excel and Google Sheets.

Can you describe a specific project where you applied one of these tools or software to extract information and visualize data? I use Excel to filter and visualize data from a list of companies. For example, filtering companies in the automotive industry within a specific region to match candidates' preferences.

Do you have knowledge of statistical concepts?

Yes, I studied statistical concepts in university, understanding that correlation indicates a relationship between variables, whereas causation indicates one variable directly affecting another.

Knowledge Application:

How often do you integrate data insights into your regular decision-making process?

Daily. We match candidates to companies based on updated data about job vacancies and company requirements, making decisions accordingly.

Can you provide an example of a time when you utilized data to make a strategic decision? We frequently update company data to match candidates with job vacancies accurately, ensuring effective decision-making.

Describe a time when you identified a significant problem using data. What steps did you take to resolve it? Occasionally, we encounter duplicate data or outdated company information. We resolve this by removing duplicates and verifying the latest data from reliable sources.

Have you ever had to convince a stakeholder to change their perspective based on your data analysis? How did you do it? Yes, by presenting detailed data analysis and insights, I was able to demonstrate the benefits and convince stakeholders to consider alternative strategies.

Can you describe a specific instance where data literacy positively influenced a business outcome? Accurate data matching has significantly improved our recruitment process, leading to better placements and satisfied clients.

Can you provide an example of a successful data-driven presentation you've given? I once presented a data-driven analysis of job market trends, which helped a client refine their recruitment strategy and improve hiring outcomes.

How do you personally advocate for and model data-driven decision-making in your role? By consistently using data to inform decisions and demonstrating its value in achieving business goals, I encourage a data-driven culture.

How do you balance data-driven decisions with intuitive decision-making? While data provides a foundation, intuitive decisions are based on personal interactions and understanding the culture of both the company and the candidate. For instance, matching a candidate's personality and requirements with a company's environment, even if not all data points align perfectly.

Cluster 3: Barriers to Adopting and Effectively Using Data Literacy and Competencies

Challenges in Adoption:

Can you identify any specific skills or knowledge gaps that make it challenging for you to become proficient in data literacy? IT knowledge, such as learning Python or other advanced tools, and staying updated on the latest data analysis technologies can be challenging.

Are there any tools or technologies related to data that you find difficult to use or understand? Learning advanced tools like Python can be challenging without a technical background.

Have you encountered any organizational resistance or cultural factors that hinder your ability to adopt data literacy? Not significantly, as I have control over how data literacy is implemented within my company.

Do you think there are any structural or policy-related barriers within your organization that affect the development of your data competencies? Time constraints and budget limitations for educational courses and investing in advanced tools are significant challenges.

Q: Are there any other challenges or barriers that hinder you from being proficient in data literacy and data competencies? Time and budget constraints, as well as the rapid pace of technological advancements.

Organizational Culture:

How would you describe the culture of data use within your organization? We prioritize data use in decision-making and regularly update our data management practices to ensure accuracy.

What steps do you think are necessary to foster a more data-driven culture? Continuous education, investment in advanced tools, and promoting the value of data-driven decision-making.

Resource Allocation:

Do you think your organization allocates sufficient resources towards improving data literacy among top management? Why or why not? As a small company, we allocate resources as needed, such as investing in JobTools for better data management.

What additional resources or support would help you better utilize data in your role? Access to advanced data analysis tools and ongoing training in the latest data management practices.

Trust in Data:

How much do you trust the data provided to you for decision-making? I trust the data about 7 out of 10, but I still verify it regularly to ensure accuracy.

What factors influence this trust? The source of the data, regular updates, and thorough verification processes.

Can you share an experience where data quality issues impacted your decision-making process? A student once entered incorrect data, leading to discrepancies that required verification and correction.

Role of Data Scientists:

To what extent do you rely on data scientists for processed information? We do not currently rely on data scientists, as we handle data processing internally.

How do you ensure that you understand and can act on the insights provided by data scientists? By verifying data accuracy and regularly updating our data management practices.

Cluster 4: Additional Questions

Client Understanding:

To what extent do your clients truly grasp and value the data insights you provide them? Clients appreciate and value the insights, as they improve their hiring strategies and outcomes.

Future Outlook:

How do you see the role of data literacy and competencies evolving in top management over the next five years? It will continue to grow due to the increasing importance of data in decision-making and strict regulations. Understanding and properly using data, especially with advancements like AI and tools like ChatGPT, will be crucial for managers.

What future challenges and opportunities do you anticipate in this area? Challenges include keeping up with rapid technological advancements and ensuring data privacy. Opportunities lie in leveraging new tools and technologies for more efficient data management and decision-making.

A7

Understanding Data Literacy and Competency

- **How would you define data literacy and data competency in your own words?**

Data literacy, it's basically about understanding how do we use data? How do we collect the data? How do we analyze the data? And then mainly is how do we maintain the data privacy? How do we anonymize data? So it's all about the ethics, ethical issues around the data. So that's having the knowledge about, yeah, how the data can be protected. So very important to understand about the data protection laws. And then it goes into more about how do we, what are the methods utilized to analyze this data? And what do you make out of the data? What is the use of this data? Where are you collecting from this data? Is it the lab data? So it all differs upon where we collect this data from. So whether it is from the lab studies or the experimental studies, or whether it is from people that you're collecting this data. And then the things kind of vary with sectors.

- **Can you describe your familiarity with data analysis and interpretation?**

Yes. So with regards to data analysis and interpretation, I do lots of, as I told you, I'm into the pharmaceutics, so which is about developing medicines for children. So we do lots of experimental studies, so where we do the data analysis. So there are the lab work where we collect the data. So we do, for example, if we are developing a product, then we would be doing some lab studies regarding measuring the viscosity or measuring the particle size of the compound. And then it's about analyzing that particle size, what's the range of this particle size and on. So that's the very specific when it comes to the administration. But then the other part of my work is doing lots of surveys like you're doing now. So it's a qualitative research. So one is the quantitative, so that would be quantitative analysis, but then I do lots of qualitative research as well, which is a survey-based. And that includes the data analysis in terms of analyzing the responses that we get from our respondents, from our participants. So using different methodologies in terms of the analysis, whether it is, if it is a survey, then it would be using the thematic coding analysis or whether we want to use any AI ML techniques like natural processing language. So that's kind of thing we get involved in doing the data analysis. And on the basis of that, it would be really the interpretation on the basis of the analysis that we do, but it is also connecting with the literature. So doing the critical appraisal with the literature, that's a label already on that topic. So the interpretation would really depend upon what's existing in the domain and then what results have you got. So on that basis, we would be doing the interpretation. So that's how we do it.

Educational Background

- **How does your educational background support your understanding of data literacy and competency?**

So my educational background, I actually did my PhD in terms of developing the database. So this was the database on the excipients, which are the inactive ingredients in our children's medicines. So the whole thing, the whole PhD kind of, I set up a whole methodology in terms of how do you collect the data? How do you analyze this data? How do you protect the data and then put that into the database so it is accessible to public for freely and publicly. So this is all kind of prepared me in terms of really understanding the data, how do I use the data? And I told you the service, we do lots of service. So that also helped me understanding about the data and how carefully I should be using the data, how I should anonymize the data if I'm doing it from the service. And then if we do some observation, this is most of the observation studies, but if I do any intervention studies, particularly, then how I should be anonymizing this data. We deal with children. So the questions that we ask them, how do we pose, phrase those questions and how we present those questions to children. So all that is very important when we are collecting the data from children, we're not putting them, understanding the ethical issues around it. That is very important so that we're not putting children or the participants into burden. So whole this thing, all with my work and the PhD, basically the educational thing, did help me with understanding the data literacy and competency.

- **Do you also have any training recently that helps you to better your understanding with being data literate and competency?**

Not necessarily, I mean, data literacy or competency, but it kind of covers into the big umbrella of data protection. So we didn't get the specific training as such, or we haven't looked into the specific training on data literacy or data competency as such, but yes, we had a training on the data protection, which covers a bit part of it. And yeah, it is kind of a mandatory thing that we have to do it in company to do the data protection.

Assessment Methods

- **What methods or tools does your organization currently use to assess data literacy among top management?**

Okay, so what they definitely do is, they, we have lots, we do lots of, not lots of, but then the one thing that they would do is they would take the HR data. So to really understand where we are going in terms of the career, so that the HR data is what is collected. That is one. Then they do the surveys with the management to really understand where they are. So through the surveys that they collect the data in terms of the top management to understand the leadership skills that we need to grow into. So that's one. Of course, the appraisals and the promotional data definitely helps them to understand the top management sort of thing. The other thing I can think about is, yeah, that's it really. These are the key kind of areas where they would get into.

So if I understand your question rightly, it's about understanding the, in the management. Is it the career related development sort of data literacy are you talking about?

No, it's like among the top management in the companies, does the company itself measure how data literate and data competent these top management are?

Ah, okay. No, we don't specifically, not specifically, there is no like specific focus on the data literacy and we're not kind of asked specifically. We are asked to provide, to take the trainings as I told you about the data protection, but they don't assess at such the KPIs or how, yes, what is this encouraged? And I don't know if that would answer your question, is the open source. So how much, you know, we do put it in the open source, how much of our data is in the open source, research data, especially. But, and yeah, but otherwise nothing specifically, I have come across anything that they would measure at such or assess that, no.

Skill Levels

- **what data analytics tools and software are you most comfortable with? SQL, Python, Power BI, Excel, Tableau?**

Ah, okay. To be honest with you, I am very familiar with the, I use quite a lot of the statistical data analysis tools. So no, Python is something that I would, I'm interested in it, I would like to learn more about it because it's picking up, but no, I don't have, and there are lots of training that is provided on the Python at the company but no, I do have some knowledge about the SQL because I do develop the databases and I use that. So SQL, yes, statistical softwares like SPSS and the Minitab, so that is something we do definitely use. Excel, yeah, definitely, I mean, that is the day-to-day thing. Anything particular as we use with the data? I mean, we do use lots of, I don't know what to do, I can't think about apart from anything from the statistics. We do use quite a lot about the open source softwares, which allows us to present the data in a graphical way, like Visio and all that, but yeah, that's it really.

About the results, yes. Yeah, you know more about it, yeah, yeah. Okay, how frequently do you use these data analysis tools and software in your daily activities?

On the daily activities, Excel, as I told you, Visio, yes, Minitablets for designing the experiments and analyzing the data, SPSS, so the statistical softwares mostly, on the day-to-day basis, the statistical softwares and Excel, this is the most used, yeah, that's what I would say, yeah.

- **And how would you rate your proficiency in using these data analysis tools and software?**

I would say Excel, I do Excel in it, so it's the high-level proficiency, I would say, Excel, yes, I mean, I use some of the macros and build up the macros and everything in Excel, so certainly Excel. We do use, I don't know if that helps, I haven't used much, but R, so the R is something that is definitely, we have picked that up in recent years, and I encourage my PhD students to learn more about R, so there are trainings provided in the company on R, so that is something we definitely have kind of, you know, started looking into it, but I would say my proficiency with the R is the beginner's level, but with Excel, with statistical softwares, it's high-level.

- **Can you describe a specific project where you applied one of these tools or software to extract information and visualize data?**

Oh, yeah, so we use it for a lot, many projects, so especially for the lab-based studies, we regularly use the Excel and we regularly use the statistical softwares to design our experiments, especially, so the mini tablets, so recently we are doing a lab project, we want to assess different factors and how these factors affect the quality of our product, so we wanted to identify which are the critical factors or the key factors that we should be looking into it, so we utilized this mini-tab software to design our experiments, because if you do it on a manual basis, then we would have to look into one factor at a time, and that means lots of experiments, so we used the statistical software to design our experiments, which reduces the number of experiments we could do, but at the same time, it will help us to assess different factors and identify the key factor that would affect the year. So, yeah, statistical software is the one best example, if I could give you. The other ones where we did, and then, of course, we do use the mini tablet, was used for the data visualization as well, because it creates different plots for you, like the scatter plots or the capability plots, if you want to identify different product capabilities, then it does the capability plots and everything for you. So, for data visualization as well, we did use the statistical software, but on the basic level, for the MSc students and all, we tend to use the Excel for the data visualization to do the plots and the bar plots and everything. Of course, R is something that we have used for some of our projects to do the plots and all that. And then, apart from that, in terms of the data extraction, we actually tried a couple of things, but then that was a long time ago. So, as I told you, when we were developing this database, we had to extract the data from the literature, the specific kind of fields and the specific information from the literature into the Excel sheets. And we tried developing this extraction tool. It's called ETL, extract and transform. So, we tried to develop this, but then it was very, very initial stages of the AI and ML then, so we were not very successful in developing this tool. But I know that the AI have now, ML and AI have advanced now. It's 10 years back that we're trying to do that. Now it is advanced, and we're now giving it a try again to develop these tools where we can extract the data using the AI and ML technologies.

- **can you briefly explain in your own word again, the difference between correlation and causation?**

Okay, now, correlation is something that we are looking if there isn't a correlation between the different factors with the results that we're looking. For example, to give you an example, it would be, if we are studying the effect of taste, for example, then is there any correlation between the different genders? And that would be, see, how does that correlate? Or for example, if we are, the best example would be, we're doing lots of studies in, because we can't do these studies in children, we have to do these studies in adults. So, how does this adult data correlate with children's data? So, that's the correlation we kind of have to look into. So, that would be the correlation data. Causation data would be what factors cause this to happen. So, that would be the causation data that we would see.

Yeah, yeah, indeed, indeed. And what about statistical terms like probability, standard deviation, regression?

Okay, so now in terms of the standard deviation, of course, we would like to have the difference between the data to see the variability in the data that we are analyzing. So, that's where we look into the standard data to assess really the variability of the data. Regression kind of gives us the idea on how linear the data is and the linearity of it. And then the other one you did mention was? So, standard deviation, I did mention the variation. So, it does tell you about the variability.

- **So, how do you decide which statistical methods to use for a particular data set?**

Okay, now it will really depend upon the number of the sample sets we have. So, sometimes like we have to use the t-test to understand the differences. Then it really depends upon the sample set that we have. If it's a high number of sample sets, we do the ANOVA as well to see the variance, analysis of variance, to see the variance in the data and how variable the data is. So, we would do the ANOVA test or we would do the statistics, the t-test, to really understand the variance or the variability between the data. So, that's kind of the test. But then, yes, as I said, it really depends upon the sample set we have and then the variance that we want to see between this. And depending upon that, we would choose what test we want to run, whether it is t-test or whether it is the ANOVA.

- **And how do you ensure the data you use is accurate and reliable?**

Ah, that actually the data accuracy, it really depends again on the method that we're using. So, the method in particular to do my research, where we have to look into the data accuracy or the reliability is to adhere to the good clinical practice or the good lab practices. It's looking into all the methods or the guidelines that have been followed. So, if we are looking, if you're doing any experimental studies, we really need to follow and see whether we have the appropriate sample size that we will need to study. That's one. Whether we are following the guidelines in terms of the laboratory experiment that we need to follow the test that we are doing. So, are we doing the standard test or not? So, all this kind of criteria. So, we kind of have a tool which helps us to, and then it goes to the criteria, which helps us to assess whether there is the accurate data or the data can be reliable if it follows all the guidelines. And if the studies are done according to all the guidelines, then it's a reliable data. Otherwise, yeah. Otherwise, then it would fall into, you know, it's basically the level of the reliability or the level of the evidence that we calculate on the basis of this tool, which kind of has all the criteria in it, and it includes all the different things. So, if you're doing it in animals and have the appropriate animal models being used, and so on. So, that all criteria needs to be satisfied.

Knowledge Application

- **How often do you integrate data insights into your regular decision-making process?**

I think so, it is a common practice and it is a day-to-day practice to look into the data to make the decision, because that kind of helps us to decide on the next set of the experiments that we would be doing. So, definitely. And then we have to look into the errors, like you said, the standard deviation. So, there could be the biases and the errors associated with it. So, we have to look into all that. And that helps us to really kind of plan our next step of experiments. So, I would say on a regular basis, we have to look into the data to make a decision for the next steps.

- **can you describe a time where you identify a significant problem using data? And how do you solve it?**

I mean, I would say when we were developing this database, you know, nowadays lots of data is available on the open source. Yes. So, the quality of the data is really a problem because we don't know, as you said, the data reliability and everything. It really affects us when we have to use the open source data, for example, to use that in our, so like I'm developing a database and I'm kind of populating all the data into this database, depending what's our label in the literature. But we really need to assess if we can put that data into our database, because we need to assess the data quality. And yeah, with the open source, there is lots of things that people tend to put in on it. So, the data quality is a very important thing that we look into. And that is a problem for us, is really assessing the quality of the data. And I know there are some standards like in peer-reviewed data. So, if it is peer-reviewed, then it is the quality is really good and then we can put it. But with the open source, that is becoming a bit challenge for us because it's not peer-reviewed, but at the same time, the quality can be good, but how do we kind of confirm that the quality is good if it's not a peer-reviewed data? That's a challenge we kind of have identified, is how do we assess the data quality if it is not peer-reviewed? Of course, I mean, we have our own tools to assess, as we told you, and we use that tools to assess the data quality and use that. But that's a thing we often fall into ways, is to take quality issues.

- **have you ever had to convince a stakeholder to change their perspective based on your data analysis?**

Yeah, I have a couple of examples. Let me think about the best one for you. Convince someone on our data. I mean, there is lots of things, like when we were developing this database, we did come across lots of situations where, especially, yeah, when we are using the literature from the, and as I mentioned to you, the quality of it, there is always this kind of debate whether to use this data or not to use this data. And that's where we, with the tools, and in fact, that was the reason we developed this tool, or developed, in the sense, adopted a tool that was already available for our purpose to really assess the quality of this data and then convince the stakeholders to say, the data that we're putting in the database is a good quality because it's not only that it is peer-reviewed, that's one, but for the non-peer-reviewed data, we're actually using this tool, and then this is how it is kind of assessed. So we tell them that we have assessed the data, we provide them with the assessment of the data quality, and then we are putting it into the database. So that's something, yeah, for the higher management, there is kind of a debate to put in the non-peer-reviewed data into the database, how do we do that? Or how do we use this non-peer-reviewed data? So that's where we have to convince them that, yeah, this tool is helping us to assess the quality, and that's how we can use this data. And then in terms of the lab work, yeah, as I told you, for the next steps, we have to always show that, okay, for example, if we have to do another batch studies and we have to show that the first batch has not really behaved well or behaved, and we need to plan other studies. So we have to convince them, showing the evidence with our results from our data, showing that, okay, these results have shown that these factors are important, and we need to kind of further go ahead, explore this factor, but the management doesn't feel that these factors are important, then we have to really go and show them this data to tell them that, oh, no, no, no, the results have shown this, and we have to consider this factor and look further or explore further into it.

- **can you describe also a specific instance where data literacy positively influenced a business outcome?**

We actually do everything in terms of the, in terms of the non-profit organization. So not in terms of the commercial output as such, but yes, the impact wise to the database definitely has shown this. So the number of the users people are using it, that kind of helps us to show the business outcome or the, you know, how do we take this database forward? So whether we want to, so there was one, there is now current a situation, whether we're thinking whether to expand this database to further or not. So, and how would, you know, if the business would put into more money into it to further expand the database. And that's where we had to look into the statistics or the statistics or the, you know, the user statistics or the user analysis to see how many people are using it, how people find the database useful to get the feedback from the people and using this data, we were able to kind of convince or maybe put our case to the funders. I wouldn't say business, to the funders saying, okay, this is how it has helped and this is the impact it had had. So which is why expansion of the database would have been really helpful for the future prospects. And then we got more funding into it for the expansion of the database. So that's how it helped in terms of the business perspective in getting more funding to the database by showing the user statistics or the user's data to the funders.

- **How do you personally yourself advocate for a more data-driven decision-making in your role?**

So, yeah. I think it's very important. It's data-driven in the sense is the evidence-based data is very, very important. It's not only important for the people who are dealing with the data, to be honest, or who are creating this data. It is also beneficial for the people, for the layman, basically for the society. We are giving back to the society with the data that we are generating. So it is kind of giving them assurance that the, you know, for example, if it's a product or if it's a database or whether it, whatever it is, it is anything that is, the users are going to use it, it kind of gives them the confidence to use that product because it's backed up by the evidence-based data. So even if it is a healthcare professional, if it needs to use any of the medicines, if there is evidence-based data showing the usability or showing the productivity efficiency, of course we do the safety efficacy studies and everything, but when it comes to the acceptability of using it, then it kind of, if there is evidence-based data out there, then it shows that, okay, the data shows that, you know, particular this medicine or particular this form of medicine is working really well. So I can then, you know, use it to my patients. I can prescribe that to my patients. So I think, so it's, yeah, it's not only important to people creating it, it is also important to people who will be using the end product.

- **How do you balance data-driven decisions with intuitive decision-making?**

Ah, very interesting. Balance data-driven decision. So yeah, sometimes it's like, you know, the data definitely helps us to see what it is, but in terms of the situations where we are yet to collect the data, the existing data does show, you know, the positive kind of outcomes, but we don't know whether we should be going in that way or not. So that's where our intuitive or the experience kind of things helps. And so we kind of use the past, I kind of tend to use my past experience to really look into it if it is, and that's where I would balance. So of course, look into the, how would I say, look into the, I won't say drawbacks, but look into the loopholes of this, and gaps. And gaps, yeah, that would be better thing. So there are, you know, even if it's a data-driven, there are some gaps into it, and these gaps can be balanced with the intuitive, so that's how what I would balance is that balancing the gap of the data-driven by plugging the gaps with the intuitive decisions. So that's how we do, yeah.If you want to put a percentage on it, like let's say you want to put it like 70% data and 30% your experience, or if you want to put a percentage on it, what would that be?Ah, it's very interesting. 70% of data or 30%, I mean, yeah, in terms of the- So that's just an example. Yeah, yeah. In terms of the percentage, I wouldn't say equal, because definitely, I mean, especially when it comes to decision-making, it does help your experience and your knowledge and all that does definitely help into it. So I wouldn't say 50-50, but definitely maybe 60-40, but definitely, I don't know in terms of the number, but I can definitely say the high percentage goes to the data, and then the less goes to the experience knowledge. So yeah, the more importance is data. So I would say 60-40 maybe, not necessarily 70-30, but yeah, 60-40.

Cluster 3: Barriers to Adopting and Effectively Using Data Literacy and Competencies

- **can you tell me what are the challenges that hinder you from improving like your data literates or data competence skills?**

I think so it is very important that we keep up to date with the latest trends and technologies in data science really, because there are lots of things with the AI and ML technologies coming up. There are lots of new kind of technologies that are coming up, and that's something I think so we need to be keeping up to date with, so taking the online courses.

- **Are there any tools or technologies related to data that you find difficult to use or understand?**

So as I told you, I'm more into the initial phases. Sorry, it might be a bit repetitive for you, but this is a very niche phase of artificial intelligence and machine learning. So that is something I definitely would like to really understand more and get more into it to really see how I can employ that or use that in my research. So yeah, it's more so understanding everything like I did mention to you about the national processing language, because this is really, really very useful, especially when it comes to the qualitative data analysis. So I would really like to understand how do I use the natural processing language in my data set. So data modeling and data analysis, data modeling, and that's another area that I think I should look at. Machine learning thing, yeah.

- **Have you ever encountered any organizational resistance or cultural factors that hinder your ability to adopt data literacy?**

Organizational data resistance, not resistance, I would say really, but it would be more of the, it would be more of the, you know, more of the encouragement. I think so it's not resistance, but I think so it's more promoting and it's more, more, more, more, more, more encouraging and motivating people to really understand more about the data data. I think so that is where, you know what happens is that people who are already into the data sort of things into the computational studies or people who are more close to the data analysis like the artificial interventions or the computations or the IT people, they tend to have more knowledge or more tend to, you know, they tend to be more closer to the data, knowledge, data literacy, but people, the researchers who are into the lab and all, we have a very myopic view on it. And I think so that's something can be brought to the surface to the researchers and that is something is needed. So there's no resistance, but there is more awareness at such, which needs to be spread by the organization among all the researchers. So at the moment, some of them are very high level in terms of data literacy, while some of them are very low. So that needs to be, the balance needs to be kept up or maybe that is something which is needed. I feel the transparency around it. So it's, yeah, it's engaging more of the employees into it. So that's something I would see. Not resistance, but more of the awareness and the education and training around it.

- **Do you think there are any structural or policy-related barriers within your organization that affect the development of your data competencies?**

I wouldn't say, yeah, challenges, especially as I told you about it, is learning and the awareness. So understanding there are, so it is all about proactive approach. So maybe this could be something which is going to be improved by the organizations is raising and focusing on raising the awareness about it. That's one thing. It is also the organizational readiness for that change. So that is something I think so, and getting the culture of data into the organization.

- **How would you describe the culture of data use within your organization?**

For example, how would you describe the culture of using data for things? As I told you, data is there, but it is not completely capitalized on. So we still really need to have more knowledge around it and we still need to have more awareness on it. I think they should have something like, I don't know, I always say that, but they should have something like a cultural ambassadors who can influence and motivate others. So there is lots going on at the moment in the office on the open science. So they do have the open science conferences and they have open science awards that kind of help people to really think about putting their data into open science and encouraging them to do that. I think so the similar things should be done in terms of the data so that we can get that organization culture and shift that culture to more on to the, so reward systems, maybe that might help because we have seen that has helped in the open science thing. So, yeah, the reward might get into that sort of culture or the other thing would be, okay.

- **Do you think your organization allocates sufficient resources towards improving data literacy among top management?**

Not one to one basis, but yeah, they do provide quite a lot of some training around it, but not necessarily as I mentioned on the data literacy at such, but yeah, there are some trainings that are available which we can utilize and get going with it, but yeah, maybe they could do some workshops and something like that, which will be a bit of hands-on for people to understand. Yeah, that's it really.

- **How much do you trust the data provided to you for decision-making?**

I think so, yeah, that is one of the factor that could be one of the factor for the resistance really, but in terms of trusting the data, if it comes to specifically generated by ourselves, it again, it comes into the data quality thing. If it is generated by ourselves and if you're following all the guidelines, then yeah, of course we would trust it. But if it's the other's data that we're using, then it's really the trust in the methodologies that they have used, the guidelines that they have used. So it's not more of the trust, but it's really more of the processes that follows, they have followed and that processes gives us the trust on it. But yeah, that would be something I would say is the processes that they are using. And that would give us the co

- **To what extent do you rely on data analysts to process the information for you?**

Salunkel: They are very important actually data analysts to process the information that we have, especially for my work when I have the database thing, where we have to send the data to the data analyst to really look so that it can be appropriately searched. They have to get into lots of data cleaning and sort of thing so that it is appropriate. And then there are no kind of, what I would say, there are no weird characters or anything in our data that would stop us from searching the data and so on. So yeah, in that way data analysts are very important. For a lab-based research as well, the data is actually of no use if we cannot analyze it and make the interpretation out of it. So we think it's very important.nfidence or the trust in using the data.

- **How do you see the role of data literacy and competency evolving in top management over the next five years?**

Data, you said data literacy and? Data competency evolving in top management over the next five years. It is coming, definitely. Over the next five years, yeah. I mean, with the AI and ML technologies and everything, it's kind of, I think so the AI, ML has really opened. It has been there for a long, long time, but it's just that with the recent advancement in the AI and ML technologies, it has really opened lots of doors or it has really kind of created that demand for the data. And so it will, in the future, is very bright. I don't know, we might have to, and the top management would start looking into or have start looking into it and embracing the AI and ML technologies. So it will be very positive and it looks very positive in the next five years.

Janet: Thank you for giving me the opportunity to interview you for my research. Your insights and answers are valuable to this research.

A8

Cluster 2: Measuring Data Literacy and Data Competencies Among Top Management

Understanding Data Literacy and Competency:
It is about focusing on data and not only focusing on gut feelings. Data competency is about using databases.

Educational Background:

I have a master's in business engineering.

Can you describe your familiarity with data analysis and interpretation?

We use data on a daily basis to make informed decisions, but it is not only data, we use experience also.

How does your educational background support your understanding of data literacy and competencies?
Yeah. I think that the courses in business, statistics, math and analysis are helping in one way to use data.

How does any training you did recently support your understanding of data literacy and competencies?
Yeah. I just finished one, which was the data acceleration program.

Assessment Methods:

What methods or tools does your organization currently use to assess data literacy among top management?
That is very hard to say. It really depends on the type of use case and the type of question at hand.

How effective do you find these methods in accurately measuring your data skills?
I don't know. We have our financial reporting and scorecards that is the driver of the company.

Skill Levels:

Which data analytics tools and software are you most comfortable with (e.g., SQL, Python, Power BI, Excel, and Tableau)?
SQL, Python, Power BI, Excel. A lot of them. Use on a daily basis. Yeah. Of course, Excel. We also have the Power BI with so Fit. Oh, okay. That's great.

How frequently do you use data analysis tools and software in your daily activities?
Yeah. Probably on a daily basis. Yeah. Okay. Okay.

How would you rate your proficiency in using these data analytics tools and software?
I think I am what you can call an advanced user.

Can you describe a specific project where you applied one of these tools or software to extract information and visualize data?
We set up a sales dashboard, getting data from the CRM system. Monitoring the conversion rates towards error and growth. That's the recent project that we are working on now.

Do you have knowledge of statistical concepts?
Can you explain the difference between correlation and causation with an example?
Can you explain statistical terms like probability, standard deviation, and regression?
Yes I have knowledge of these.

How do you ensure the data you use is accurate and reliable?
By verifying and validating the data.

Knowledge Application:

How often do you integrate data insights into your regular decision-making process?
Yeah. We do it on a frequent basis. It's normal to hear. Yeah.

Can you provide an example of a time when you utilized data to make a strategic decision?
Ah, the CRM. Okay. The finance dashboards, the cash flow planning. That's all data. Okay. Okay.

Describe a time when you identified a significant problem using data. What steps did you take to resolve it?
From our runway, we decided to raise additional funds. So that's one of the key areas where we use data today is you're making proper decisions.

How do you personally advocate for and model data-driven decision-making in your role?
We use data as a basis to make informed decisions, and then we add our experience to that. We saw that the runway was declining, and then you have different possibilities that you can either expect revenue to go up, can cut down in costs, or you can raise additional funds. And then based on our experience of what the market is doing, the financial market, we decided to spend this to raise.

How do you balance data-driven decisions with intuitive decision-making?
We use the data as a basis to make an informed decision and then add our experience to that.

Cluster 3: Barriers to Adopting and Effectively Using Data Literacy and Competencies

Challenges in Adoption:

Can you identify any specific skills or knowledge gaps that make it challenging for you to become proficient in data literacy?
But I think the biggest challenge is time. “Resources, along with informed decisions given the limited resources we have. We don’t have the money for these tools. So, we can consider money as a challenge here as well”.

Have you encountered any organizational resistance or cultural factors that hinder your ability to adopt data literacy?
I guess not, there are no resistance because we're a data company. Yeah. Our values. We use data every day also as a customer. So we specialize in data data integration. So I think for us, it's a little bit atypical from a normal data.

Are there any other challenges or barriers that hinder you from being proficient in data literacy and data competencies?
Money for expensive tools.

Organizational Culture:

How would you describe the culture of data use within your organization?
We use data every day. It's a normal thing.

What steps do you think are necessary to foster a more data-driven culture?
Thinking about how I did it. But it all starts with choosing the right tools at hand. Because if I look at our customers that have all legacy systems, they are doing a lot in Excel. They have closed down systems that do not allow for the data to be used. So that's the real first step that you need to do is open up the data and bring it use on getting the data, buying the data that they need. And you have to give them the tools at hand.

Can you share an experience where data quality issues impacted your decision-making process?
Yeah. And how does that impact, your decision-making process? Really going to indent search, which is advanced work, to really make sure that the data is correct. Which just takes a lot of unforeseen time.

Role of Data Scientists:

To what extent do you rely on data scientists for processed information?
I am usually involved in the setup. When we the datasets or when we decide the report, then I am involved to define the execution is done by the data scientist. And then the validation is done by me.

How do you ensure that you understand and can act on the insights provided by data scientists?
Validation is done by me.

A9

Understanding Data Literacy and Competency

How would you define data literacy and data competency in your own words?

For me, data literacy is about interpretation and understanding what the data represents and being able to draw conclusions or whatever from the data. And data competency is more about what skills you have in handling the data. So, transforming, maybe transformation or that interpretation of modeling that data, that's more the competency.

Can you describe your familiarity with data analysis and interpretation?

So, I have data interpretation, data, yeah, let's say change. So, data interpretation and modeling and that kind of like recreation and data science. Yeah, I have some, I have quite some background in that. So, my PhD was about Python and data analysis and modeling. So, from that perspective, yeah, that's it.

Educational Background

How does your educational background support your understanding of data literacy and competencies?

I have a Master in Bioscience Engineering and a PhD in Applied Biological Sciences.

I think you already mentioned briefly. Yeah, I mentioned it briefly. So, yeah, to do my master's and my PhD, I did a lot of, yeah, let's say data interpretation, let's say calibrations of models and that. So, from that perspective, yeah, let's say that competency, that capability of handling data, interpreting data, that's really, yeah, was more developed, let's say, in that stage of my study.

How does any training you did recently support your understanding of data literacy and competencies?

Do you have any training from work or personal training or something? I'm now currently following a full stack development trajectory, let's say. So, training at Coursera, but it's not really fully aimed at the data literacy. It's more kind of like expanding, let's say, the programming capabilities. So, that's all. But not specifically for the data science or the data competency, let's say.

Assessment Methods

What methods or tools does your organization currently use to assess data literacy among top management?

I don't think we really assess that data literacy top management. So, no.

Skill Levels

Which data analytics tools and software are you most comfortable with e.g., SQL, Python, Power BI, Excel, and Tableau?

So, SQL, Python, Julia, Matlab, R, Excel. So, I think that those are the... But most of the time, mostly it's Python and Excel, but the other ones are kind of like I can use them when I need them. It's kind of like that.

How frequently do you use data analysis tools and software in your daily activities?

Multiple times per week. Maybe not daily. Maybe daily is maybe over the top, but almost daily. So, let's say three, four days a week, I would say.

How would you rate your proficiency in using these data analytics tools and software?

You can give a percentage or I would say 8 out of 10. There's still room for improvement, let's say.

Can you describe a specific project where you applied one of these tools or software to extract information and visualize data?

Yeah. So, for one project, there was a lot of data available in the database, but it was not being used. However, we had a specific challenge we had to fix. So, what I did is I queried all the data. It was... I didn't have the access. I had the access to query, so I used SQL. So, internal snowflake I used. I grabbed all the data. I transformed the data. I manipulated it in a way that I could use it. And then, in fact, I did modeling using Python. I made visuals also with Python to, let's say, to show people what was the impact of certain conditions or a way of manufacturing in order to convince them that we had to make changes to the process. So, that was kind of like...

Do you have knowledge of statistical concepts?

Can you explain the difference between correlation and causation with an example?

Yes. So, correlation is that there is... Yeah. You see connection or you see kind of like there is a trend between two independent variables or you think independent variables. Causation is kind of like that there is also logic between those two variables that if you change one parameter, one variable, that also the other variable would change. That's causation in one specific direction. But with the correlation, it can be that there is a correlation, but it doesn't mean that there is correlation that per se those things have anything to mean to each other.

Can you explain statistical terms like probability, standard deviation, and regression?

Probability is the... I'm not a statistics guy. So, for me, it's kind of like the chance that something will happen. That's kind of like how probable is that that is easy to have that case. Standard deviation is kind of like how much variability you can expect based on your mean prediction. So, yeah, that's something you want to deduce. And then the last one was the regression. Yeah. That's kind of like to derive, let's say, how your dependent variables change as a function of your independent variables.

How do you decide which statistical method to use for a particular data set?

Yeah, it's good. Yeah. So, from the statistical part, I more look to the problem itself, kind of like what do I find in literature and how can I describe it? So, I don't look from it most of the time on a purely statistical level. I look more kind of like from a mechanistic level, kind of like, okay, what can we from a physical point of view expect? What are the fundamental laws it should follow? And then I try to apply that to that specific problem. But then, yes, purely statistically, it's not that we apply that to common data. Data sets are sometimes too small to really go for a full-blown ML or AI model. So, that's kind of like...

How do you ensure the data you use is accurate and reliable?

So, I just investigate myself whether it makes sense from a logical point of view, mechanistic point of view. So, based on how I interpret, let's say, the literature, the models and the lines. And then also connecting, let's say, with the expert who generates the data, kind of like what kind of variability of what kind of challenges they typically have with respect to data gathering or kind of like making that process happen. Because that you cannot get out of the data directly. So, I try to get some more feeling, kind of like what can I expect? How representative is it? But it's a qualitative measure, let's say, for data quality. It's not something I can quantify, kind of like it's high. Yeah, I can just say it's probably high or low, it's average, but that's all.

Knowledge Application

How often do you integrate data insights into your regular decision-making process?

Rick, let's say, in most of the cases, I do. Sometimes, if it's a more easy problem, then I try to just rely on my expert knowledge to say, kind of like, yeah, don't worry about that, do this. But you feel that the people in the organization are asking, kind of like, yeah, yeah, but they want to see a number. Memory, yeah, yeah. So, that's kind of like, so, in most of the cases, I'm still pushed to make a number. However, for the easy cases, I'm, oh, it's 100% aligned with my expert knowledge. So, it's kind of like, so, that's most of the time. So, let's say, 70, 80% of the time, I do it directly with choosing data. And then, for the other 30%, I mean, 99% of the cases, still pushed. So, to come up with a number.

Can you provide an example of a time when you utilized data to make a strategic decision?

I think for, so, we had the project. It's linking, it's also linking with the previous question, maybe a little bit about how we use data. Yes, yes. So, the strategy I built is kind of like, we had the data sets coming from source A, we had data sets coming from source B. And in order to, yeah, to come up with a strategy, let's say, most of the time, what you would have is that people would look to data set A and B independently. However, they were both influencing the product. So, what I did is kind of like, I was bridging between the two data sets, which were resembling a different, let's say, underlying mechanism. So, it was not that it was two types covering the same, we were not measuring the same thing. One test, we were measuring A and the other test, we were measuring B, but they were both influencing, let's say, the outcome. So, what I did is, I combined the impact of A and B on the outcome, let's say, in order to guide and to come up with a strategy, kind of like how we could control our outcome by putting some limits on both A and both B. That was kind of like the approach, let's say. Is that clear for you? Yes, yes, yes. I saw you looking a little bit puzzled, but then you can... No, I can put it together. Yeah, yeah, yeah.

Describe a time when you identified a significant problem using data. What steps did you take to resolve it?

So, what I typically do is, I'm informed that there is a problem with the product. And then I start looking at the data and try to see, kind of like, but most of the time, I already got leads, they tell me, this is the problem with the product, have a look, have a look. And then I try to see, is there any... What is now impacting this product? Do I see any relation between the problem or correlation? It's a factor between the problem and what is available in the database. But it's not that I will proactively, let's say, try to extract problems from our data by using that kind of like... Ah, okay, so you know the problem first and you just use data. Yeah, they indicate to me there's a problem with this. We have a problem with, for example, dissolution. That is kind of like... Dissolution is kind of like how fast... It's a method to describe how a product is dissolving in a certain solution, let's say. And that should capture, let's say, certain physical properties. For example, if you change the particle size of your API, your dissolution method should pick it up. But if that sensitivity is too high, then we have to meet certain standards. So it can be that we don't meet certain standards. And then they check to come to me, kind of like, okay, could you, based on the data, see if there is... If it's just a one-time failure or maybe it's something... Or we see that trends really as a function of that specific... Okay, for particle size, you can most of the time easily discriminate. But, for example, for other parameters, like the water content of the tablet, that's a more difficult one, depending on the stage or whatever. So that's kind of like the things which can come up.

How do you personally advocate for and model data-driven decision-making in your role?

I try to make people aware that we need to move away from individual Excel files and that everything needs to be the databases and that we need to have central structure and whatever. But there is... I've tried it for already years, but it's quite difficult to... Change people. To change... It's not per se that people are not seeing the value, but people... There is no strategy, let's say, at the high level to make it happen or no. So it's a slow process, let's say.

How do you balance data-driven decisions with intuitive decision-making?

Personally, let's say, for the more complex problems, I use the data and I also make figures. So whenever I try to pre-prep the data for other people, because if they see a table of numbers, they cannot... It's difficult to make your mind up, but I try to present it in such a way that they can... In five seconds, let's say, I can bring a certain story or bring a certain message, let's say, to the table. For the easier problems, I just... Like I said before, I just say, kind of like, okay, do this and it will be better and it will be in control. But most of the time, after that, I have to present still the number or whatever. So it's... That intuitive part, for me, it's becoming more important the longer you're in the function. In the beginning, I was... 95% of the time, I was going to the data, but because you can become more experienced with certain problems, that level is dropping, because you know how to deal with a problem and you also know the limitations of what we can do in practice. So in the past, you still were making up your mind, thinking about what are the possibilities theoretically, how can we control it. But in theoretical possibilities, they are quite rapidly narrowed down to only two options in reality, because they all say, we can only do this or this, instead of the 10 things you come up in the beginning. So in the end, if you get that problem again, they can only change two things. So you say, okay, just do this and it will be fine. So that's kind of like that.

Cluster 3: Barriers to Adopting and Effectively Using Data Literacy and Competencies

Challenges in Adoption

Can you identify any specific skills or knowledge gaps that make it challenging for you to become proficient in data literacy?

Yes, I think on the data... From a database perspective, I think there I could still grow. Because now I can consume the data and I can work with the data, whatever. But to really weigh in on how we should structure our data, I could still grow

Are there any tools or technologies related to data that you find difficult to use or understand?

Maybe the database management systems? Yeah, maybe that's... Yeah, to set up a date. I think that's challenging. Maybe that really the database management and setting it up and controlling it, that's kind of like, that's a skill I don't have. So that's maybe still something to work on.

Have you encountered any organizational resistance or cultural factors that hinder your ability to adopt data literacy?

They generally support it, let's say, that you become more data literate, let's say. But it's not that they would look... They would just say, oh yeah, do it for a course, whatever. But they will not change the system or the vision, let's say, at a company or a department level to create that kind of data literate organization. That's not part of that current vision. So it's on an individual basis, yes, but on a department level basis or higher, it's lacking, I think.

Do you think there are any structural or policy-related barriers within your organization that affect the development of your data competencies?

So do they have a policy or structure that makes it difficult for you to even be data competent? Maybe they don't have the system or something like that. The systems are very slowly deployed. A lot of administration or whatever. So it's quite difficult to get things moving, let's say. So it's generally, let's say, slowness, I think, in the bigger organization.

Are there any other challenges or barriers that hinder you from being proficient in data literacy and data competencies?

I think just a vision and a way forward, I think, from a top management level. That's what I feel.

Organizational Culture

How would you describe the culture of data use within your organization?

It's limited, let's say. I think it's stuck with, let's say, less than a few percent of the people that can work decently with data and have, let's say, a more, let's say, long-term view of what should happen. The others are just dealing with their own piece of data on a daily basis, but not challenging it in Excel most of the time. So that's kind of like the level

Resource Allocation

Do you think your organization allocates sufficient resources towards improving data literacy among top management? Why or why not?

No, I don't think so. No.

Trust in Data

How much do you trust the data provided to you for decision-making?

Let's say 80% or something like that. So what I always try to do is to rely on common sense, kind of like I want to understand what the data is representing, how the underlying mechanism is working. And if my thinking is not matching the data, then I will ask more questions to the experts. And then if it's not still matching up, then I will, yeah, I sometimes stop, let's say, my efforts. So that's kind of like the... It depends on the data type. If I've seen the data before, how used am I to that specific data, where it's coming from, then I need to be equated with the data. And if that's the case, then I can move forward, let's say.

A10

Understanding Data Literacy and Competency:

How would you define data literacy and data competency in your own words? I think it's to do with the ability to let data or numbers speak, so to turn data into information. You see data or numbers, and they have to become information. You have to know what's behind the data, how it correlates to a target spec, if you see a trend, if there are two numbers correlating, or whatever, but maybe that means something else. So it's kind of seeing the links between the numbers and the information and making that information useful.

Can you describe your familiarity with data analysis and interpretation? I'm head of R&D, so I think what we typically do is more technical and has been obviously data-driven for a while. I act as a stat SME, meaning I'm not a statistician but have been trained as a lead statistician. Typically, I'm the first point of contact if they want to define a sample size or do some statistical analysis on numbers.

Educational Background:

How does your educational background support your understanding of data literacy and competencies?

I'm a pharmacist and industrial pharmacist, and I did an additional year postgraduate in business administration. I need to understand what they are trying to prove and what the data they are asking for really represents. My background as a pharmacist, with internally trained statistics and knowledge of lab methods and drug product formulation, helps in understanding the problem and coming up with solutions.

How does any training you did recently support your understanding of data literacy and competencies? We have an initiative dating back to the early 2000s on employing Six Sigma. I was trained in Six Sigma technologies and processes. Recently, we've had initiatives to have start SMEs as a first line of contact, emphasizing the use of proper statistics in our SOPs and ways of working.

What additional educational opportunities would you find beneficial? There is a curriculum available for getting more familiar with AI, and we have online resources for statistical training.

Assessment Methods:

What methods or tools does your organization currently use to assess data literacy among top management? We have questionnaires and stage gates in the development process where we present data to top management.

How effective do you find these methods in accurately measuring your data skills? These methods are effective as they allow us to present updates and address questions backed by experience and data.

Skill Levels:

Which data analytics tools and software are you most comfortable with, e.g., SQL, Python, Power BI, Excel, and Tableau? Tableau is often used for basic data presentation, and I use Excel and Minitab**.** Also, typically Minitab, but there is also use of R and Python.

How frequently do you use data analysis tools and software in your daily activities? Weekly, as we make reports and design experiments regularly.

How would you rate your proficiency in using these data analytics tools and software? I'm familiar with Minitab but don't consider myself a statistical expert. I know what to use when but may not be able to explain all the details.

Can you describe a specific project where you applied one of these tools or software to extract information and visualize data? An example is identifying an impurity in a formulation, tracing it back to the process impurity, and implementing improvements at our supplier's end.

Do you have knowledge of statistical concepts? Yes.

Can you explain the difference between correlation and causation with an example? Correlation can be random, like the story of storks and babies. Causation is when you understand why something is causing an effect, such as a chemical reaction explaining a result.

Can you explain statistical terms like probability, standard deviation, and regression? Probability is like the chance of rolling a specific number on a die. Standard deviation measures variation around the mean. Regression involves finding a model that explains the relationship between two parameters.

How do you decide which statistical method to use for a particular data set? It depends on what you are trying to prove and understanding the methods used to get an idea about accuracy and error margins.

How do you ensure the data you use is accurate and reliable? We have a history of reliable methods and formal validation processes. For external data, understanding the definition and methodology used is crucial.

Knowledge Application:

How often do you integrate data insights into your regular decision-making process? We have stage gates where we present data monthly, and continuous process evaluation for mature products.

Can you provide an example of a time when you utilized data to make a strategic decision? I explained about identifying an impurity and improving our instructions for use based on transportation effects.

Describe a time when you identified a significant problem using data. What steps did you take to resolve it? Identifying an impurity, conducting a DOE, and implementing process improvements at the supplier's end.

Have you ever had to convince a stakeholder to change their perspective based on your data analysis? How did you do it? Yes, during a human factors study for a suspension product, showing the effect of transportation on resuspendability.

Can you describe a specific instance where data literacy positively influenced a business outcome? The example of improving the instructions for use and shipping orientation for the suspension product.

Can you provide an example of a successful data-driven presentation you've given? Presentations to top management during stage gates, focusing on critical parameters and trends.

How do you personally advocate for and model data-driven decision-making in your role? By ensuring that our conclusions are statistically sound and data-backed.

How do you balance data-driven decisions with intuitive decision-making? By considering both statistical significance and practical relevance of the data.

Cluster 3: Barriers to Adopting and Effectively Using Data Literacy and Competencies

Challenges in Adoption:

Can you identify any specific skills or knowledge gaps that make it challenging for you to become proficient in data literacy? AI and sophisticated statistical tools are evolving, and keeping up requires continuous learning.

Are there any tools or technologies related to data that you find difficult to use or understand? Advanced AI tools and modeling technologies can be challenging without a strong background.

Have you encountered any organizational resistance or cultural factors that hinder your ability to adopt data literacy? Not specifically mentioned, but continuous training and evolving methodologies indicate a supportive culture.

Do you think there are any structural or policy-related barriers within your organization that affect the development of your data competencies? The response did not highlight specific structural barriers.

Are there any other challenges or barriers that hinder you from being proficient in data literacy and data competencies? Keeping up with the evolving field of AI and advanced modeling techniques.

Organizational Culture:

How would you describe the culture of data use within your organization? It's getting more data-driven, with top management presentations increasingly focusing on data and trends.

What steps do you think are necessary to foster a more data-driven culture? Continuous training and integration of data insights at all levels.

Resource Allocation:

Do you think your organization allocates sufficient resources towards improving data literacy among top management? Why or why not? There are online resources and training available.

Q: What additional resources or support would help you better utilize data in your role? Continued access to training and the time to engage with new learning opportunities.

Trust in Data:

Q: How much do you trust the data provided to you for decision-making? A: Trust depends on understanding the source, definitions, and methodology behind the data.

Q: What factors influence this trust? Knowledge of the data source, validation processes, and consistency in definitions.

Role of Data Scientists:

Q: To what extent do you rely on data scientists for processed information? Data scientists are crucial for complex statistical analysis and providing deeper insights

Q: How do you ensure that you understand and can act on the insights provided by data scientists? By engaging with the data, understanding the methodologies used, and continuous learning.

Future Outlook:

How do you see the role of data literacy and competencies evolving in top management over the next five years? With advancements in AI and data modeling, the role will likely become more intuitive and integrated into decision-making processes.

What future challenges and opportunities do you anticipate in this area? Keeping up with evolving technologies and integrating them effectively into business practices.