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From intuitive to data-driven decision-making in digital transformation: A framework of prevalent managerial archetypes

Philipp Korherr [a,*], Dominik K. Kanbach [a], Sascha Kraus [b,c], Patrick Mikalef [d,e]

[a] HHL Leipzig Graduate School of Management, Jahnallee 59, 04109 Leipzig, Germany
[b] Free University of Bozen-Bolzano, Piazza Università, 1, 39100 Bolzano, Italy
[c] University of Johannesburg, Department of Business Management, Johannesburg, South Africa
[d] Norwegian University of Science and Technology, Sem Sælandsvei 9, 7491 Trondheim, Norway
[e] SINTEF Digital, Department of Technology Management, S P Andersens vei 3, 7031, Trondheim, Norway

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ABSTRACT

The use of analytics in corporate decision-making processes demands a paradigm shift within companies, and particularly among their top executives. Corporate leaders represent a major lever for this change. Therefore, a deeper understanding of their managerial capabilities, characteristics and contribution in this context is required. Aiming to provide actionable guidance on how to manage the shift to data-driven decision making, this study helps to develop a more profound understanding of this emerging managerial role by examining managerial success factors following a semi-structured interview approach. With insights from interviews with 32 top executives from Germany across different industries, this paper research proposes four managerial archetypes that are relevant to mastering the digital transformation towards analytics-based decision-making processes. Furthermore, it sheds light on the characteristics, capabilities, and contributions of the four archetypes—Analytical Thinker, Coach, Guide, and Strategist. Although the archetypes have differentiated attributes and qualities, all four seem of importance in manifesting analytics in organizations. Our findings provide guidelines to assess the top management's abilities to manage digital transformation projects. Furthermore, the results serve as basis for future empirical research on the human aspect of analytical capabilities regarding leadership.

1. Introduction

Digitalization is changing modern economic realities at an unparalleled speed (Kraus et al., 2022; Kraus, Jones, Kailer, & Weinmann, 2021). A wide variety of digital trends and technologies are forcing companies to change their business models, organizational structures, and corporate processes (Kiron, Prentice, & Ferguson, 2014; Bouncken, Kraus and Roig-Tierno, 2021). The half-life of certain technologies and digital opportunities is becoming ever shorter, and companies must adapt to these dynamic conditions and transform themselves accordingly (Bouncken & Kraus, 2021). The use of data, artificial intelligence, and analytics plays a key role in this process, and "exploiting vast new flows of information can radically improve […] company's performance" (McAfee & Brynjolfsson, 2012, p. 1). Companies of varying sizes and from various industries are pushing to become data-driven and apply a variety of digital tools (Corvello, De Carolis, Verteramo, & Steiber, 2021). However, some companies have been less successful than others in mastering this transformation.

Research on the digital transformation of organizations must keep pace with this exponential development in practice, and current scholarship is focused on the use of data for improved decision-making processes (Korherr, Kanbach, Kraus, & Jones, 2022; Power, Cyphert, & Roth, 2019). Research has shown that the use of data has a positive influence on the decision-making process and associated outcomes—in other words, the quality of the decision (Duan, Edwards, & Dwivedi, 2019). Studies have determined that relevant management capabilities and leadership skills for actively managing this change are of high importance for an effective transformation (Heubeck & Meckl, 2021; Korherr & Kanbach, 2021). This finding has prompted further research into which management characteristics and skills positively influence

* Corresponding author.
E-mail addresses: philipp.korherr@hhl.de (P. Korherr), D.Kanbach@hhl.de (D.K. Kanbach), Sascha.kraus@zfke.de (S. Kraus), patrick.mikalef@sintef.no (P. Mikalef).

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the shift toward data-driven decision making (Korherr & Kanbach, 2021). While current research shows that this shift requires a great number of resources (Ransbotham et al., 2020), managers largely remain puzzled and uncertain about how they should manage the transition from intuitive to analytics-based decisions (Korherr et al., 2022; Leemann, Kanbach, & Stubner, 2021). Hence, a profound understanding of the newly emerging managerial role, including expected key leadership characteristics and capabilities, has become critical to managing the transformation (Shamim, Zeng, Khan, & Zia, 2020; Singh, Klarner, & Hess, 2020). In order to develop an understanding of how to master the strategic challenge, the human dimension and psychological aspects must be understood in great detail; therefore, a scientific framework to guide practitioners on how the digital manager of the future should look is required (Elgendy, Elragal, & Päivärinta, 2022; Tabrizi, Lam, Girard, & Irvin, 2019). Although the importance of data is constantly rising and companies push for the application of analytical solutions, studies show that through 2025 the majority of responsible executives will fail to foster the required data literacy among employees in order to become a data-driven company (Goasduff, 2022). While at the same time, there is a great discourse regarding research in applied analytics and the operationalization of analytical methods in companies (Batistič & van der Laken, 2019). It is of fundamental importance that science in this context creates a deeper understanding of potential management success factors, respectively managerial capabilities, characteristics and the contributions of managers (Arunachalam, Kumar, & Kawalek, 2018; Caputo, Cillo, Candelo, & Liu, 2019; Janssen, van der Voort, & Wahyudi, 2017).

To address the identified research gap, this study aims to investigate which set of characteristics and capabilities enables a firm's top management to adapt effectively to this dynamic environment. The goal of this paper is to identify and analyze prevalent managerial types and their emerging role in digital transformation in order to successfully manage the change from intuitive to analytics-based decisions. Hence, this study is guided by the following research question:

Which managerial characteristics, capabilities and contribution to change are suitable to enable the implementation of analytics in the decision-making process?

Following a semi-structured interview approach, the managerial characteristics that play a key role in leading the digital transformation are investigated. Interviews conducted with German top executives, facilitating the direct reports of top management from diverse industries, reveal four management archetypes—*the Analytic Thinker*, *the Coach*, *the Guide*, and *the Strategist*—and their related characteristics, capabilities, and contributions to mastering the digital transformation. The insights collected in talks with managers sampled from a range of companies in different industries provides a broad understanding of the topic at hand. The identified archetypes and resulting coaching needs can thus serve as an academic guide for practitioners who are currently facing the challenge of transforming their decision-making methods toward an analytics-based approach (Ferraris, Mazzoleni, Devalle, & Couturier, 2019).

2. Theoretical background

In line with the increasing importance of data across various business models, this burgeoning field of research examined the necessary organizational and individual capabilities for the application of analytical methods (e.g., Gupta & George, 2016; McAfee & Brynjolfsson, 2012).

2.1. Value of data-driven decision-making

Academia recognized at an early stage that data on its own is a useless asset (Lamba & Dubey, 2015) and that decisions based on an individual's knowledge are prone to error (Minciu, Berar, & Dobrea, 2020). Building on these insights, analytical models have emerged as a differentiating factor in global competitive environments within the last two decades (Lavalle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; Yalcin, Kilic, & Delen, 2022). Whereas in the early days primarily internet companies and organizations with intangible products, such as the banking sector, benefited from data analytics (Srivastava & Gopalkrishnan, 2015), the digitalization of industrial production is now making its way into the manufacturing sector ('Industry 4.0') as well (Bousdekis, Lepenioti, Apostolou, & Mentzas, 2021).

Academia has also taken up this topic and started to investigate how data can be used to add value to the decision-making process within distinct industries and contexts. Various domain-specific contexts have already been investigated (e.g. Mikalef, Boura, Lekakos, & Krogstie, 2020; Shuradze, Bogodistov, & Wagner, 2018), such as the application of data in the area of healthcare (Hsu, Liou, & Lo, 2021; Wang, Kung, & Byrd, 2018), manufacturing (Dubey et al., 2018) or mining (Bag, Wood, Xu, Dhamija, & Kayikci, 2020). In addition to these industry-specific contexts, this issue has been examined from a variety of existing theoretical perspectives, including the resource-based view (Perdana, Lee, Koh, & Arisandi, 2022), dynamic capabilities (Chae & Olson, 2013; Garbellano, Da Veiga, & do R., 2019) and information processing theory (Song, Zhang, & Heng, 2020).

Using these theories as basis, various research streams have focused on highlighting the question of how analytics can contribute positively in a corporate context. In an attempt to answer this question, the positive impact on e.g. an organization's innovative strength (Trabucchi & Buganza, 2019), process improvements or firm performance was validated. Other areas of research addressed the question of which fundamental capabilities are required to apply analytic methods successfully in the decision-making process. Data-related capabilities (Côrte-Real, Ruivo, & Oliveira, 2020), operational capabilities (Mikalef, Boura, Lekakos, & Krogstie, 2019), and specific Big Data Analytics capabilities (Gupta & George, 2016) were examined by scholars to provide a profound basis for future research and an orientation for practitioners who are interested in knowing the skills required to use analytics effectively. Besides factors such as culture (Upadhyay & Kumar, 2020), governance (Mikalef, Boura, et al., 2020), or organization (Ashrafi, Zare Ravasan, Trkman, & Afshari, 2019), in particular the leadership aspect was identified as a central lever for using data effectively for value creation purposes in the organizational setting (Yasmin, Tatoglu, Kilic, Zaim, & Delen, 2020).

2.2. Individuals and their roles in orchestrating analytics initiatives

Academic research on analytics initiatives that intend to foster the usage of tools and methods within decision-making processes have shown that executive behavior and management are key elements (Ciampi, Demi, Magrini, Marzi, & Papa, 2021; Pedro, Brown, & Hart, 2019; Shet, Poddar, Wamba Samuel, & Dwivedi, 2021) for implementing digital methods sustainably (Konopik, Jahn, Schuster, Hoßbach, & Pflaum, 2022). The top-down management of such large-scale change initiatives requires detailed knowledge and distinct skills (Caputo et al., 2019), especially in the area of leadership capabilities (Holopainen, Ukko, & Saunila, 2022). Skills that have been identified as important are specifically the coordination and orchestration of diverse resources (Akter, Gunasekaran, Wamba, Babu, & Hani, 2020; Shokouhyar, Seddigh, & Panahifar, 2020). What all of these human capabilities have in common is that they can be assigned to a specific person, and can evolve over time as an executive develops further in an organizational context (Korherr & Kanbach, 2021). Thus far, however, academia has provided executives with only vague and generalized concepts regarding the general implementation of Big Data Analytics (e.g., Ciampi et al., 2021; Rialti, Zollo, Ferraris, & Alon, 2019; Yasmin et al., 2020). General scientific concepts for digital transformation were outlined without being fully applicable in the business reality, given a clear disparity between science in practice (Batistič & van der Laken, 2019). Hence, detailed empirical evidence that sheds light on the role of top management as a main driver for applying analytical methods within the decision-making process is needed (Elgendy et al., 2022). Existing empirical studies reveal that many executives are still struggling with the use of analytics (Reggio & Astesiano, 2020) and lack a clear understanding of how to manage this digital transformation within their organization (Arunachalam et al., 2018; Barroso & Laborda, 2022; Leemann et al., 2021). Yet it is precisely this group that is able to exert a fundamental influence by actively steering this change (Bughin, Deakin, & O'beirne, 2019) and driving a cultural shift from top-down (Gurbaxani & Dunkle, 2019).

This study aims to establish an in-depth understanding of managerial capabilities and characteristics, as well as to provide managers who face this challenge of change with profound, pioneering concepts and applicable best practices (McCarthy, Sammon, & Alhassan, 2021; Singh et al., 2020).

3. Research approach

This paper applies a qualitative, explorative, and inductive methodology to investigate the characteristics and capabilities that top executives should display in order to successfully master the analytical transformation to data-based decision making. This qualitative approach is particularly suited to examining human-related abilities, behaviors, and relationships—a complex and elusive issue for quantitative research (Aspers & Corte, 2019). The aim of applying this methodology is to gain a holistic understanding of the role of the manager in this transformation process, and to examine that role from various perspectives (Gioia, 2021).

3.1. Research design and sample

By applying a semi-structured, open-ended interview format, this study aimed to extract maximum information from the participants in order to develop a fundamental academic basis with limited bias and high empirical testability (Morse, 2010). Collecting data from German organizations across different industries allowed the researchers to gather multi-faceted insights about the managerial role in mastering the digital transformation to establish generalizable findings.

Germany has a high density of innovative and extremely competitive companies across all industries. The high diversity of product variants, company sizes, and industries in Germany forms the ideal mix from which to address the topic of digital transformation (Schweer & Sahl, 2017). Germany is internationally recognized for its strength in engineering and manufacturing, the backbones of its economic performance nowadays (German Federal Statistical Office, 2022). To sustain their competitive advantage in a competitive market environment, German companies are undergoing a radical digital transformation to integrate data into their products, business models, and company processes (Wiech et al., 2022). This situation offers an ideal precondition for assessing managerial types relevant in the digital transformation, for identifying best practices, and for deriving valuable insights in order to establish a sound theoretical framework (Shamim, Zeng, Shafi Choksy, & Shariq, 2019).

A total of 32 interviews were conducted during 2021 and 2022. Thus, a broad variety of industries was included for a highly heterogenous sample of sufficient size to reach theoretical saturation (Thomson, 2010). Initially, interviewees were approached via the network 'LinkedIn'. At the end of each interview, participants were asked to provide recommendations of potential additional candidates to be interviewed. After a positive initial requirement assessment, the suggested candidates were contacted for an interview. The authors also paid attention to diversity in the selection of interviewees, covering a range of industries in the sample to ensure generalizability. In order to examine top management capabilities and skills relevant to the implementation of analytical methods within the decision-making process, a key informant methodology was applied. The key informant method questions specific organizational members about organizational phenomena as a whole. In contrast to the standard practice of qualitative interviews, this approach allows researchers to access individuals who are in possession of detailed information about the phenomena under analysis (Kumar & Analyst, 1989; Taylor & Blake, 2015). This method is more beneficial and appropriate than conducting interviews with random employees, as

Table 1
Chronological interview list of key informants with industry and industry experience and analytics experience in years.

#	Key Informant Interviewee	Industry	Industry experience in years	Analytics experience in years
1	Manager	Biopharmaceutical	6	4
2	Manager	Consumer Goods	10	2
3	Chief Executive Officer	Finance	27	11
4	Vice President	Automotive Engineering	23	5
5	Vice President	Automotive Engineering	17	3
6	Senior Vice President	Industrial Engineering	25	10
7	Manager	Industrial Engineering	7	2
8	Director	Industrial Engineering	22	5
9	Vice President	Industrial Engineering	5	1
10	Specialist	Automotive Engineering	20	8
11	Vice President	Chemical Engineering	15	10
12	Chief Information Officer	Industrial Engineering	17	15
13	Manager	Chemical Engineering	12	11
14	Manager	Mechanical Engineering	26	5
15	Manager	Mechanical Engineering	4	3
16	Vice President	Mechanical Engineering	16	4
17	Vice President	Automotive Engineering	11	6
18	Director	Materials Engineering	12	8
19	Vice President	Materials Engineering	15	9
20	Manager	Aerospace Engineering	21	14
21	Vice President	Electrical Engineering	6	5
22	Specialist	Electrical Engineering	13	6
23	Specialist	Electrical Engineering	7	4
24	Vice President	Civil Engineering	13	2
25	Specialist	Automotive Engineering	16	9
26	Chief Executive Officer	Insurance & Healthcare	22	12
27	Vice President	Logistics	17	3
28	Managing Partner	Marketing & Advertisement	20	13
29	Vice President	Marketing & Advertisement	20	12
30	Chief Information Officer	Public Transportation	15	3
31	Council Member	Supplier (Automotive Engineering)	33	7
32	Manager	Supplier (Mechanical Engineering)	4	2

typically not all executives are directly involved in digital transformation projects. Table 1 provides an overview of all key informant interviews, their area of responsibility within the company, industry experience and period of Analytics application in practice. The interviewed key informants worked in companies of different sizes, from approximately 500 employees up to 40,000+ employees. This spread allows to cover a broad range of various organizational forms with varying perspectives towards steering digital transformations.

3.2. Data collection and analysis

The 32 key informants provided information regarding selected analytics projects in which they had an active role during the implementation of analytics and the corresponding change process, or—if the informant had the overall lead—about the whole digital transformation of their company. These personal experiences were recorded using a semi-structured interview approach, allowing the interviewees to share their experiences in an open setting (Adams, 2015). The entire selection and analysis process was aligned with Yin's criteria of validity (Yin, 2013). Each empirical report collected through the interviews represented a mini-case. The construct validity, chain of evidence in the selection and coding process, internal and external validity, with pattern-matching of interview statements and explanations, as well as the reliability, with a transparent evaluation process were targeted by the authors. For example, all participants had extensive experience in transformation projects and the use of Analytics. Furthermore, they held senior positions in their companies and were willing to share verbal and documented information, both positive and negative, about the introduction of analytics-based decision-making processes. All participants were verbally assured at the beginning of each interview that the contents of the interviews would be processed and published in accordance with the principles of anonymity and confidentiality. Due to the COVID-19 pandemic situation during 2021 and 2022, all interviews were conducted via online business communication platforms Zoom and Microsoft Teams, recorded on video or audio, and subsequently transcribed.

To ensure the necessary validity of the information, additional resources such as reports, internal documents, and shared information from the interviewees were included in the data collection process where possible (Yin, 2018). The interview period lasted from May 2021 to February 2022. All 32 interviews lasted between 24 min and 88 min. The average interview time across all key informant interviews was 38 min.

The entire data collection and analysis process consisted of eight steps, with iterative processes for conducting and coding the interviews. First, following an extensive literature search, a basic template for the semi-structured interviews was created based on gained insights. Emphasis was placed on asking open-ended questions and adhering to the rules for the selected interview form (Aldiabat & Le Navenec, 2018). Second, the first round of semi-structured interviews was conducted and followed by the third step, the processing and analysis of the interview data. Subsequently, two more rounds of interviews and data analysis were conducted (step 4 to 7). In a final, eighth step, the authors validated and detailed the results with the research group of the university chair. Appendix 1 provides an overview of all data collection and analysis steps conducted. After each interview, the vocal recording was transcribed immediately. In some cases, these transcripts were recirculated with the key informants to verify the validity of their statements. Following the inductive approach for analyzing qualitative data proposed by Thomas (2006), transcripts were coded using MaxQDA software. Fig. 1 provides the approach taken for analyzing the interview data.

In keeping with the iterative framework of Thomas (2006) and Creswell (2002), subsequent iterations of data collection, analysis, and inductive coding were conducted until a theoretical saturation was reached (Corbin & Strauss, 1990).

During the initial reading of the transcripts, the authors created a deeper understanding of the material. Based on these insights, relevant text segments were identified in a second step. The initial labels of these passages emerged from the actual phrases of the text sections. Throughout the coding process, these labels were further detailed and consolidated into 60 final categories by the author team. Refinements were then made along the dimensions of "characteristics", "capabilities" and "contribution". Regularly, coding labels were compared, potential differences discussed until the authors reached a consensus. Table 2 shows an example of interview statements, how they were labeled—along the coding process of Fig. 1—and assigned to certain archetypes. Statements that overlapped thematically or had a similar meaning were given the same label. Furthermore, preliminary findings were pressure-tested with Author's research group in order to mitigate the researcher bias. This data analysis approach enabled the authors to analyze and interpret raw interview material, translating it into an evidence-based

Table 2
Exemplary labels with quotations from the interviews.

Interviewee	Quotation/ text segment from interview transcript (German interviews translated)	Label	Archetype
Interviewee 11	"As a manager you have to have and corresponding analytical affinity and the mindset to understand what's going on in the project."	Analytic mindset *(characteristics)*	*Analytical Thinker*
Interviewee 4	"You have to ensure that everyone can work together and act in concert. You have various characters and backgrounds and it is your task to bring them together.!	Collaboration facilitation *(capabilities)*	*Coach*
Interviewee 8	"Freedom is important, but you also have to critically reflect on the possible options."	Challenging alternatives *(contribution)*	*Guide*
Interviewee 30	"I approach it with a visionary mindset, while the team is working on day-to-day tasks, as a leader you have to think about what the future holds in terms of applying analytics."	Thought leader *(characteristics)*	*Strategist*

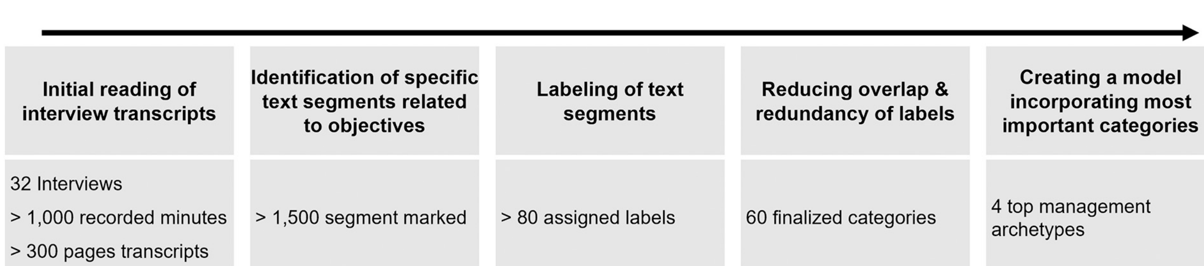

Fig. 1. Coding process from Thomas (2006) and Creswell (2002), with relevant facts for each step.

management archetype framework. (Thomas, 2006). (See Table 3.)

Periodically, critical aspects were discussed in the author group to establish a common understanding of the coding process, marked segments and corresponding labels for identified interview segments. These alignment meetings were also used to discuss controversial topics and different viewpoints in order to reach mutual agreement (Denyer & Tranfield, 2006).

4. Findings

This study aims to identify managerial archetypes and correlating skill sets that play a key role in managing the digital transformation toward the application of analytics-based decision-making processes. The overarching goal is to create a better understanding of the human aspect and the emerging managerial role in this context. Reviewing and categorizing the labels of the interviewees led to the identification of four critical top management archetypes. Table 2 illustrates those archetypes: *Analytical Thinker* (4.1), *Coach* (4.2), *Guide* (4.3), and *Strategist* (4.4).

The following sections illustrate in detail each archetype's individual characteristics, capabilities, and contributions to the solution development and transformational process. All sections follow an identical structure to enhance the flow of reading, promote understanding of the particularities of each archetype, and facilitate this study's practical applications for organizations. First, the typical character traits inherent to the archetype are introduced. Second, the archetype's leadership capabilities are specified in more detail and assessed with regard to their value and contribution to the transformation process. Finally, each section concludes with a short summary.

In the following chapters, the four archetypes are described using the singular *they* in regard to APA style to simplify the text and to avoid undue interruptions to the flow of the material. That said, all archetypes are completely gender-neutral and this framework can be applied to managers of all sexes and genders.

4.1. The analytical thinker

The empirical analysis clearly highlighted one archetype with a very strong technical focus. Henceforth, this archetype is termed the *Analytical Thinker*.

As a rational and analytical type, the *Analytical Thinker* has an extremely strong focus on all technical aspects of implementing analytical models intended for use in the decision-making process. Their technological understanding, ability to grasp new analytical models, and available toolkit of mathematical methods help them to easily familiarize themself with such topics, captures problems rapidly, and, due to their character traits, also want to immerse themselves in these issues completely. By adopting new technologies, advanced hardware or agile working methods, they bring in new perspectives and are able to discuss with data specialists on eye level. Thus, can be described as early adopters. They are one of the first users in the field of technological innovations, and are unafraid to test them in lighthouse projects within the organization. The analysis of the interview data has shown that this type is also characterized by a high degree of attention to detail. The *Analytical Thinker* prefers to address analytical problems and technical challenges that arise extensively via the transformational process. As a result, their technical understanding grows rapidly, and they quickly assume an expert status within the organization. Hence, they often hold an exceptional position in subsequent projects, is viewed as a Subject Matter Expert, and is drawn on as an advisor for other teams.

This expert status enables the manager to closely guide employees and project members within the digital transformation process, and to steer the project efficiently in a specific direction by tracking technical key performance indices (KPI). This close leadership of employees enables companies to perform their transformation with a low expenditure of resources. Furthermore, they detect unnecessary resource investments within a project and to counteract those early on in the project, thus increasing the efficiency and effectiveness of the entire initiative. The goal of this archetype is to share their knowledge and relevant technical expertise with each employee. The interviews also showed that the *Analytical Thinker* archetype is frequently well-connected not only within the company, but also with external know-how providers and specialists.

In terms of contribution, the *Analytical Thinker* strives for a technologically perfect solution and the optimal analytical model to answer a specific question or operational issue. The drive for perfection prompts them to initiate in-depth discussions with experts to find the optimal solution and exploit technical limits. In practice, analytics implementation within a company typically takes place in small, incremental steps, meaning that an analytic solution is first designed and implemented for a specific use case. If this project is successful and the analytical application functions as intended, further projects are initiated. The *Analytical Thinker* ensures that, in this initial and all subsequent projects, solutions are designed in a modular structure so that they can be reused in different corporate contexts accordingly.

Research shows that the expert status displayed in the *Analytical Thinker* archetype is emerging within top executive level. However, many analytical experts frequently hold lower ranks within a firm. Given that a high degree of familiarity with the subject of analytics enables a manager to steer their organization throughout the data transformation, it is clear that top management must also acquire such expertise.

4.2. The Coach

With a strong focus on employees and human resources, the *Coach* has emerged as the second major archetype of executive who actively manages the digital transformation of companies.

As a communicative, open leader with a distinctive focus on the individual, this archetype particularly emphasizes social interaction during the introduction of analytical models and methods. Especially in a technically demanding area such as the use of Big Data through analytics, they explicitly focus on the human component. The well-being of the project members and all those involved in the implementation of this

Table 3
Overview of identified archetypes with coded labels along three ontological categories - characteristics, capabilities and contribution.

Archetypes	Characteristics	Ontological Categories Capabilities	Contribution
Analytical Thinker	• Technology interest • Analytic mindset • Early adopter	• KPI-driven leadership • Technical know-how • Sustainable operation	• Exploiting technical limits • Working agile (incremental) • Seeking perfection (solution)
Coach	• Diplomatic interest • Social competence • Situational awareness	• Laissez-fair leadership • Collaboration facilitation • Cultural understanding	• Collaboration with specialists • Actively driving change • Involving external specialists
Guide	• Market/ Industry expertise • Extensive network • Trusted advisor	• Authoritarian leadership • Lean management • Setting boundaries	• Challenging alternatives • Active involvement • Project management
Strategist	• Open-minded • Trendsetter & innovator • Thought leader	• Visionary leadership • Fostering personal growth • Enabling teamwork	• Team custody • Thinking out-of-the-box • Incorporating corporate strategy

transformation is the top priority for this archetype, the Coach shows strong social competence. Through his highly diplomatic nature, they manage to bring the various parties and opinions to the table and efficiently steer them through the entire project. Their soft skills—such as problem-solving, conflict resolution, communication, patience, and situational awareness—enable this archetype to remain widely acknowledged as a capable leader despite their laissez-faire approach to leadership. Analytics projects pose a great risk of friction between different stakeholders with regard to the analytical solution—here, industry experts meet data specialists with varying approaches, ideas and a divergent understanding of analytics—a *Coach* is able to play to his strengths and proactively mitigate sources of conflict.

The *Coach* strives to create an atmosphere in which everyone feels comfortable and each team member can perform at their best. Coaches expect employees to respect commonly acknowledged cultural values and norms of organizations, as well as to value the company's own culture. Analytics projects demand the cooperation of a wide variety of experts from industry-specific areas, such as production or marketing, as well as IT experts, including programmers and data specialists. This archetype succeeds in leading employees so that all parties involved cooperate in a constructive manner to achieve a common goal, and to overcome potential intercultural prejudices along with personal attitudes and inclinations in the course of cooperation. As a manager, this archetype remains in the background and serves as a facilitator, leaving the operative project work to subject matter experts wherever possible. If necessary, their social recognition within the organization enable them to gain additional resources for the project and to integrate internal as well as external parties.

If the *Coach* is actively involved in the project and intervenes in the design of analytical models or methods, they focus on the usability of the solution and its seamless, as well as optimal integration into the value creation process. This archetype's main strengths lie in the subsequent transformational process. Employing the described capabilities, Coaches are able to put responsibility for change to subordinates with an appropriate skillset or knowledge and therefore, actively drive the change. In doing so, they contribute directly to the adaptation of processes and responsibilities. Due to their distinct problem-solving ability, they can implement any emerging modification requirements to the analytical solution (as a result of changed framework parameters) both quickly and in a resource-saving manner.

Although this archetype contributes less actively to the design of the analytical solution, their competencies and characteristics are decisive components that enable an organization to face the digital transformation. Particularly in such a technology-focused and driven area, the human resource component should not be neglected.

4.3. The Guide

Top management positions are often occupied by very experienced employees who have rendered outstanding performance to the company over many years. This fact was confirmed in the conducted interviews, and thus characterizes the third archetype: the *Guide*.

Based on the statements of the key informants, this top management type is characterized by their long-term leadership experience within the company, the industry, or a similar hierarchical role. Hence, they possess extensive expertise regarding the market, customers, and competitors, making them a highly valuable asset for a firm undergoing a digital transformation. Given the high degree of novelty inherent to analytical solutions, a strong backing from the top management levels is needed to drive implementation. Based on a their past successes in combination with their broad industry experience increases the value of the *Guide* as a change enabler and trusted advisor. Furthermore, the broad network that the guide has built up over the years facilitates a potential integration of internal or external stakeholders as needed. In addition, this archetype is characterized by the fact that they proactively set the right course to nip potential threats in the bud.

Their personality is characterized by an authoritarian leadership style that enable them to steadfastly pursue the agreed strategic thrust of the organization and, as an opinion leader, also allow them to steer the mid-term course of action. They stringently manage the digital transformation for the use of analytics, assuming clear leadership responsibility and providing strong guidance to colleagues. The fact that analytics is often performed by younger employees gives this archetype the opportunity to closely supervise and provide strong guidance to young colleagues. Especially during turbulent project phases, which are characterized by uncertainty and change, the *Guide* can counteract and handle the situation smoothly. The application of analytical methods generates a broad scope of solutions, and offers numerous opportunities for inexperienced employees to get lost in less important topics. The *Guide* limits the scope of movement for project members due to their past experience and sets clear framework conditions for the execution of the project. by constraints, rules, and policies that outline distinct areas of action. One strength of the *Guide* is that, while they view themself as the protagonist in a team or project setting, they also recognize necessary antagonistic traits in subordinates, identifying them as employees with pronounced visionary capabilities. The *Guide* acknowledges the importance of this creative and innovative thinking in developing analytical solutions, and thus provides corresponding room for creativity.

Due to their assertive personality, this archetype is very strongly involved in the development process of the analytical solution for the issue. In doing so, they closely align the entire project and thus also the analytical solution with the company's business needs. Hence, a frugal yet substantial result is derived. Alternative solutions and possible approaches are critically challenged and subjected to experience checks in order to ensure consistent quality. If the *Guide* find themself in a setting in which they must introduce analytics from scratch, they manage the change with lighthouse projects. Those set-ups allow a transformation within a clearly defined space and prerequisites. Through this piloting, the archetype thus limits the resources required, ensures that the objectives are well-defined, and restricts the project staff's sphere of action to a previously-defined solution spectrum. The *Guide*'s experience has taught them that such sounding can reveal initial pitfalls, identify weaknesses in both the organization and the overall approach, and facilitate the implementation of larger projects in terms of scope and resource requirements.

This archetype, according to the empirical data gathering during this study, represents a large percentage of executives, meaning that companies must inevitably contend with the presented capabilities and characteristics of this archetype. As a result of his wealth of knowledge, the *Guide* is a solid leader and can successfully master digital transformation.

4.4. The Strategist

Executives with a strategic, visionary mindset are in high demand, particularly at the top levels of an organization, to ensure the company's long-term success. These characteristics and capabilities for mastering digital transformation emerged during the key informant interviews to result in the *Strategist* archetype.

As an open-minded type, the *Strategist* is characterized by a focus on strategic, visionary thinking. Thus, characteristic traits of *Strategists* include a strong enthusiasm for technical innovations and new products. In this context, their private drive for innovation also transfer to their top management position within the organization. As a creative, open-minded individual, this archetype enjoys dealing with strategic questions and is skilled at combining abstract ways of thinking with a relentless work ethic, even when experiencing setbacks, they remain focused on long-term development and keep the corporate vision for digital transformation in mind. Aiming to convey their visionary approaches with unconventional methods and tools enable them to successfully respond to unexpected events within an analytics transformation project. Therefore, this combination of strategic understanding and analytical curiosity makes this archetype a thought leader in the organization, who should be consulted on issues arising in this context.

These characteristics are also reflected in the visionary leadership style. *Strategists* provide employees with the necessary scope for action in order to allow them to unleash their creativity and invent unconventional solutions. Unconventional approaches like guest lectures and awareness training sessions designed to help employees break out of entrenched, rigid processes and thought patterns and foster personal growth. Interviews revealed the great importance to discuss specific project steps with an open mind, allowing even unconventional solutions to be heard and considered within the project team. Furthermore, this archetype is aware that, within the change process and especially given the infinite possibilities of analytics, they require a counterpart in the team to maintain the project within realistic boundaries, structured approaches, and experience.

Regarding their contribution to developing solutions for analytical models and methods, the *Strategist* is committed to the team's developed solution, even if it sometimes exceeds the functions and goals of the initial scope. This archetype's capability for providing operational freedom allows them to promote a creative ideational process and out-of-the-box thinking among more junior staff (e.g., Maaravi, Heller, Shoham, Mohar, & Deutsch, 2021); thus, the developed analytical models and methods reflect this freedom by offering atypical functions or approaches. The handover of specific responsibilities and tasks, which can be described as trust packages, offers subordinates a broad scope of action in which they can operate independently to develop a creative solution. Consequently, this approach may also result in a certain level of uncertainty regarding the results of the work package. Hence, it is crucial that top managers can handle these uncertainties using the appropriate management methods and tools to allow for freedom while ensuring that critical project milestones are reached. For the strategist, it is essential to encompass corporate's long-term strategy to stringently align daily business tasks accordingly and thus keep the company on track.

Especially for well-established companies, a certain degree of freedom provides a decisive competitive advantage. Thus, the agility provided by the *Strategist* archetype contributes to change—and organization—is essential if the company intends to continue operating in a globally competitive market environment.

5. Discussion

This study focuses on the emerging role of managers mastering digital transformation within their organizations, and consequently outlines the key capabilities and personal characteristics that are required in this context to extend the current body of knowledge regarding applied analytics in a corporate setting (e.g., Côrte-Real, Oliveira, & Ruivo, 2017; Erevelles, Fukawa, & Swayne, 2016; Gunasekaran et al., 2017; Olabode, Boso, Hultman, & Leonidou, 2022). As the outcome of interviews with key informants, four top management archetypes are identified and presented. In line with previous research, the results revealed that top managers are a highly relevant and powerful resource, and are the change drivers for fostering analytical tools and methods of decision-making (Korherr et al., 2022; Shamim et al., 2020). Their capabilities and characteristics are key differentiators in a digital transformation journey (Corvello et al., 2021; Singh et al., 2020). The identified capabilities and characteristics of the four top management archetypes provide a basis for further research on the application of analytics in the decision-making process of managers and executives (Ferraris et al., 2019).

Big Data and the application of analytics have disruptive potential for decision-making processes and correlating structures, and they must be effectively handled by executives to avoid such disruption during implementation. The conducted interviews reveal that not only are existing processes, workflows, and organizations changed during a transformation, but that disruption occurs iteratively during the deployment of analytical methods and tools at the same time. Proposed archetypes offer a clear guidance to develop a proper managerial behavior to assess their capabilities and therefore, avoid common pitfalls in the transformational process to analytics-based decision. The application areas of analytics are evolving at a rapid pace—top executives who undergo this digital transformation must also face these dynamics of changing analytic opportunities (Merendino et al., 2018). Academia has addressed the required early flexibility in the change process, as many publications based on the theoretical model of Dynamic Capabilities show (e.g., Ciampi et al., 2021; Lin & Kunnathur, 2019; Yasmin et al., 2020). The presented managerial capabilities extend the current understanding of the Dynamic Capabilities concept, explaining the phenomenon in the context of the shift to analytics-focused transformations in detail. The archetype descriptions of *Analytical Thinker*, *Coach*, *Guide*, and *Strategist* address the capabilities of sensing, seizing, and transforming; moreover, they showcase best practices for various sub-capabilities (Leemann & Kanbach, 2022).

The characteristics of the proposed archetype descriptions match the respective Dynamic Capabilities specifications. Thus, the *Guide* can leverage his strengths particularly within sensing and seizing. Here, his broad network throughout the company allows him to identify possible applications for the use of analytics (Eggers & Kaplan, 2013). In addition, his extensive market and industry experience facilitates the structured evaluation of processes and procedures (Li, Easterby-Smith, & Hong, 2019). In contrast, the *Coach* can primarily exploit his strengths within transforming. He accompanies cultural changes and focuses on people during this digital transformation. His diplomatic and social skills enable him to reconfigure internal and external resources and to promote the acquisition and exchange of knowledge (Ellonen, Wikström, & Jantunen, 2009). It should be noted that both of these types also exhibit capabilities that can be found in the other dimensions. In the *Strategist* and *Technical* archetypes, by contrast, capabilities are distributed linearly across all three dimensions.

Evidence from the key informant interviews reveals the managerial capabilities necessary to master the digital transformation to the application of analytics-based decisions, and are hence positively correlated with firm performance (Shamim et al., 2020). These four archetypes, with their personal characteristics, abilities to guide employees, and competences within the solution development sphere, extend the existing understanding of the management capabilities necessary to apply analytics in a corporate context (Shokouhyar et al., 2020). Thus, the proposed archetypes constitute a stable framework for the human dimension of the digital transformation process towards a data-driven company which is a highly dynamic phenomenon.

To avoid misunderstandings, it is important to understand that all represented archetypes are beneficial and necessary for mastering the shift to analytical decision-making. Nevertheless, all four archetypes also demonstrate deficits with regard to their characteristics, capabilities, and contributions to the transformation. Consequently, any one type cannot be described as better suited to mastering the digital transformation than any other. Instead, a diverse skillset can be reached either through combining various archetypes into a cohesive team or further developing a certain archetype into a more well-rounded profile. Their application depend on the individual status of the organization and it's corresponding top management team composition. As the result of interviews with executives coming from a diverse range of industries, these archetypes reveal best practices from different executives and companies who have already experienced digital transformation.

5.1. Theoretical implications

Our research has two major implications for academia and research regarding the digital transformation and the emerging managerial role.

Firstly, by the detailed description of capabilities, characteristics and the executive's contribution the findings expand literary base on managerial role within the transformational process (Shamim et al., 2020; Singh et al., 2020). Furthermore, those key informant interviews of executives already performed various change projects in order to implement analytical methods. Therefore, the presented aspects and archetypes form the basis to deepen the understanding of management success factor in this context (Caputo et al., 2019). With an emerging understanding for the leadership aspect in the context of analytics, those psychological aspects can be understood in detail (Janssen et al., 2017) to complement a theoretical basis about how managers should handle the transformation from intuitive to analytics-based decision-making (Arunachalam et al., 2018).

Second, our findings provide a scientific framework to guide practitioners about managerial aspects by closing the gap of future digital manager's skills, characteristics and responsibilities (Elgendy et al., 2022). Furthermore, those prevalent managerial archetypes foster the understanding on how managers can master this strategic challenge (Tabrizi et al., 2019). Hence, those archetypes and the related explanations aim to diminish the disparity regarding research in the field of applied analytics and the operationalization of analytical models to foster the required data literacy in organizations (Batistič & van der Laken, 2019; Goasduff, 2022).

5.2. Practical implications

The results of our study have implications for how to understand, handle, and harness the human component as the so-called "soft side" of the transformational process. The presented four archetypes summarize the characteristics and capabilities of various management styles, along with their contribution to mastering digital change (Elgendy & Elragal, 2016), and thus equip management teams with powerful knowledge. It is necessary to fully understand an organization's top management team and to accurately assess their skills, abilities, and resulting gaps accordingly. Moreover, the interviews provide convincing evidence that top-level executives are the most decisive factor for driving change (Jha, Agi, & Ngai, 2020). Therefore, the results of this paper serve as orientation for managers and can be used as a self-assessment tool to determine where the strengths and weaknesses of the individual executive lie. Hence, help a firm to detect, act on, and fill capability gaps that may prevent their effective transformation toward an analytics-based approach. We suggest that this analysis should become an essential part of the transformation process, given that the management board is a critical component for the success of such change. This newly emerging role must be acknowledged and practiced proactively by the particular manager.

5.3. Limitations and future research agenda

While this study offers valuable implications for both academia and practice, there are nonetheless certain limitations of our research which at the same time represent opportunities for future research. The key informant interviews were conducted with top executives and their direct reports from companies based in Germany. In addition, most respondents have worked in well-established organizations. The organizations ranged from medium-sized firms to globally operating corporations. Individual managerial characteristics that affect the digital transformation process and emerging role of management often depend on cultural aspects and norms. Therefore, it is unclear to what extent the results are transferable to other cultural areas, such as countries, and organizations—especially with regard to company's size, organizational structure and maturity of applying analytical methods. However, the study included various industries and diverse executives in an attempt to provide a valid framework applicable to various top managers across contexts. Hence, the authors are confident that the tool is applicable and helpful across national borders. Future scholars could potentially extend this empirical research to various cultural areas, different organizational forms, or business model maturity levels in order to assess the validity of the presented archetypes. Additionally, as our research had a strong manufacturing and engineering focus, it would be interesting to deep-dive into selected industries and check for similarities and differences, using the proposed archetypes.

An additional limitation of this work is the character of the research. This study collected data from various organizations and executives with regard to digital transformation toward the usage of analytics in decision-making processes at one point in time only. The results propose four management archetypes with a strictly deductive combination of characteristics and capabilities. Longitudinal case studies assessing the long-term success of applied analytics and associated human aspects could further enrich our understanding of the topic at hand and also provide an assessment if one type is more successful in mastering such transformation. Thirdly, exploratory research in a semi-structured interview setting and the subsequent coding process are inherently limited by the fact that the interviewer must subjectively interpret the collected data. In addition, during data collection, theoretical saturation was reached in the given research setting. The authors followed a structured approach for data collection and coding to mitigate that limitation. Given that the authors defined similar characteristics and capabilities for the archetypes independently from one other (Thomas, 2006), the validity of the derived findings is supported. However, a robust, large-scale quantitative research approach using surveys could further validate the proposed framework. While the authors followed a distinct data analysis approach to ensure unbiased coding, unintended bias may still have occurred. Therefore, the application of sound statistical methodologies on a large data set would help to confirm the proposed findings.

6. Conclusion

Digital transformation toward the use of analytics is one of the biggest challenges facing companies in modern times; hence, management must respond accordingly to this revolution. Big Data requires a profound management paradigm shift, and executives are in need of tools to help actively guide employees and the organization throughout this change. Executives across industries and organizations should pay the necessary respect to this challenge in order to avoid a costly underestimation of the situation and required resources. Technological, employee-focused, experience-based, and visionary managerial skills and abilities play an extremely significant role in this context. The associated characteristics and skills enable companies to remain successful in a global, highly competitive market environment. The constant changes in requirements and the new opportunities that arise from the use of analytics demand that executives both adapt existing skills and develop new ones. With the proposed framework of the four top management archetypes, this study aims to provide managers with guidance for this change. The aim is to close the gap between theoretical, scientific concepts and practical experience. Digitalization will continue to develop at high speed, and science must keep pace to provide the urgently needed advice.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix 1 Overview of data collection and analysis steps

Step #	Phase	Description
1	Literature screening & template creation	• Literature review for semi-structured interview approaches • Literature review for data analysis & coding procedure • Set up of semi-structured interview template
2	1st round of interviews	• Conduct first round of interviews • Transcription of voice-recorded interviews • Recirculation of interview transcripts with interviewees
3	Data processing & analysis	• Initial reading of interview transcripts (of 1st round) • Identification of text segments and first labeling • Exchange of findings within authorship
4	2nd round of interviews	• Conduct second round of interviews • Transcription of voice-recorded interviews • Recirculation of interview transcripts with interviewees
5	Data processing & analysis	• Initial reading of interview transcripts (of 2nd round) • Identification of text segments and labeling • Exchange of findings within authorship
6	3rd round of interviews	• Conduct third round of interviews • Transcription of voice-recorded interviews • Recirculation of interview transcripts with interviewees
7	Data processing & analysis	• Initial reading of interview transcripts (of 3rd round) • Identification of text segments and labeling • Exchange of findings within authorship • Reduction of overlapping labels • Creation of archetypes along most important categories
8	Validation of findings	• Validation of findings within research group • Finalization of archetypes and model

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