# The Role of Management in Fostering Analytics: The Shift from Intuition to Analytics-Based Decision-Making

**Abstract**

Numerous studies have shown that approaches of AI&A decision-making have the power to increase the quality of decisions. However, many firms have not adopted these approaches and many decisions are still made intuitively. Those decisions often fail to achieve their intended results, lead to negative consequences, and sometimes must be reversed. This paper sheds light on the question of how management can drive the shift from intuitive to data-based decision-making.

An in-depth single-site case study was conducted with a large publicly listed German manufacturing company. Building on 22 interviews, this empirical study identifies the root causes and overarching factors that need to be addressed to facilitate the shift from intuitive to analytics-based decision-making. These include management behavior, top management and strategy, analytics infrastructure, organization and governance, HR management and development, and culture. These factors form a hexagonal framework that offers actionable lessons for practice.

The derived framework can serve as a basis for further research on the topic of analytical decision-making. In addition, it provides company leaders a useful tool to manage the transformation of decision-making in organizations.

**Keywords:** analytics, decision-making, management, digital transformation, case study.

# 1. Introduction

Despite the growing importance of analytics in the economy, many companies still tend to favor the highest-paid person's subjective opinion when making decisions of significant impact (McAfee & Brynjolfsson, 2012). Research has shown that relying on subjective managerial inputs rather than hard data has a negative effect on decision quality (Henry & Venkatraman, 2015). Artificial intelligence and analytics (AI&A) approaches have the potential to improve the decision-making process (Power et al., 2019; Yigit & Kanbach, 2021). Big data allows executives to gain better insights and make more decisions of higher quality than ever before (Duan et al., 2019). It is argued that organizations intending to establish AI&A should develop a *we know* rather than *we think* mindset, meaning they should stop relying on assumptions and intuitions and start developing data-based knowledge (McAfee & Brynjolfsson, 2012).

As the importance of data in business has increased, academic discussions have turned to the ways analytic methods can lead to better decisions and help businesses sustain their competitive advantage (e.g., Iglesias et al., 2019; Pappas et al., 2018). Various studies published within the last few years have shown that analytics-based decision-making has a positive impact on firm performance and that big-data analytics is one of the major drivers of this development (e.g., Elgendy & Elragal, 2016; Thirathon et al., 2017). Furthermore, several studies have contributed to a deeper understanding of relevant capabilities for analytics that lead to enhanced firm performance (e.g., Akter et al., 2016; Gupta & George, 2016; Lavalle et al., 2011). In addition, it has been shown that analytics-based decision-making is strongly associated with better decision outcomes (e.g., Chaudhuri et al., 2011; Guillemette et al., 2014). These results support the thesis that executives who apply a structured approach to decision-making (i.e., engaging in the dedicated use of analytical tools and methods) increase the frequency of positive outcomes and contribute to value creation (Simon, 1987). However, organizations still struggle with the shift from intuitive to analytics-based decision-making, and it remains unclear how to manage the transition. It is argued that research should explore this phenomenon in various organizational contexts (Arunachalam et al., 2018). Janssen et al. (2017) claimed that the decision-making process itself and several related factors require a deeper understanding of analytics and the development of relevant capabilities. Furthermore, Shamim et al. (2020) argued that an in-depth understanding of the role of management in decision-making is important to enable the development of a data-driven culture. This study aimed to identify critical success factors affecting the use of analytics in the era of big data and to provide best practices by addressing the following research question:

*RQ: How can management facilitate and enforce a shift from intuitive to analytics-based decision-making?*

A critical case-study approach (Flyvbjerg, 2006; Yin, 2018) was chosen to create an experience report on decision-making through interviewing various executives at different hierarchy levels within a manufacturing corporation. The result was an empirically grounded framework for how management teams at large enterprises can address AI&A in practice. This study identifies factors affecting the transition from intuitive to analytics-based decision-making to help firms utilize the power of analytics in the manufacturing industry. Focusing on one case allowed us to gain a detailed understanding of the topic. The framework derived is intended to guide executives through this fundamental change in the way they make decisions. This phenomenon has not been researched in depth until now (Ferraris et al., 2019).

The paper is structured as follows. First, detailed information on the qualitative research design applied is provided, together with background information on the case. Next, in section 4, the results and findings of this study are presented. The paper closes by discussing the findings, putting forward their theoretical and practical implications, examining the limitations of the study, and providing an overview of future research directions.

# 2. Research Design

This paper applies the methodology of an in-depth single-site case study, which allows researchers to gain a deep understanding of challenges, responses, and experiences of executives with respect to applying analytics. Many interrelated factors influence the way executives make decisions, and all of them must be understood in order to grasp how analytics can improve the quality of decision-making (Power et al., 2019). Therefore, it is important to identify concrete factors that enable the use of AI&A to effectively improve firm performance (Janssen et al., 2017). A case study allows the authors to gain the insights that are needed for theory-building (Eisenhardt & Graebner, 2007) and to assess a specific context in an exploratory and explanatory way (Yin, 2018). This paper focuses on *how* to achieve the target state by uncovering the factors that are relevant to the shift from intuition- to analytics-based decision-making.

The case-study approach has been widely applied in the context of investigating decision-making and related topics (e.g., Annosi et al., 2020; Phipps & Shelton, 2020). According to Yin (2013), this inductive approach enables a comprehensive understanding of a dynamic phenomenon through gathering a broad variety of feedback within one case study and considering the process of decision-making in its context and with respect to its influencing factors (Baxter and Jack, 2015).

## 2.1 Research Setting—Case Description

A multinational high-tech manufacturing company headquartered in Germany was selected as the case study for this empirical research. AI and analytics have disrupted their internal processes and forced the firm to act. The firm must rethink and adapt its internal decision-making processes to sustain a competitive advantage in its industry (Berns et al., 2009; Pappas et al., 2018). With over 100 years of history in manufacturing, the company is engineering-driven, and many business decisions are still made based on the intuition of experienced employees. The company is currently navigating a complex situation, with certain areas already having analytics initiatives in place, while others rely more heavily on traditional procedures. This imbalance poses a challenge for managers at different levels and raises the question of how management can encourage the holistic shift from intuitive to analytics-based decisions. The organization considers data-driven decisions and the harnessing of data in business processes crucial to remaining successful in a globally competitive market.

The company can be seen as a critical case, as it provides actionable lessons for practitioners and scholars alike (Flyvbjerg, 2006). Its characteristics also qualify it as a candidate for a blueprint development. First, high-tech manufacturing is one of the core industries of the global economy. There is a large base of similar firms that could learn from the case study. Furthermore, the case-study firm operates globally and has various subsidiaries. That setup poses challenges that many other organizations will have to face in a global economy with increasing connectivity across supply chains, manufacturing processes, and product innovations. Another argument for the authors' choice of this case is that the company, with over 29,000 employees, is listed on the stock market and must thus consider and harmonize various interests when making business decisions.

### 2.2 Data Collection and Analysis

This study builds on extensive qualitative data to analyze the highly dynamic and complex phenomenon of decision-making to explain the *why* (reason for change) and *how* (managing the shift) in this sample case (Yin, 2018). To assess current perspectives and arrive at a comprehensive understanding of these, interviewees were selected carefully by the authors. A total of 22 semi-structured interviews were conducted in three iterations between May and August 2021. Each interview lasted between 30 and 60 minutes and was digitally recorded and transcribed in its original language. Table 1 provides relevant details about the interviews. Detailed interview questions are given in the Appendix. To guarantee construct validity (Lee & Lee, 1999), we used multiple sources of evidence, such as reports, internal documents, and information, provided by the contact persons and interviewees. Furthermore, the documented data-collection process provides reliability and follows the chain of evidence of Yin (2018), as the authors reflected their findings with feedback from key informants in the organization.

**Table 1** Overview of interviewees, language, duration of interview, and iteration

| | Interviewee | Language | Duration (minutes) | Iteration |
|---|---|---|---|---|
| **1** | Vice president | German | 59 | 1st |
| **2** | Vice president | English | 58 | 1st |
| **3** | Senior vice president | German | 60 | 1st |
| **4** | Manager | German | 55 | 1st |
| **5** | Director | German | 47 | 1st |
| **6** | Vice president | German | 43 | 1st |
| **7** | Specialist | German | 53 | 1st |
| **8** | Vice president | German | 50 | 1st |
| **9** | CIO | German | 43 | 1st |
| **10** | Manager | English | 37 | 2nd |
| **11** | Manager | German | 41 | 2nd |
| **12** | Manager | English | 43 | 2nd |
| **13** | Vice president | German | 35 | 2nd |
| **14** | Vice president | German | 48 | 2nd |
| **15** | Director | German | 52 | 2nd |
| **16** | Vice president | German | 48 | 2nd |
| **17** | Manager | German | 42 | 3rd |
| **18** | Vice president | German | 44 | 3rd |
| **19** | Specialist | German | 52 | 3rd |
| **20** | Specialist | German | 47 | 3rd |
| **21** | Vice president | German | 36 | 3rd |
| **22** | Specialist | German | 45 | 3rd |

Three subsequent iterations of data collection, analysis, and inductive coding were conducted following a collaborative approach by the authors until theoretical saturation was reached (Corbin & Strauss, 1990). Figure 1 provides an overview of the entire data-collection and analysis process using the iterative framework of Prachi and Hopwood (2009) to create new insights from reflexive qualitative data analysis.

The analysis began by reading all interview transcripts and accompanying notes. The authors frequently came together to discuss the main aspects of the interviews to ensure common understanding of the coding process. We used MaxQDA software to code the interviews according to the procedure outlined by Gioia et al. (2012). At regular intervals, coding results were compared, and potential differences discussed, until mutual agreement was reached. To mitigate researcher bias in the coding process, the preliminary findings were pressure-tested within the authors’ research group, confirming the categorization for most of the coding results, while smaller adjustments were made for others.

**Figure 1** Data collection and coding process following Prachi and Hopwood (2009)

# 3. Findings

The main objective of this study was to identify factors that are relevant for managers who intend to shift from intuitive decision-making to analytics-based decision-making. We identified six major factors that were then organized into a systemized framework. Figure 2 illustrates the framework: management behavior, top management and strategy, analytics infrastructure, organization and governance, HR management, and development and culture. The following sections explain these six aspects in detail and illustrate concepts through examples and interview quotations.

**Figure 2** Framework for “managing the shift”—six factors to consider when shifting to data-based decision making

## 3.1 Management Behavior

Management behavior—how executives act in general and when dealing with employees in particular—consists of various intraorganizational factors that are relevant when planning the shift from intuitive to analytics-based decision-making. Throughout the interviews, three major aspects of management behavior were identified: executives’ personality, leadership abilities, and their decision-making.

One of the most decisive factors in anchoring analytical decision-making is the executive's personality. During interviews, personality traits, such as openness, empathy, and teamwork skills, emerged as relevant. The leader must be open to the change and must be willing to act like an empathic role model. Introducing analytical methods into an existing static–dynamic organization and establishing them successfully requires the cooperation of a wide variety of stakeholders who all have their own characters, convictions, and beliefs. Managers must be able to keep an eye on the needs and demands of these stakeholders and respond accordingly.

> If managers do not have confidence and do not believe in analytics, it ends in disaster because the employees do not follow the appropriate shift. (Interviewee 18)

Acting as a role model and leading the change requires the willingness to engage with analytical methods and associated tools and processes in detail. This knowledge enables leaders to initiate well-grounded discussions about solutions and approaches with specialists and gives them the tools to reduce potential fears among employees.

The second element of the management-behavior dimension is the executive's leadership behavior. The implementation of analytics and associated new processes in established organizations requires managers to have confidence in the strengths, knowledge, and skills of their team. The key to success is to give employees and decision-makers enough time to go through this transformation. Management should be realistic and consider resource constraints for planning and implementation.

> Best practice in this context is trust, team-oriented leadership, and definitely diversification in the team to reflect the different perspectives. (Interviewee 6)

Supervisors should try to mitigate the fear of data or analytical methods that may prevail among decision-makers and strive to create a high level of trust and transparency. Preconceptions about data-based decision-making may be addressed through open communication within the team. It is necessary to create a continuous learning process and to work closely with decision-makers in their first attempts at deploying analytical methods. It is important to provide encouragement and support so that decision-makers gradually dare to leave their comfort zone of purely intuitive decision-making and start consulting data.

The decision-making of the supervisor emerged as a third, success critical factor. If leaders use analytics in their decision-making, it emphasizes that the shift is being taken seriously. It also increases the transparency and comprehensibility of the decisions, which drives the acceptance of analytical methods among employees. The interviewees said that if leaders use analytical methods to make decisions and take the time to explain them and show their advantages, employees have a higher level of confidence in the decisions and the methods behind them.

> Today, we can derive results from analytical systems, and it is widely different from what we did before. Certain steps are followed and ensure a transparency that helps to gain trust and show people that the personal bias is taken out. (Interviewee 21)

While basing decisions on data is generally thought to result in better decisions, managers should be aware that some decisions must still be made intuitively. For example, when building a team, managers should consider interpersonal factors that no algorithm can detect. To manage the shift successfully, managers should employ a balanced approach to decision-making and explain their choices to their team.

## 3.2 Top Management and Strategy

The top-management team play an important role in the shift from intuitive to analytics-based decision-making, and not only because of their hierarchical position. Their responsibility as drivers of transformation, their objectives and compensation system, and their responsibility for overall corporate strategy represent three aspects that are critical to success: change driver, objectives and compensation, and corporate strategy.

The interviews showed that the highest management level within the organization must act as a change driver.

> If it’s coming from the top down, we have more power and influence, especially for the others who do not want to change easily. (Interviewee 2)

The board of directors in particular has immense influence in a company, as all organizational areas are represented by different board members. Employees are more critical when it comes to the behavior of top management versus the behavior of those holding lower management positions. Board members must be aware of their influence and use it. Showing trust in analytical methods, their application, technology, and data as sources of valuable information helps to drive change in the organization.

A key determinant of how top management understands their role is the setting of objectives and compensation models. Board members are mostly appointed for a limited period, and in most cases the objectives are also set for the short term. Far-reaching, long-term transformations, such as the shift to analytics-based decisions, usually exceed this period, leading to a situation in which previous objectives are no longer pursued once a board member is replaced. In addition, compensation and incentive models often do not motivate top management to act with the long-term growth of the company in mind but are rather based on short-term key performance indicators.

> Incentivization must include short-term corporate development, but also long-term perspectives beyond their appointment to the Executive Board to ensure that you future-fit the organization. (Interviewee 7)

In this context, publicly listed companies face a major challenge, as objectives may differ by stakeholder and a short-term decline in one key performance indicator may not be tolerated, even if it is a necessary precondition for long-term success. Firms are well advised to align their compensation and incentive structure with their long-term objectives. In our context, that means the decision-making transformation must be set as an official objective and reflected in compensation models.

To set the conditions for a sustainable shift to data-based decision-making, corporate strategy must express the appropriate objectives. Interviewees indicated that the company’s vision and mission must align with the transformation goal.

> Analytics is a question of future sustainability, and if you don’t master it, you run the risk of losing touch. (Interviewee 9)

Only if top management emphasizes the objective in the overall corporate strategy can the new direction cascade down to lower levels in all divisions. Given that many stakeholders must be on board, it is critical to ensure holistic acceptance of the new philosophy. Corporate management has the responsibility to set the direction and to provide clear orientation and guidelines for employees regarding how to carry out their tasks.

## 3.3 Analytics Infrastructure

The interviewees noted that the availability of data and a processing system is an additional core prerequisite. The analytics infrastructure comprises a data ecosystem, an IT infrastructure with software and hardware, and the central provision of analytical assets.

Establishing processes to handle data throughout their life cycle ensures that analytical models and predictions are of high quality. A holistic data ecosystem facilitates the application of analytical methods.

> The data creation must have a high level of maturity, and be high quality, to ensure the decision they make is of high quality, too. (Interviewee 14)

Data can only be of high quality if the process of data creation is already of high maturity. Firms need to ensure that analytical methods develop coherently within the organization to enable the establishment of an effective data ecosystem. If that is not the case, data-structure discrepancies emerge and prevent subsequent analytical processes from running smoothly. It is important to assign clear responsibilities to employees, who then take full ownership of the development of the data ecosystem. This data and ownership process promotes high levels of data quality and consistency and facilitates exchange between internal and external stakeholders of the data ecosystem. This covers such processes as data creation, data processing, and removal or storage of data that are no longer needed.

The basis of high-quality data collection and processing is a sound IT infrastructure. Infrastructure includes systems that collect data and software that processes the data and supports the decision-making process.

> We need an IT infrastructure that is capable of providing the master data consistently in order to be able to apply analytics to it. (Interviewee 4)

The assigned data owner should ensure that the data-creation systems provide high-quality and processable results. In addition, system compatibility and adaptability to new systems must be guaranteed. To motivate decision-makers to use data and systems, flexible and easy-to-use solutions should be provided. A good user experience is key to the sustainable application of these tools, and hence facilitates the shift toward analytics-based decision-making.

In large multinational organizations in particular, the assignment of central analytics responsibility drives the consistent use of analytical methods.

> A responsible group, with dedicated expertise, to outline available options, discuss them and build an appropriate solution, which is then made available company wide. (Interviewee 1)

Establishing new ways of working and associated structures is a time- and resource-intensive undertaking for organizations with established processes and responsibilities. Setting up a central unit responsible for such change is an effective and efficient way to integrate analytics in the firm and to introduce employees to these methods. Such an “analytics hub” can prove particularly useful in initiating the first step of the transformation, such as spreading the word, maximizing the utility of existing processes, and ensuring consistency in data and systems.

### 3.4 Organization and Governance

A radical transformation of the decision-making process requires the organization to rethink and realign its control and steering systems. In this context, it is important to consider the corporate organization and both organizational and data governance.

Making analytics usable across the organization requires a dismantling of the often-prevailing “silo” thinking. The organization needs to establish a collective willingness to share data and apply analytic methods. Particularly in companies that are well established, organizational structures can be deeply entrenched and present an obstacle to the establishment of new forms of collaboration. In applying AI&A approaches, however, organizations must take unconventional paths to be successful. Agile teams staffed with experts from different areas play a crucial role in the shift from intuitive to analytics-based decisions.

> The IT department must support the operational units as a strategic partner and business partner, and it must go beyond standard solutions. (Interviewee 10)

In addition to the aforementioned analytics hub, the IT department has a prominent role when it comes to driving the use of analytics. Companies must switch their mindset and start to consider the IT department no longer as a low-cost service provider but as a center of competence with a clear strategy and operating model that can support the new, agile organizational units.

Dedicated organizational governance is essential in facilitating this mindset shift. Assigning clear responsibilities and explicit roles within the organization makes it easier for operational staff to act on changed expectations. It also ensures that transformation efforts are bundled centrally and distributed across smaller individual initiatives.

> True governance ensures that workflows, processes, and results are comparable and creates transparency about tools and methodologies." (Interviewee 16)

Streamlined procedures increase the effectiveness of a decision-making process. At the same time, individuals should be granted a certain level of flexibility within predefined guidelines. This helps to achieve the right balance of ensuring organization-wide consistency while taking situational conditions into account.

Data governance also contributes to data and process consistency across departments. It establishes a clear scope of action for the collection of data, provides guidelines for the data ecosystem, and ensures transparency for all organizational units.

> Especially for analytics, a single source of truth is crucial. Transparency and traceability are elementary for business decisions. (Interviewee 19)

With the help of clear guidelines for processing data, decisions can be traced and validated. This process strengthens the confidence of both decision-makers and employees in the decisions that have been made, which in turn creates more confidence in the applied analytical methods. This is an iterative process.

## 3.5 HR Management and Development

Implementing the aforementioned changes will trigger a need to implement corresponding changes in HR management. To support the shift from intuitive to analytics-based decisions, realigned recruiting processes, adjusted training and development measures, and new team composition are required.

Big data and analytics are changing what is expected of employees in almost all areas. Recruiting, HR management, and supervisors should adapt role descriptions and staffing processes accordingly.

> When filling new vacancies, it is important from a strategic point of view to avoid looking for a candidate who has old skills and knowledge. (Interviewee 13)

Finding a candidate for a position cannot be based on the old job profile. The increasing use of analytical tools and methods and changing working styles demand new skills. During the hiring process, accounting for changed expectations reduces the amount training required later. Updating role descriptions and ensuring compliance in the recruiting process helps to manage the increasing usage of analytics in a resource-saving manner.

Training and development efforts must be tailored to the job profile, development path, and capability gaps of each employee. Close cooperation between operational managers and the HR department ensures that all relevant skill and knowledge gaps are considered in the training content.

> It was important to train the leaders first and then drill it down into the workers and the other guys, not just the guys working with decisions day to day. (Interviewee 12)

A holistic top-down approach should be followed, meaning that managers receive the training first and employees are trained soon after. Managers are often the first point of contact for questions that arise, and are thus in a better position to address issues once they participate in training. Furthermore, same level of knowledge facilitates a substantive discussion.

The use of analytics also requires new forms of collaboration. A step-by-step approach with lighthouse projects creates visibility and trust. Cross-functional teams of operational employees and data specialists can create an effective balance of skills and contribute to the success of these projects.

> Teams of subject-matter experts and data scientists are indispensable to ensure exchange. (Interviewee 10)

Balance in terms of educational background, gender, and other factors supports the exchange of opinions and thus helps teams to be more productive. Heterogeneous ways of thinking can define new perspectives on issues and establish the basis for productive discussion. A diverse team setup shapes the corporate culture significantly.

### 3.6 Culture

> Culture connects us employees in the organization. Everything pays off and everything depends on it. (Interviewee 22)

The aforementioned factors are not independent levers that can be pulled to shift to analytical decision-making. Such factors are not to be understood as independent, but rather as interdependent and mutually enforcing. All these factors are connected by a certain kind of “invisible glue”—the organizational culture that permeates the organization. Organizational culture is a multilayered, complex concept that comprises a variety of aspects, such as the behavior of superiors, which influences the leadership culture, and the composition of teams, which shapes the culture of communication and cooperation. The interviews showed that culture is a lever that cannot be interpreted on its own, but must be looked at as an overarching, all-encompassing factor.

A key cultural element is a common understanding of the objectives to be achieved with analytics, yet it is even more important to have an organization-wide definition of analytical terms and methods. Only with this overarching understanding can a mindset change be triggered among employees. In turn, that shift is the only way to ensure that carefully drafted plans are carried out.

> Often, it is only buzzwords that are thrown around and a common understanding is missing. (Interviewee 14)

Furthermore, this common understanding creates trust in new technologies and systems among employees. The use of analytical methods can no longer be an option—it must be the default.

# 4. Discussion and Concluding Remarks

## 4.1 Detailed Discussion of Findings and Implications

The shift from intuitive to analytics-based decision-making is a major endeavor for organizations. This study puts forward a framework for how to manage this transformation, building on the analysis of interview information gathered in a single case study in the manufacturing industry.

This in-depth case study of 22 interviews with experts at various hierarchical levels revealed six factors that enable the shift toward evidence-based decisions: management behavior, top management and strategy, analytics infrastructure, organization and governance, HR management, and development and culture. In line with the research of Arunachalam et al. (2018) and Janssen et al. (2017), executives must act as role models to lead the change. The behavior of top management was mentioned by almost all interviewees. More than any line manager, top managers must act as role models in the use of analytics. This finding confirms and extends the conclusions of Shamim et al. (2019), who found that differentiating between various management levels is an important change driver. Top managers are responsible for structuring and managing transformation and creating a common understanding of terms, methods, and processes. This study showed that large, publicly traded companies face multiple organizational challenges in making the shift from intuitive to analytics-based decisions. Extending the findings of Thirathon et al. (2017), we point out that organizational structures, processes, and also regulations captured in organizational governance are relevant factors. Another specific and mission-critical factor is the appointment period of board members. Board members are often appointed only for a limited time and are incentivized to achieve short-term successes. Such an incentive structure poses an obstacle in the attempt to implement a profound and comprehensive strategic and operational realignment, as the return on investment may be generated only after the appointment period. Organizations that try to manage the shift should reconsider appointment periods or adjust incentive systems accordingly.

Manufacturing companies are often engineering-driven, and manual labor to create tangible products is more familiar to employees than AI&A. IT employees must be introduced to new methods and need support to become trusting and capable users.

This is important, as the use of analytical methods for processing large amounts of data is not a unique and differentiating feature anymore. Rather, it imposes a strategic imperative on firms that want to stay competitive in dynamic, competitive global markets.

## 4.2 Limitations and Future Research Directions

Although this study offers comprehensive empirical insight and an actionable holistic framework, there are some limitations that represent opportunities for future study. The single-site case-study design is a limitation, as only one firm with specific characteristics was assessed. However, the selected manufacturing company is a critical case, as it has special experience in the application of AI&A approaches and thus helped in answering the research questions appropriately (Flyvbjerg, 2006; Yin, 2018). Several executives at various hierarchy levels were interviewed, which enabled the collection of nuanced and illuminating data. To prevent biases in interviewees' attitudes toward the employer, results were triangulated with secondary internal company data. Another limitation of our research is that the company we analyzed has a degree of maturity regarding the transformation from intuition to analytics-based decision-making. Organizations with different maturity levels regarding the application of AI&A may find different factors to be important or may emphasize one factor more strongly.

Future research should address this point and determine the relevance of the identified factors in terms of different maturity levels to increase the effectiveness of the framework. In addition, it could be interesting to assess whether the framework developed is valid across industries or must be adapted when applied in other contexts. Tailoring research efforts to such specifics would help to establish a broader understanding of the phenomenon and provide practitioners across industries and firms with insight on how to manage the shift towards analytical methods in decision-making.

# 5. Appendix

a. Questionnaire for data collection (English version)

**General | introduction**

1. Would you please briefly describe your scope of duties with 2-3 sentences?
2. What is the professional designation of your supervisor?

**Definitions**

3. What is your understanding of big data and big-data analytics?
4. What do you understand of a data-driven company?

**Decision-making | status quo**

5. What is the ratio of decisions you currently make intuitively/based on your own knowledge and decisions you make based on data?
6. What are the factors why you make a decision intuitively, i.e., based on your own knowledge?
7. What are the factors that determine why you make a decision based on evidence/data?
8. What is your perspective regarding opportunities and possibilities of data-based decisions?
9. What are possible challenges or threats you see from the use of analytics in decision-making?

**Management aspects of analytics-based decision-making**

10. What influence has your superior on whether you make a decision intuitively or based on data?
11. What could your superior manager change regarding his behavior, so you apply more analytics within the decision-making process?
12. From your perspective, what would be the “best practice” management behavior of your direct supervisor, you use make data-based decisions?
13. In your opinion, what are management factors that promote the use of analytics in decision-making?
14. What opportunities and possibilities do you have as a manager to promote the use of big-data analytics in decision-making among your employees?
15. What do you see as strategic factors that promote the use of analytics in decision-making?
16. What impact would anchoring data-driven decisions within the overall corporate strategy (vision, mission) have on you?
17. What impact does top management (CxO) behavior have on your use of data in decision-making?
18. How can top management (CxO) encourage the use of analytics beyond investments?

19. What do you think management should do to not encourage the shift from intuitive to data-driven decisions? Are there differences between middle management and top management here?

**Organizational factors for making data-based decisions**

20. Do you see challenges for the use of big-data analytics in the decision-making process due to the organizational structure?
21. What organizational changes would increase your use of big data for decision-making?
22. What impact would strategic and operational alliances with external data specialists have on your use of big data for decision-making?
23. How should a “best practice” governance look in order to optimally support the use of analytics in the decision-making process?

**Closing questions**

24. Is there anything else you would like to share with me regarding big data analytics and your decision-making process?

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