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Artificial Leadership: Digital Transformation as a Leadership Task between the Chief Digital Officer and Artificial Intelligence

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Abstract
Artificial Intelligence (AI) is increasingly being used in all business areas and will have a significant impact on the associated business processes. This will be particularly the case where data is the basis for an improvement as well as an acceleration of the associated workflows, because it is precisely this data that is the input for the algorithms of AI. However, the rapid progress in the performance of these algorithms will also increasingly lead to the output of the algorithms, which are not only being used to support data-driven business processes "for" humans, but also transitioning into data-driven business decisions where the AI will also provide the resulting instructions "to" humans. This will lead to a blending of the operational and strategic levels of business management and will raise many new questions for the related theoretical and practical foundations. This paper aims to highlight this area of tension, discuss the various theoretical influences, and identify the associated research needs. This is exemplified in an area that is directly affected by this field of tension because it is determined by data like no other: the "Digital Transformation" of existing, and the "Digital Innovation" of new, business models and processes as well as the associated corporate management in the form of "Digital Leadership". This is where the human (in the form of a Chief Digital Officer - CDO) and the machine (in the form of Artificial Intelligence - AI) will meet directly. At the end - based on a decision-making theory for a homo economicus vs. a machina economica - there is the first draft of framework for the influence of AI on operational and strategic corporate management, which can be used as a basis for further research and practice-related considerations. In this context, the term "Artificial Leadership", as a further development of "Digital Leadership", is also introduced and defined for scientific research for the first time.

Keywords: digital transformation, chief digital officer, artificial intelligence, digital ambidexterity, digital leadership, artificial leadership

1. INTRODUCTION

Decision-making belongs to one of the fundamental disciplines of human life as well as the business area. Therefore, it is not surprising that it has received a great deal of attention in research across various fields, trying to understand how we make decisions, which factors influence decisions, and how future decision-making might be improved (Johnson & Busemeyer, 2010; Letmathe & Noll, 2021). Furthermore, considering the significance of decision-making in business, the discipline of strategic decision-making plays a crucial role in organizational success and is highly influenced by the role of top management and the operational and strategic decision-making process (Papulova & Gazova, 2016). Moreover, within the modern, globalized, and digitalized economy, it is evident that information and data already play a critical role within organizations and management (Tuffaha et al., 2022, p. 82). They have become a factor in production and competition, with a direct or indirect influence on organizational management and decision-making (Kollmann 2022a, p. 56 ff.). The competitive pressure, together with the growing availability of new technologies, which continue to increase the availability and quality of data, have led to the implementation of data in the decision-making process, termed "data-driven decision-making" (Brynjolfsson & McElheran, 2016).

Overall, the wide-scale emergence and adoption of data-driven decision-making has led to increased firm performance in terms of output and productivity, as well as asset utilization, return on equity, and, eventually, market value (Brynjolfsson et al., 2011). However, with increasing data availability, it is also becoming increasingly difficult for management to keep track of the data. Today, the amount of data has become so overwhelming that most companies have trouble making data-driven decisions, as merely 32% of German decision-makers know which data is available to them (Amerland, 2021). Also, in the USA, only 28% of workers said they would be comfortable using data for their jobs (Qlik & Accenture, 2020). In turn, this leads to the conclusion that the vast majority of companies do not consider all the data that is available to them, leading to an increased risk of less informed and poor decisions. Furthermore, the increasing availability and complexity of structured but especially unstructured data is leading to an overload of information, becoming progressively more challenging to collect and analyse. This development not only poses difficulties for decision-makers but also for traditional information systems (Llave, 2018).

A possible remedy for the limitations of Information Technology (IT) in collecting, preparing, and analysing large amounts of data from different sources are the advances in Business Analytics (BA), which have started having an increasing impact across industries to leverage data for decision-making (Tamm et al., 2021). Davenport (2018) has described how companies have developed analytical capabilities to enhance decision-making over several stages, recently entering the era of "Artificial Intelligence" (AI). Over the last years, AI has been at the forefront of technological developments and has proved to be applicable in a variety of use cases. Overall, the adoption of artificial intelligence continues to rise, with over 56% of companies using AI in at least one function in 2021 (Chui et al., 2021). As one of the most important, but also most complex, applications of AI, advances in the capabilities of AI systems are bringing the benefits of the technology to the decision-making field into sharper focus (Duan et al., 2019). However, in doing so, the use of data and the improved extraction of insights through artificial intelligence (still) raise questions about the need for human judgement and oversight, especially in strategic decision-making (McAfee & Brynjolfsson, 2012). Considering the human variable, especially in its relationship to artificial intelligence, factors such as trust, acceptance and experience play an important role in the overall decision-making process in this regard. The concept of intuition in particular has been categorized as critical within organizational decision-making, especially when there is pressure for high speed decision-making (Wilson & Daughtery, 2018). Therefore, it is crucial to understand the relationships between the different factors that play a role in human decision-making and the respective interplay with artificial intelligence when applied in data-driven decision-making.

Against this background, the use of AI will influence many theoretical and practical areas of the business. In the area of marketing, AI will be able to identify new correlations and patterns in customer analysis and customer behaviour forecasting. AI will also be able to better analyse the behaviour patterns of competitors and derive strategies for its own positioning. Further, AI will be able to better analyse and thus optimize production and organizational processes. Accordingly, AI will have a general impact on almost all scientific theories via the following aspects: data analysis, prediction and simulation, the discovery of correlations, and an increased consideration of rationality. In view of this contribution, however, what stands out surely is the theory of corporate management (even if there is not only "one theory", but different "theory areas"), which is of special interest. The associated management approach deals therefore with the concrete arrangement of a company, thus in particular the management with the associated organization as well as the additional functions such as procurement and production. With regard to the influence of AI on related short-, medium- and long-term decisions in a company, there will also be a central theoretical practical issue in particular, which addresses the following question: where and how will an AI take over the concrete tasks of management in terms of actions and decisions in the operational and strategic area with regard to current and future business models and processes?

The aim of this paper is to build an initial structure for the broad new topic area of the influence of AI on decision making in business management. As an example, the area of "Digital Transformation" is considered, as this is strongly influenced by data. Here, the human as manager and the machine as AI meet directly, but this will also be observed in other areas of the company (e.g. AI in the context of digital procurement vs. the manager in a purchasing department). Based on a decision theory for a homo oeconomicus vs. a machina economica, the first draft of a framework for the influence of AI on operational and strategic business management is established. This will serve as a basis for further research and practical considerations. The term "Artificial Leadership" is introduced and defined for the first time for scientific research in this context as a further development of "Digital Leadership". Accordingly, the article is structured as follows: after a basic motivation of a "Digital Transformation" for every company, the human factor of related corporate management in the form of the Chief Digital Officer is presented first. We then focus on the machine factor in the form of Artificial Intelligence and its increasing influence on corporate management. Through a subsequent double differentiation of the application field between an existing business and an innovative business, as well as a consideration of the possibilities between an exploitation and exploration, we come to the construction of a new framework, in which a distinction is made between a Digital Leadership and an Artificial Leadership for operational and strategic corporate management. The paper concludes with theoretical and practice-oriented implications.

2. THE NEED FOR A DIGITAL TRANSFORMATION

The importance of the Digital Economy and the associated Digital Business is a significant factor for any kind of economic nation. In the USA, digital value creation already accounts for 8.2% of total gross domestic product, while in Germany it is only 5.7% (IW, 2021). Accordingly, it is important for a country's companies, and thus for the entire economy, to be internationally competitive in the area of digitization. In 2022, Denmark was the top country in the Global Digital Competitiveness Ranking (IMD, 2022), ahead of the USA. The IMD-Ranking aims to analyse a country's ability to adopt digital technologies and implement these technologies in businesses and government organizations. United Kingdom ranked only 16th, Germany only 19th, and Japan 29th. According to a PwC study, Germany will only be the ninth largest economy in the world by 2050 (Hawksworth et al., 2017). Other studies paint a similar picture – also for other industrial countries – if they do not succeed in launching digital innovations and mastering the challenges of Digital Transformation.

This finding is independent of economic fluctuations and other economic or social developments that may have an impact on the associated need for Digital Transformation. This is because it fundamentally changes entire industries, companies, and their business models (Kollmann, 2022a, p. v ff.) and this development has become even clearer and accelerated since 2020 and the COVID-19 pandemic, when lockdowns made the real economy impossible. As a result, companies must shift to digital contacts and intensify the digital economy. The Corona pandemic has put additional pressure on digital transformation and shown companies where previously neglected weak points and areas for action lie in relation to digitization (Kollmann, 2022a, p. v).

Even economic development with the possibility of a looming recession since mid-2022 does not diminish the importance of Digital Transformation as a cross-sectional task for all areas of a company. Either the need for further cost reductions through digitization or the search for additional or new sources of revenue through digital business models or processes is addressed (Nambisan et al., 2017). Therefore, according to Kollmann (2022b) Digital Transformation continues to affect all companies “because the effects of digital processes, products and platforms with the associated new digital business models continue to influence the familiar real trading level just as they dictate a new digital trading level”. Small and medium-sized enterprises (SMEs) as well as family businesses and also large established companies, such as industrial and retail companies, face particular challenges. While SMEs and family businesses need to ensure that they can build up the necessary digital Know-how and invest in a digital future, large companies also have to both continue to expand their existing real business (through digital automation) and develop innovative digital business models. Consequently, Digital Transformation can be defined as follows (Kollmann, 2022c, p. 2)

> *Digital Transformation (also referred to as "digital change") is an ongoing and far-reaching process of change in society, business and politics based on digital technologies that has a fundamental impact on information, communication, and transactions between the players involved and leads to a new understanding and behaviour in the social, economic and political spheres of life.*

Companies are subject to constant change and have to address new opportunities and threats to their operational business (Nambisan, 2017). In this regard, from a more practical perspective, the concept of Digital Transformation encompasses the "use of new digital technologies, such as social media, mobile, analytics or embedded devices, in order to enable major business improvements like enhancing customer experience, streamlining operations or creating new business models" (Horlacher & Hess, 2016, p. 5126). In this context, digital technologies such as artificial intelligence (AI), Big Data, blockchains, cloud services, and sensor technology are repeatedly presented as the drivers of Digital Transformation (Wobser, 2022). In other words, Digital Transformation can be understood as the digitization of a company's products and services, which enables the company to pursue new business models to design greater customer benefits (Haffke et al., 2016, p. 2).

The questions that companies should ask themselves in this context are about responsibility: Who is taking care of Digital Transformation in the company? Are the associated changes a "technical button" that can simply be pressed in some digital (IT) system, or is an "evolutionary head" needed who understands and consistently implements the digital business models and processes? In this regard, the role of a CDO is often brought into play, who, as an acting leader, is to anchor the Digital Transformation in the company via corresponding Digital Leadership and shape it both strategically and operationally (Kollmann, 2022c, p. 24). The focus here is on human intelligence/competence and the associated experience. At the same time, enormous developments in machine intelligence/competence with associated algorithms can be observed, with the result being that AI can increasingly take over operational and strategic tasks in management (Agrawal et al., 2019). As an example, the company NetDragon Websoft made a name for itself, as, in September 2022, it was probably the first company in the world to appoint AI as its company director, who was christened Tang Yu (Ignor, 2022). Thus, there are essentially two aspects to the initial question: can, should, or must a "human" or a "machine" take care of the Digital Transformation in the company?

2.1 The Role of a Chief Digital Officer (CDO)

As with many other organizational processes, Digital Transformation also requires appropriate leadership. In this context, the CDO has been established as a new C-level position representing Digital Leadership within the company. The CDO is the executive responsible for the Digital Transformation of a company, including the formulation, execution, and control of the Digital Transformation strategy for products, services, and business models, seeking digital solutions that are only made possible by digital technologies (Berman et al., 2020, p. 32; Singh, & Hess, 2017, p. 8, Neumann, 2017). In this context, there is a widespread perception that the CDO is a role that is not clearly delineated and whose functions and responsibilities could also be distributed among various members of the executive suite. Contrary to this view, a study by Mindtree (2019) found that 74% of business and IT professionals surveyed today saw a clearly defined responsibility for the CDO within their organization, while 81% also felt that responsibilities were sufficiently differentiated for a separate CDO position to be necessary and warranted.

In addition to this rather theoretical view, the platform markenrebell.de (2020) has also elaborated on the tasks of a CDO from a practical perspective: the CDO needs to determine which technologies and structures are required to make internal company processes more efficient through digitization (Digital Processes). Further, he/she has to identify which potentials of digitization can be exploited for the company. To this end, they also need to develop new digital services and products that increase the company's revenues on the one hand and enhance customer satisfaction on the other (Digital Services and Digital Products). The CDO has to discover which tools and methods need to be used to drive the Digital Transformation forward in the company. In addition, they have to evaluate what Know-how the company's employees need to be able to implement the individual steps (Digital Culture and Digital Know-how). Further, he/she also has the task of developing a digital marketing, sales, and communications strategy. They have to determine which digital channels are to be used, what budget is required, how sales can be increased via digital channels, and how customer acquisition, sales, and support are to be structured via digital channels. They are also responsible for developing a social media strategy (Digital Marketing and Digital Sales). Finally, the CDO needs to have an overview of what data the company collects and how it evaluates and uses it (Digital Big Data).

Against this background, companies are increasingly handing over responsibility for digital transformation to a Chief Digital Officer. According to the Chief Digital Officer Report (Strategy& & PwC, 2016), the global share of companies with a CDO rose from 6% to 19% between 2015 and 2016, thus tripling. In the following years, the share increased again to 21% until 2018 (Strategy& & PwC, 2019). Europe continues to record the highest CDO density world-wide. There, the proportion of companies with a CDO more than doubled from 13% to 34% compared to 2015, according to the Chief Digital Officer Report (Strategy& & PwC, 2016). In North America, the CDO share climbed to 23%. 13% of South or Latin American companies have a CDO, and only 7% of companies from the Asia-Pacific region entrust digitization responsibility to a specific manager. Within Europe, France is the clear leader with a CDO rate of 62%, followed by Germany (39%), the UK (35%), Spain (33%) and Switzerland (33%). Globally, according to the Chief Digital Officer Report (Strategy& & PwC, 2019), large companies with annual revenues of more than $24 billion in particular delegate their digital strategy to a dedicated manager; their 39% share is by far the most significant. The vast majority of digital officers are named CDO; other common titles are also CIO (Chief Information Officer) and CTO (Chief Technology Officer).

The increased importance of the position of a CDO in practice has subsequently made this figure increasingly a research subject for theoretical consideration as well. Research on CDOs originated in the information systems literature and then transitioned into the strategic management literature. Following Moker (2020, p. 4), CDO research can be divided into several literature streams, such as position, person, and environment. However, the research on the person and the environment is somewhat underrepresented in this process, compared to the extensive research on the position of the CDO. The literature on the CDO's position includes work on their anchoring in the company (e.g., Stein & Kollmann, 2021; Stein et al., 2022), their tasks (e.g., Berman et al., 2020; Horlacher & Hess, 2016), and leadership role types (e.g., Horlacher & Hess, 2016; Tumbas et al., 2020). In addition, the competencies of a CDO (e.g., Kollmann, 2022c; Singh & Hess, 2017; Tahvanainen & Luoma, 2018) and their position within organizations have been examined (e.g., Kollmann, 2022c; Singh et al.; 2020). Regarding the CDO as a person, previous research has tended to consider its personal characteristics as a by-product while analysing its position within the organization (e.g., Berman et al., 2020; Chhachhi et al., 2016). Finally, there have been studies on the environment, with research focusing on the interaction between the CDO and the proximate chief information officer (CIO) (e.g., Haffke et al., 2016) and the impact of the appointment of a CDO on stock market performance (e.g., Drechsler et al., 2019).

Against this backdrop, Sebastian et al. (2017) studied 25 large companies and found two digital thrusts, which they pursued during the Digital Transformation process: improving customer engagement and implementing digital solutions. The companies studied aimed to "build customer loyalty and trust by creating thoughtful, innovative, personalized, and integrated customer experiences" (Sebastian et al., 2017, p. 199). Additionally, companies intended to improve their operations by digitizing their product and service offerings (Sebastian et al., 2017, p. 199). The CDOs can support both thrusts, as they are inherently responsible for developing new digital products, services, and business models and can thus contribute to repositioning the company's value proposition vis-à-vis the customer. Therefore, it is also suitable for improving the customer experience on this basis.

Another issue is where and how the CDO is anchored in the company. This organizational design parameter refers to the structural embedding of CDOs in the company. Research has found that the influence of the CDO on Digital Transformation depends in particular on the degree of their integration into the organization (e.g., Horlacher & Hess, 2016; Singh et al., 2020) According to Singh et al. (2020, p. 9) the CDO can be integrated centrally into or decentralized in the organization. Either the CDO is integrated centrally into the executive board with all decision-making powers or is decentralized in an individual department, which, in the latter case, leads to distributed decision-making power between the business units (Horlacher & Hess, 2016, p. 2; Singh et al., 2020, p. 9). According to Horlacher and Hess (2016), decentralized CDOs have a difficult time mastering Digital Transformation, as they do not have sufficient decision-making authority and may lack support from the management level. Only by adding a CDO to the executive board (C-level) does the position have the same significance as other management positions. However, this can also lead to interface conflicts between the CDO and other leaders. However, is there a correspondingly large number of CDOs at the board level in large German companies? Stein and Kollmann (2021) and Stein et al. (2022) answered this question based on their study of the DAX DIGITAL MONITOR and a corresponding analysis of DAX30 (2021) and DAX40 (2022) companies in Germany (www.dax-digital-monitor.de). At 72% of the companies (Stein et al., 2022), digitization responsibility and competence are firmly anchored at the board level (in 2021, the figure was 60%). However, an independent CDO, who would explicitly represent digitization responsibility and competence at the board level as a separate department, could only be observed at five companies in 2022 (3 in 2021).

Sungkono (2021) used the analysis technique of DAX DIGITAL MONITOR and applied it to the companies in the Dow Jones-Index: “According to the analysis, it has been identified that 19 out of 30 companies are anchoring digital responsibility or have digital competence at the executive board level. This indicates that 63% of the Dow Jones companies fulfil this criterion. Be that as it may, out of all 19 companies, there is only one which has the role of Chief Digital Office clearly assigned in the executive board level. Other companies typically embed digital responsibility into existing positions such as Chief Development Officer, Chief Innovation Officer, Chief Information Officer, or Chief Technology Officer. Based on this finding, it can be concluded that the role of Chief Digital Officer is not commonly employed in the Dow Jones companies.”

This is all the more problematic if, in addition to the operational tasks of a CDO already mentioned, their strategic orientation as a leader is added. It is in the nature of a company's management to be (co-)responsible for both the initiation of strategies and their operational implementation by creating the appropriate environment for this (Gibson & Birkinshaw, 2004, p. 223; Raisch & Birkinshaw, 2008, p. 391). The CDO reviews the existing business models and, if necessary, adapts them to new framework conditions with new digital solutions and reviews, develops, and implements the new business models associated with digitization (Kollmann, 2022c, p. 26). However, the examination and development of new digital business models and processes, in particular, is a strategic component because it affects the future orientation or realignment of the company. Therefore, the CDO can be defined as follows (Kollmann, 2022c, p. 26):

The Chief Digital Officer (CDO) is responsible for the strategic and operational development of the digital strategy based on IT. His main focus is on the effective and efficient development of new digital business models with the help of information technology. He tends to be oriented toward a flexible organization with modern and agile tools.

In all these operational and strategic tasks relating to the digitization of existing and future business models and processes, the CDO can, should, or must be supported by data to make the right decisions, particularly regarding the associated Digital Transformation. Thus, data have a hybrid degree of effectiveness: They are the basis for existing or new operational digital portfolio business (digital value creation; Kollmann, 2022a, p. 56 ff.), and they are also the basis for strategic developments regarding future digital innovation business (data-driven business decision making). However, when the data are used, the CDO remains the ultimate authority for the actual interpretation of the data and the subsequent final decision making at the operational and strategic level with the associated work instructions to an organization.

2.2 The Role of Artificial Intelligence (AI)

With the advent of information technology (IT), its impact on decision-making processes and decision making in a company has increased to a new level. Information technology can be defined as "computer-based technology for the acquisition, storage, processing and communication of information" (Molloy & Schwenk, 1995, p. 285). One of the earliest empirical studies on the use of IT in decision making, by Molloy and Schwenk (1995), concluded that IT improves both the efficiency and effectiveness of the strategic decision-making process. They also found that the impact of IT on firm performance was positively related to the extent of IT use by actors within a firm. Referring to Simon's (1960) original sequential decision-making process, there have been numerous subsequent adaptations of related theoretical considerations with the addition of IT (e.g., Citroen, 2011; Darioshi & Lahav, 2021; Mintzberg et al., 1976). It has been consistently found that the use of IT is usually most beneficial, especially in the initial collection or preparation phase.

In this regard, it is important for further discussion to understand how managers (and thus CDOs) gather their information at the beginning of the decision-making process. Nutt (2008) distinguished between two types of approaches to information gathering. Under the "idea-imposition approach," the decision maker gathers only limited information that corresponds to the original goal or idea. In the "discovery approach," on the other hand, the decision maker also has to gather information about possible alternative courses of action outside the original goal or idea by first collecting a variety of information. Nutt (2008) examined the two approaches in an empirical study and concluded that the "discovery approach" is more successful in almost all areas. Based on this finding, Guerra-Lopez and Blake (2011) put Nutt's (2008) findings into a data context by using information gathering and data collection synonymously. Their results showed that leaders were more satisfied with the data collection process when they took more of a "discovery approach."

Following this realization, extensive sources of information and data were built up as part of the Big Data approach. The Big Data approach has thus had, and continues to have, a major impact on decision making and the associated process. To efficiently use the Big Data approach for management decision making, the development of analytical skills has been identified as one of the driving factors for organizational success (Davenport, 2006). Davenport (2013) and by extension Kollmann (2020) identified three (later four) distinct developmental phases of data-related business analytics: "Analytics 1.0" (Davenport) or the "Data Phase" (Kollmann) was the era of management information programs (MIPs) that dealt with descriptive analytics (e.g., spreadsheets). This first phase was driven by computer technology, which addressed the initial collection of relevant internal data for fact-based insights as the basis for management decision making. "Analytics 2.0" (Davenport) or the "Big Data Phase" (Kollmann), on the other hand, was characterized by management information systems (MIS) and the use of Internet technology to access not only internally generated data linked through various programs but also external and thus real-time data in bulk. Finally, "Analytics 3.0" (Davenport) or the "Big Intelligence Phase" (Kollmann) and the associated Business Intelligence Systems (BIS) introduced data-enriched processes that analysed data at the interface with the customer and the market. Every device, every delivery, and every customer leave a data trail in the process. With these data trails, companies have the ability to incorporate analytics and optimization into every business decision made for the customer. With "Analytics 4.0" (Davenport) or the "Big Responsibility Phase" (Kollmann) and the associated artificial intelligence systems (AIS), an individual and (hopefully also) responsibility-oriented customer orientation come into play in this respect. It is a question not only of shaping the current customer contact but also of predicting the customer's future need for products and services in a targeted and appropriate manner (prescriptive/ predictive analytics).

Against this backdrop, empirical research has shown that companies using data-driven decision making outperform their competitors on both the financial and operational levels. Therefore, it has long been argued that data-driven companies tend to make better decisions (Brynjolfsson et al., 2011; McAfee & Brynjolfsson, 2012; Russom, 2011). However, the human use of data also has its limitations. Alharthi et al. (2017) analysed some of the barriers to Big Data and categorized them into three types. In addition to "organizational barriers" related to culture and "human barriers" related to a lack of digital skills, "technological barriers" related to the complexities of data also play a significant role. Accordingly, conventional information systems can and will reach their limits. This is precisely where systems with AI should be used now and in the future for "Analytics 4.0" (see above). AI is a highly effective technology that is becoming increasingly widespread. In 2021, more than half of all companies were already using "artificial intelligence" (Chui et al., 2021). Among the multitude of applications, the field of decision making has been identified as one of the most important tasks (Duan et al., 2019).

The increasing amount of data as well as the rapidly growing possibilities of processing data enable an increasingly better machine imitation of human thought and behaviour patterns. Consequently, the term AI in particular is increasingly used linguistically. In the literature, there are many different definitions of AI, so there is no uniform definition in the narrower sense. The term was first used in a proposal for a research project on this topic by McCarthy et al. (1955). Their understanding of AI was quite broad and aimed at the simulation of human intelligence by machines. A modern interpretation by Kaplan and Haenlein (2019, p. 17) defines AI as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation." Uniformly, however, AI is described as a subfield of computer science in which "intelligent agents" (Franklin & Graesser, 1997, p. 21) are researched and developed (Buxmann & Schmidt, 2018). An "intelligent agent" is characterized by its ability to independently solve problems and thus autonomously produce artificial content (Buxmann & Schmidt, 2018; Carbonell et al., 1983; Kollmann & Schmidt, 2016, p. 49 ff.).

One particular aspect of AI is machine learning. Samuel (1959) defined this as a field of research that enables machines to learn without having been explicitly programmed. This capability thus enables knowledge generation based on experience. Machines can be fed with existing data sets (experiences), evaluate them, and draw optimal conclusions based on a developed function. A subfield of machine learning that is becoming increasingly important is so-called deep learning. Deep learning is a concept that aims to better recognize patterns (also called representations) in data by overlaying and linking multiple successive learning layers (Chollet, 2018). Due to the structure of the different layers, which are based on a natural neural network and thus resemble it, the literature often refers to (artificial) neural networks (Rojas, 2013). The possibility of machine learning opens up a very large spectrum for the potential application fields of AI, which are conceivable in almost all areas of life. For companies, the use of artificial intelligence can lead to increases in efficiency and productivity and enable a better response to customers, which can create added value (Gentsch, 2019). Especially in industries where large amounts of data are generated, the application of AI can lead to competitive advantages (Brynjolfsson et al., 2011).

With regard to decision making, Berente et al. (2021) bring even more exciting aspects into the discussion. With the aspect of "autonomy," they emphasize the increasing ability of artificial intelligence systems to act independently of human intervention. In addition, the aspect of "learning" refers to the ability of AI to automatically improve itself by learning from data and experience. Finally, the "inscrutability" aspect describes AI's ability to develop new algorithmic models on its own that are understandable only (if at all) to a specific audience, which sometimes does not include humans. The question that can now be asked is whether and to what extent AI can completely take over a decision-making and decision-implementation process against this background, and thus replace humans in the form of a manager (without authority to issue directives) or a leader (with authority to instruct). The first practical applications of AI as a decision-making authority already exist. According to a report in the NGG (2019), Aqua Römer Mineralbrunnen in Göppingen is using an AI called "Mary" that independently "talks" to the logistics employees via radio, guides them to the exact pallets to be picked up on the basis of its own decisions, and organizes a large warehouse via these work instructions. This has both advantages and disadvantages because, while "Mary" makes work easier, AI has also led to a reduction in the number of logistics personnel required by about 25% and a subsequent loss of jobs. In addition, the employees no longer communicate with each other during work, since "Mary" now constantly issues and demands instructions and reports.

There are numerous aspects and questions associated with this example. Digital Transformation is particularly suitable for AI because in this area—perhaps even more so than in other areas—it is precisely data that forms the basis. In this respect, the following discussion is particularly relevant to this area. Data is becoming more and more extensive through increasing digitization and is thus the basis for operational as well as strategic decisions and related work instructions for an organization. This means that, in addition to human knowledge and existing experience, data are also the basis for the work of a CDO. At the same time, data becomes the basis for growing machine knowledge, in which experience is built up very quickly via the associated algorithms. The question is whether there is a trade-off or a threshold in this respect above which decision making by AI leads to a better result than that made by a CDO. On the one hand, a possible answer must certainly be differentiated into a more automated area within the framework of a current existing business, in which it is a matter of clear (also calculable) operational efficiency or effectiveness criteria within the framework of known knowledge (exploitation). On the other hand, it enters into a more creative area in the context of a future innovation business, where it is about assessable (not necessarily calculable) strategic development and positioning criteria in the context of unknown knowledge (exploration). This leads to the ambidexterity of Digital Transformation.

3. THE AMBIDEXTERITY OF A DIGITAL TRANSFORMATION

Due to the increasing complexity and speed of digitization and the associated market and competitive environments, it is particularly important for today's companies to succeed in balancing the digitization of existing and new business areas to remain competitive in the long term (Kollmann, 2022c, p. 32). Christensen (1997) has already described a similar problem in the context of the "innovation dilemma", in which companies are often unable to devote themselves to technological innovations because they concentrate too greatly on optimizing existing business areas. Kodak and Boeing are just two examples of formerly dominant companies that have been unable to adapt to technological changes in the market and have thus lost an enormous amount of competitiveness (Stein, & Kollmann, 2021). While Kodak was the leading supplier of analogue photography and missed the leap to digital cameras, Boeing was unable to defend its former leading market position against Airbus in the aviation industry. Although this dilemma between existing business and innovation business is a well-known challenge in strategic management (Ijigu et al., 2022, p. 48), many companies find it difficult to combine these two fields of activity successfully. Almost two-thirds of companies currently see themselves as competitive in the future with regard to their core business, but only about one-third of respondents rate their company as competitive with regard to new business areas and topics (HAYS, 2018). Against this backdrop, executives (or perhaps AI) are particularly in demand to steer their companies in relation to the changing market circumstances and define strategic guard rails in the process. According to Kollmann (2022c, p. 33), they have to be able to maintain the efficiency of the (real) existing business (exploitation), on the one hand, and to address the agility and adaptability of the (digital) innovation business (exploration), on the other. The compatibility of these two aspects in a balanced relationship, with the aim of ensuring the necessary ability to act, particularly in connection with Digital Transformation, can be described as Digital Ambidexterity (Latin for using both hands; Kienbaum, 2019; Kollmann, 2022c, p. 33):

> *Digital Ambidexterity describes the ability of organizations to simultaneously maintain (real) existing business (exploitation) and promote (digital) innovation business (exploration) in order to remain competitive for the digital economy.*

Both the digital management level and the digital organization are of central importance for the successful reconciliation of existing business and innovation business. This raises the question of how decision-making processes are designed and whether more human- or machine-based data-driven decisions are (or should be) used. This must certainly be differentiated with regard to the "cannibalization" of the (real) existing business as exploitation or to the development of the (digital) innovation business as exploration.

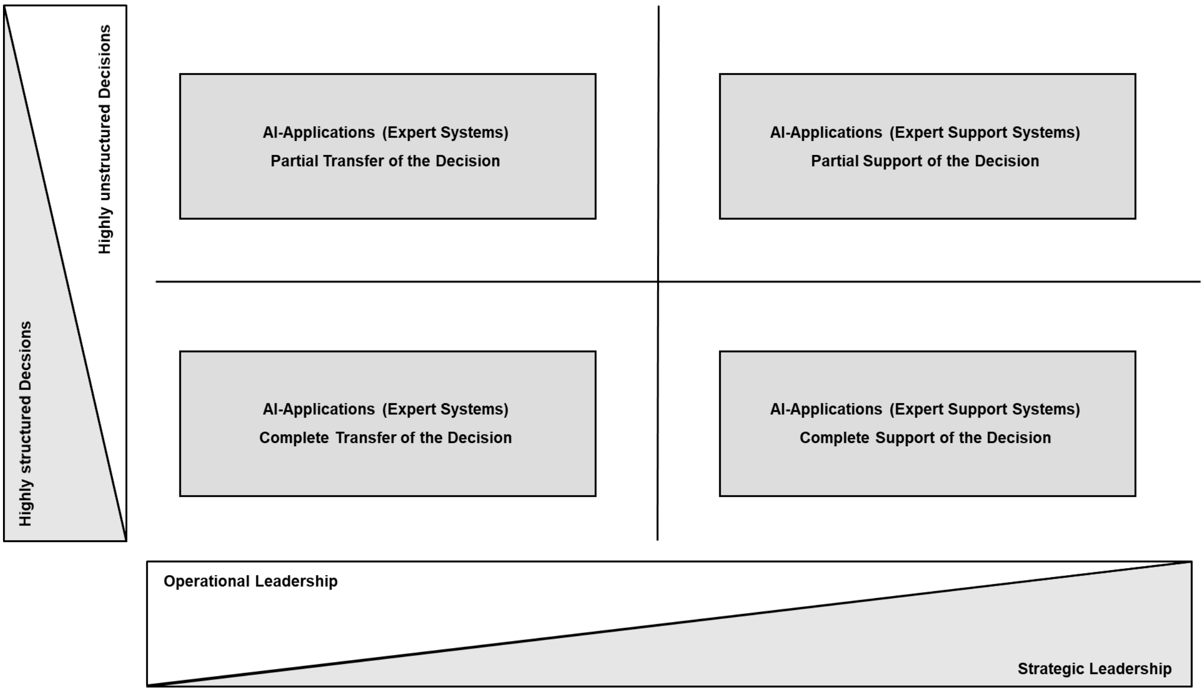
3.1 The Digitization of the Existing Business

The first task to be considered is digitization of the existing business. In this area, the aspect of "exploitation" includes the refinement and improvement of existing business processes, routines, and structures. However, the result here is often "only" a more or less familiar digital automation of existing processes. However, this automation of processes is a simple necessity, as is the response to related topics such as the digital customer journey, dynamic pricing, interactive ordering, and tracking. Alongside this, the digitization of products will play an increasingly important role; sensors, the Internet of Things, and remote maintenance are just a few of the keywords here. However, the development of digital platforms for or around existing product or service offerings should not be overlooked, as these platforms have proven to be a superior business model in the network. In line with this 3-P model (processes, products, and platforms), the digitization of existing business focuses on the following aspects (Kollmann, 2018, 2022c, p. 4): Digitizing and automating existing business processes and, thus, supporting existing and known business activities (Digitization of old processes); Digitizing and supplementing existing products and services with digital value creation based on data (Digitization of old products); Building associated digital market and customer platforms for existing business models and processes (Digitization of old platforms).

In principle, this area can be reduced to the following statement: "You digitize what you already know." Here, the operational focus is clearly on the existing business. This means that the operational and related organizational processes can be improved at this point (strengthened by digital automation), whereby the existing business can be made more effective. One example is a digitally supported approval process, which, in the context of purchasing, relieves the control authorities (i.e., primarily senior employees) and leads to an acceleration of the procurement process. This is justified, in particular, by the new possibility of digital automation of procurement-related decisions. In the normal case, decision rules are still given by humans, who now (also) have, on the basis of digitization and pertinent data analysis to procurement behaviour, a data-based foundation for this default. However, if data is the essential basis for a decision, then AI could arrive at the right insights just like a human being and perhaps control the processes better, especially those related to routines.

Consequently, the area of procedural decision making in the routine-oriented inventory business has become one of the most important applications of AI. The importance of the choice of human or machine decision-making structures and their impact on business performance is increasingly influenced by the rapid adoption of AI, and, therefore, represents a new strategic factor that needs to be considered by management (Shrestha et al., 2019). In general, the application of AI in decision making is not initially unproblematic. The general normative nature of formalizing, replicating, and simulating human decision making is as much an issue for AI programming as the specific behavioural nature in individual situations (Pomerol, 1997). Considering this, organizational decision making, in particular, requires both analytical and intuitive approaches. AI's strengths certainly lie (at this moment) in the first area. Therefore, a collaborative or complementary approach is often proposed that enables synergies between humans and machines (Puranam, 2021).

Figure 1. Support and transfer function of AI-Applications for decision making in the context of corporate governance



Source: In further development of Duan, Edwards, and Robins (2000, p. 44)

Although AI applications currently fall short of expectations, they help deploying companies achieve higher productivity and profits through improved decision making (Durkin, 1996, cited in Edwards et al., 2000; Moody et al., 1999). In search of a theoretical framework for the use of AI applications in business, Edwards, Duan, and Robins (2000) examined the role of AI expert systems and their respective effectiveness at different levels of an organization. Their results showed that AI can replace decision makers on an operational and tactical level, while on a strategic level, AI only plays a supporting role (see Fig. 1). In the existing digital business, with its related routine-oriented processes or predefined development paths for products in the context of an exploitation, this would mean that the executives (and thus also a CDO) could be pushed further and further into the background by an AI application. However, this might not be the case.

3.2 The Digitization of the Innovative Business

The second task to be considered is the digitization of the innovative business. In this area, the aspect of "exploration" includes the development and construction of new business models and processes. Exploration thus involves the creation of space and time to enable the innovation process in the context of idea and solution generation (Hobus & Busch, 2011). The result is the partial or complete rebuilding of processes, products, or platforms with the help of digitization. This rebuilding of new digital processes could, for example, lie in the use of blockchain technology, while new digital products could be designed specifically for the metaverse. By building new digital platforms (e.g., digital marketplaces), one could transfer any trading expertise to completely new industries in which one had not previously been active. In line with the 3-P model already introduced above (processes, products, platforms), the digitization of the innovation business focuses on the following characteristics (Kollmann, 2018, 2022c, p. 4): Digitizing new business processes as the basis of new and future business activities (Digitization of new processes); Digitizing and developing new products and services with digital value creation based on data (Digitization of new products); Building new digital market and customer platforms for future business models and processes (Digitization of new platforms).

In principle, this area can be reduced to the following statement: "It's digitizing what you don't know yet." Here, the strategic focus and future business are clearly at the centre. This means that at this point (strengthened by digital development), the strategic and related organizational structures can be improved, making the innovation business more effective. An example would be the decision of a textile producer to venture the new development of a digital fashion label in the metaverse in addition to the real business, where the avatars of the users are dressed by him with a purely digital pixel fashion. A decision here is based on a complex construct of data-related but also experience- and situation-related influencing factors. In addition, there is a high degree of uncertainty about the further development of all framework parameters (technology, user acceptance, market access, etc.) with simultaneous high/higher costs for the development and construction of this new digital business model or the new digital business processes. The question is whether one would leave such a decision to AI, follow the competence or experience of a CDO, or find a combination of humans and machines.

In this context, Jarrahi (2018) investigated how humans and machines (AI) can collaborate in organizational decision-making and concluded that there are two possible types of collaboration. Either the AI's focus is on the analytical approaches and the human's focus is on the uncertain and intuitive approaches, or, since all complex decisions have some degree of uncertainty, almost all complex decisions are a combination of human and machine. In this setting, Shrestha et al. (2019) defined one of the first organizational structure frameworks applicable to decision making as involving AI (see Fig. 2). By considering five specific dimensions (horizontal—with no "examples" column), management can determine which of the four organizational structure options (vertical) is most appropriate for decision making involving AI.

Figure 2. Support and transfer function of AI-Applications for decision making within the organizational structure.

Organizational structure	Specificity of the decision search space	Interpretability	Size of the alternative set	Decision-making speed	Replicability	*Examples*
Full human to AI delegation	**High** (required for AI to function)	**Low** (due to absence of human involvement)	**Large** (not restricted by human capacity)	**Fast** (not restricted by human capacity)	**High** (computationally standardized)	*Recommender systems, digital advertising, online fraud detection, dynamic pricing.*
Hybrid 1: AI to human sequential decision-making	**High → Low** (high in the first phase, low in the second phase)	**High** (due to human involvement in the final decision)	**Large** (due to involvement of AI in the first phase)	**Slow** (due to human decision-making as a bottleneck)	**Low** (vulnerable to human variability)	*Idea evaluation, hiring.*
Hybrid 2: Human to AI sequential decision-making	**Low → High** (low in the first phase due to human involvement and high in the second phase for AI)	**Low** (due to AI involvement in the final decision)	**Small** (due to human involvement in the first phase)	**Slow** (due to human decision-making as a bottleneck)	**Low** (vulnerable to human variability)	*Sports analytics, health monitoring.*
Aggregated human-AI decision-making	**Low** (for decisions allocated to humans) **High** (for decisions allocated to AI)	**High** (for decisions allocated to AI) **Low** (for decisions allocated to humans)	**Small** (same set of alternatives are evaluated by both humans and AI)	**Slow** (due to human decision-making as a bottleneck)	**Partial** (replicability only guaranteed in decision elements allocated to AI)	*Top management teams, boards.*

Source: Shrestha et al.,2019, p. 71.

In full human-to-AI (AI) delegation, decisions are made autonomically by AI algorithms without human intervention. AI/AI-to-human and human-to-AI/AI are both sequential hybrid models related to Jarrahi's (2018) first mode of collaboration (see above). Within these processes, humans and AI algorithms make their decisions separately but sequentially so that the output of one decision maker is the input of the other (Shrestha et al., 2019). However, according to Shrestha et al. (2019), the final aggregated human–AI decision-making structure, which is also consistent with the second type of collaboration in Jarrahi (2018) (see above), is best suited to managerial decisions. In this structure, whole or parts of decisions are assigned to the human or AI decision maker according to their respective strengths, and the results are merged into a collective decision. Given that there is often no clear human or AI superiority for a decision or parts of it, Puranam (2021) also argues that an aggregated form of collaboration is most beneficial and can lead to improved decision quality. This would mean that in the digital innovation business and its related new processes and unknown development paths for products in the context of an exploration, the executives (and thus also a CDO) could at least be supported but not displaced by an AI application. However, it is possible that this has not yet been taken to its conclusion or that no one has as yet dared to take this to its conclusion.

Such considerations would immediately lead to the realization that if the AI components of Berente et al. (2021) and the possibilities of deep learning are combined, the increasing amounts of data as well as the rapidly growing possibilities of processing data would enable an AI algorithm to increasingly imitate human thought and behaviour patterns more accurately. However, if AI continues to replace humans, taking over more and more of their creative tasks on the basis of self-learning algorithms, then the question must inevitably be asked as to whether, at some point in the future, creative and intuitive or strategic tasks in the context of an innovation business might not also be taken over by a machine. Kollmann and Kleine-Stegemann (in press) have already thought these considerations through with regard to entrepreneurship. They determined, at least conceptually, that there could certainly be a variant with intelligence entrepreneurship in the future, in which the probabilities of particularly promising future startups could create outputs with the help of AI (predictive business forecast). In the future, according to Kollmann and Kleine-Stegemann (in press) "it can also be expected that AI will also be able to make investment decisions independently and thus still be able to implement an entrepreneurial decision (prescriptive business movement)."

However, in the present decision space of Digital Transformation with associated corporate management, we will initially stick to the distinction drawn between the influence of AI for digitization in the existing or innovation business and the support or takeover of decisions within the framework of either operational or strategic corporate management. It is now clear that in the case of operational decisions in the existing business, where exploitation is the focus, the transfer of decisions to an AI application, and the subsequent authority to issue instructions, appears perfectly understandable (so-called Artificial Leadership or AI-Leadership). It is also clear that in the case of strategic decisions in the innovation business, where the focus is on exploration, the competence, intuition, and experience of the human (CDO) "still" remains decisive for decision-making (so-called Digital Leadership), and this can at best be supported by AI applications. However, the combination areas that, together with the two basic orientations, span a conceptual framework as a leadership model for decision making in the context of Digital Transformation are certainly also exciting.

4. THE LEADERSHIP MODEL FOR A DIGITAL TRANSFORMATION

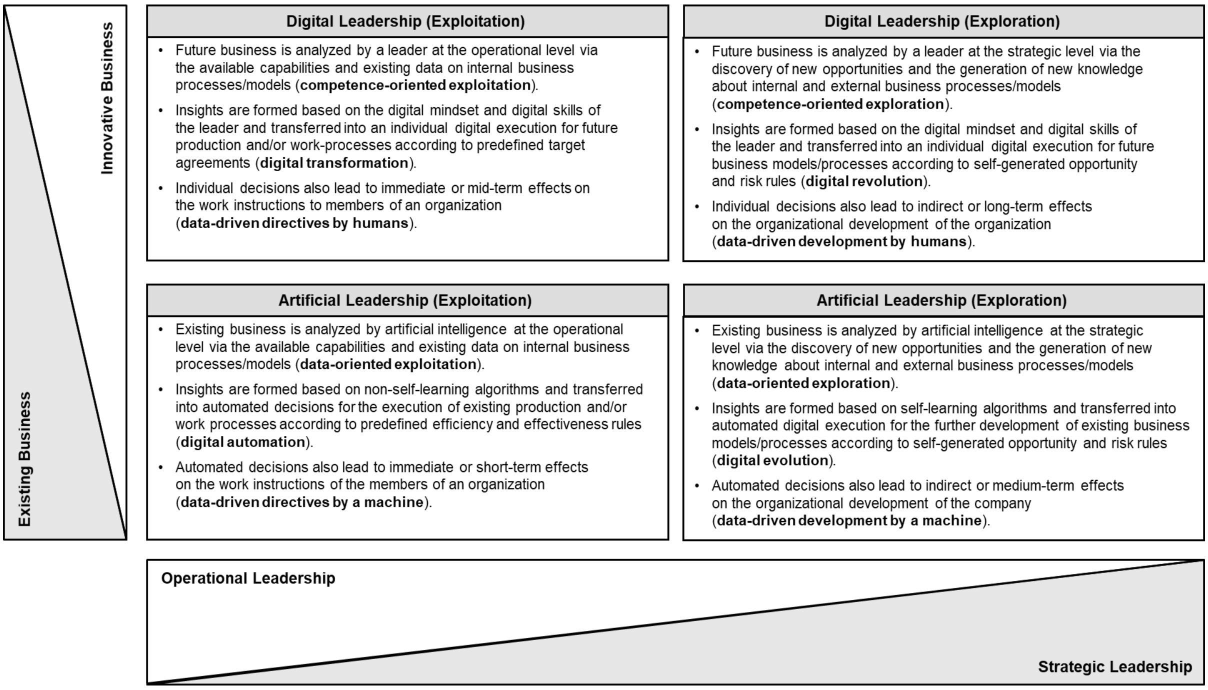
Based on the previous explanations, it is now possible to set up an overarching conceptual framework for a management model for Digital Transformation in a company. First, a distinction must be made between the digitization of existing business in the areas of processes, products, and platforms and the development of new digital business models and processes with a view to innovation business (vertical axis; see Fig. 3). In addition, a differentiation must be made between an operational and a strategic level for the effects of the associated decisions with regard to the orientation of the associated corporate management (horizontal axis; see Fig. 3). This opens up a new decision-making space, and thus a "double Digital Ambidexterity," between the existing and innovation business and the operational or strategic decision-making via humans (CDO) or machines (AI). As a further differentiating characteristic of the solution with regard to the use of humans (CDO) or machines (AI) in this double Digital Ambidexterity, a distinction between exploitation and exploration as the direction of thrust could also be helpful (see Fig. 3).

The different combinations now result in two approaches for an already known "Digital Leadership" and two approaches for a new "Artificial Leadership". In the first case, the human being—in the area of Digital Transformation, the CDO in particular—sits in the "driver's seat" for the associated decision-making and implementation. In the second case, it is the machine—in the area of Digital Transformation, artificial intelligence in particular—that is responsible for the associated decision making and implementation. In this context, the latter consideration is initially made in a completely value-free and rational manner. It is also significant in this case that it is made without discussion about the ethical and social question of whether a machine may decide over a human being. At this point, it must suffice to assume that the associated legal and social framework conditions have been clarified and that both the human being (CDO as homo economicus) and the machine (AI as machina economica) "mean well", making their decisions as independently as possible from external disruptive factors. Both associated management approaches will be described in the following section to fill the framework with life.

4.1 Digital Leadership

Overall, "Digital Leadership" can be summarized as leadership behaviour that integrates the external influences and patterns of digitization (by a person) and transfers them into a contemporary leadership style (Buhse, 2014, p. 230). However, this also makes it clear that digitization means change and that people have to really want the change. Many managers already find this difficult because they actually want to continue to profit from their experience and the positions they have acquired as they did in the past (Kollmann, 2022b, p. 42). However, this usually leads to a defensive attitude and a clinging to the status quo—which no longer works in view of the profound changes brought about by digitization. This is because companies are aggressively targeted by these from the outside and cannot be managed from within. According to Kollmann (2018, 2022c, p. 37) it is particularly important for companies in the digital economy that executives want Digital Transformation (Digital Mindset), have the necessary knowledge for this Digital Transformation (Digital Skills), and consistently implement the resulting measures as part of the Digital Transformation (Digital Execution). Only then is the complete scope of action of a digital leader addressed (Kollmann, 2022b, p. 42).

Figure 3. The Leadership-Model for Digital Transformation between Digital Leadership for innovative and Artificial Leadership for the existing business.



A digital leader should, therefore, be open to change and disruptive digital innovations and, ideally with the help of a CDO, have the necessary digital skills to implement a corresponding operational implementation and conceptual strategy in the company. Kollmann (2022c, p. 38 ff.) describes these three aspects as follows: “The Digital Mindset is understood as the inner basic attitude and positive attitude toward already known and new digital possibilities. This includes openness and curiosity about digital technologies and forms of work, questioning existing procedures and processes, and the will to proactively bring about changes in the future. The Digital Skills are understood as concrete background knowledge and know-how relating to digital business models and processes in relation to the digital economy. This includes basic knowledge of digital data as well as the resulting digital value creation for processes, products, platforms, and related developments. The Digital Execution refers to the content-related and organizational implementation or management of digital projects and/or the associated company in the course of the Digital Transformation of existing real business or the establishment of new digital business models and processes.” As a result, "Digital Leadership" can be defined as follows (Kollmann, 2022c, p. 37):

> *Digital Leadership describes a management style in which a person (in the best case as CDO) not only wants the Digital Transformation (Digital Mindset), but also has the necessary knowledge for this Digital Transformation (Digital Skills) and can finally also consistently implement the resulting measures within the framework of the Digital Transformation (Digital Execution).*

In merging these fundamentals with the framework already outlined for a leadership model for Digital Transformation in a company, the respective axes (existing/innovation business and operational/strategic management) must now be merged with the thrust of exploitation and exploration. This results in two fields of action in particular, where Digital Leadership would be more advantageous in terms of decision making and implementation (see Fig. 3).

Digital Leadership as Exploitation in the Context of the Innovation Business for Operational Leadership

- Future business is analysed by a leader at the operational level via the available capabilities and existing data on internal business processes/models (competence-oriented exploitation).
- Insights are formed based on the digital mindset and digital skills of the leader and transferred into an individual digital execution for future production and/or work processes according to predefined target agreements (digital transformation).
- Individual decisions also lead to immediate or mid-term effects on the work instructions to members of an organization (data-driven directives by humans).

Digital Leadership as Exploration in the Context of the Innovation Business for Strategic Leadership

- Future business is analysed by a leader at the strategic level via the discovery of new opportunities and the generation of new knowledge about internal and external business processes/models (competence-oriented exploration).
- Insights are formed based on the digital mindset and digital skills of the leader and transferred into an individual digital execution for future business models/processes according to self-generated opportunity and risk rules (digital revolution).
- Individual decisions also lead to indirect or long-term effects on the organizational development of the organization (data-driven development by humans).

4.2 Artificial Leadership

Overall, "Artificial Leadership" (or AI-Leadership) can be summarized as a leadership behaviour that integrates the inner influences and patterns of the algorithms (by a machine) and transfers them into a data-driven leadership style. On the one hand, AI as a machine is particularly strong at performing repetitive, routine tasks and thinking systematically and consistently. This already implies, according to de Cremer (2020, p. 3 f.), “that the tasks and the jobs that are most likely to be taken over by AI are the hard skills, and not so much the soft skills. In a way, this observation corresponds with what is called Moravec's paradox: What is easy for humans is difficult for AI, and what is difficult for humans seems rather easy for AI.”

This clearly argues for the use of AI applications in the area of automation, and, in terms of exploitation, this is most likely to come into play in the operational management of existing business. An Inside Business article on the WLW (n.d.) platform (AI is interpreted here as a robot boss) states that “a study by MIT not only confirms higher productivity in plants with robo-bosses, but employee satisfaction is also greater. This is due to the fact that they receive their instructions from a robot in a sober, analytically sound, and fairly distributed manner. The examples of Amazon and Hitachi could set a precedent. Robots not only record the work processes of individual employees. They can also quickly register the workload and productivity of the entire plant and offset them against variable external factors. They issue their work instructions not on the basis of personal preferences or spontaneous emotions, but on the basis of objective facts. Thanks to modern machine learning programs, the robots are constantly evolving, automatically contributing to process improvement.”

On the other hand, AI applications are already capable of performing creative and intuitive tasks (e.g., music compositions and art creations) and can thus also be used for exploration in the context of strategic corporate management for the consistent further development of the existing business. In science, different types of creativity are distinguished (Boden, 2016). Laux (2022) picks up on these types and states: "It can be briefly summarized that AI applications with recourse to big data can be particularly convincing in the case of formative creativity." This includes the combination of existing elements or the imitation of a certain style. However, AI reaches its limits when it comes to leaving a given conceptual space and transgressing existing rules. For this transformative creativity, there have thus far been hardly any well-functioning AI applications (Laux, 2022). Nevertheless, the formative creativity of AI seems to be sufficient for the explorative task of logical further development of the existing digital business, also in the context of strategic corporate management, or it will become sufficient in the near future.

However, it is particularly important for companies in this area in the digital economy that AI is provided with the required data in sufficient quantities and with sufficient quality (Data Source) so that AI can/may be allowed to evaluate this data with self-learning algorithms without interference (Data Analysis). The results are then not only comprehensible to humans, but are also implemented as instructions for action (Digital Results). Consequently, these three aspects can be described as follows: “In the context of the Big Data-Approach, the Data Source describes the necessity of the data that is provided to a higher-level AI for an analysis being made available in sufficient quantity, variety, speed, and quality. In the context of the Deep Learning-Approach, Data Analysis describes the possibility of the algorithms that are used for an analysis learning more with each calculation and thus being allowed to improve continuously; the higher-level AI is allowed to adjust independently. In the context of the Data-Driven-Approach, Data Decision describes the consequence of the results that are obtained from the analysis being comprehensible to humans; thus, the resulting orders of action are accepted. Therefore, "Artificial Leadership" (or AI-Leadership) can be defined as follows:

Artificial Leadership describes a style of leadership in which a machine (in the best case as an AI) not only obtains the required data via a Big Data approach (Digital Source), but can also evaluate it independently with the associated algorithms via a deep learning approach (Digital Analysis) and finally the results which emerge are also accepted as an order for action by humans via a Data-Driven approach (Digital Decision).

In merging these fundamentals with the framework already outlined for the leadership model for a Digital Transformation in a company, the respective axes (existing/innovation business and operational/strategic corporate management) must now be merged with the thrust of exploitation and exploration. This results in two fields of action in particular, where Artificial Leadership would be more advantageous in terms of decision making and implementation (see Fig. 3).

Artificial Leadership as Exploitation in the Context of the Existing Business for Operational Leadership

- Existing business is analysed by artificial intelligence at the operational level via the available capabilities and existing data on internal business processes/models (data-oriented exploitation).
- Insights are formed based on non-self-learning algorithms and transferred into auto-mated decisions for the execution of existing production and/or work processes according to predefined efficiency and effectiveness rules (digital automation).
- Automated decisions also lead to immediate or short-term effects on the work instructions of the members of an organization (data-driven directives by a machine).

Artificial Leadership as Exploration in the Context of the Existing Business for Strategic Leadership

- Existing business is analysed by artificial intelligence at the strategic level via the discovery of new opportunities and the generation of new knowledge about internal and external business processes/ models (data-oriented exploration).
- Insights are formed based on self-learning algorithms and transferred into automated digital execution for the further development of existing business models/processes according to self-generated opportunity and risk rules (digital evolution).
- Automated decisions also lead to indirect or medium-term effects on the organizational development of the company (data-driven development by a machine).

5. DISCUSSION AND IMPLICATIONS

Research into the influence of AI on corporate management and the related operational and strategic decisions is certainly only just beginning. What is certain is that the proportion of data-driven decision-making will continue to increase as more and more AI-Systems are deployed in companies. This certainly also applies to any resulting "Artificial Leadership" (often interpreted in the press as "robot boss"), which will be increasingly influenced by the further development of AI-Technology. In this context, there are certainly political and ethically relevant aspects that must be included in the human–machine consideration. Perhaps it would be helpful to transition from a "better" or "worse" view to a goal-oriented view in the span of hard and soft skills that are needed to make and implement decisions more effectively (also with regard to the Digital Transformation) and to implement them. Accordingly, it is not (at least at the moment) an "either/or" decision but rather an "also" decision when it comes to shaping the Digital Transformation in a company with a Chief Digital Officer (CDO) and AI. Because the digitization of data is the basis for all development in both the existing business and the innovation business, we have a particularly exciting field of investigation between the competence of a human (CDO) and the algorithms of a machine (AI). Used correctly, both the one, in the context of Digital Leadership, and the other, in the context of Artificial Leadership, can lead to Digital Transformation for a company to succeed.

With regard to further research, however, the presented framework can only be a starting point to first test it in the context of an empirical review and thus to validate it theoretically in order to subsequently motivate its proper use in practice. With regard to the review and validation, the following questions are central:

- Will there be a measurable and significant difference for the differentiated consideration of an application of AI between the tasks in operational (e.g. optimization of production processes) and strategic corporate management (e.g. investment in new business areas)?
- Will or must the related conception of AI with the associated algorithms be different for the data-driven business processes (e.g., arrangement in the context of production processes in the inventory business) as opposed to the data-driven business decisions (proposal in the context of a competitive positioning in the innovation business)?

- Will there be a measurable and significant difference for the differentiated consideration of a use of AI in the areas of exploitation (more formative creativity) and exploration (more transformative creativity)?
- Where and why will analyses, results, interpretation as well as decisions based on them be significantly different between a human (Digital Leadership) and a machine (Artificial Leadership) and how can the consequence be measured?
- What is the measurable impact of data-driven business processes and decisions based on Artificial Leadership as opposed to Digital Leadership on the respective followership of employees at the implementation level and are there significant differences here?

The results of the related further research would accordingly lead to a confirmation of or the necessity for an adaptation of the framework (Limitation) presented here. Either way, from a theoretical point of view, this model is intended to provide a direct and differentiated view of the use of AI in the company from the outset, as this differs in the various areas. It calls for empirical measurement models that are still necessary in this regard to be differentiated according to the various areas (existing vs. innovative business and operational vs. strategic leadership) and influences (exploitation vs. exploration). The model thus offers a first structured approach to the field of application of AI for business management, which could certainly find an application in other task areas beyond the first exemplary topic area of Digital Transformation. In addition to these model-related issues and reference points for related future research, however, there are certainly numerous other aspects that can be explored with respect to the impact of an AI on the theoretical areas of the business:

- What influence does the use of an AI have on the associated acceptance at the various hierarchical levels and how can the associated dimensions of attitude, action and use be measured?
- What impact does the use of an AI have on the operational functions of work and organizations and how can an associated value creation between humans and machines be measured?
- What is the impact of how an AI arrives at an outcome and how can this outcome be measured and evaluated in terms of consequences in the form of AI-KPIs?
- What changes will be observed when AI outperforms humans in terms of outcomes, and how will this impact the evaluation of human performance, power structures, and careers?
- How can the value of an AI or its associated algorithm be determined from a shareholder and stakeholder perspective for business valuation?

All points are subject to the requirement of developing empirical measurement models that can unambiguously separate and measure the impact of humans and AI in order to work out the relevant influences. Assuming that this is possible and that the results from the research that is still needed support the validity of the framework, against the background of these theoretical requirements, there are also some exciting implications and necessary analyses and topics for the practical point of view, among others:

- Through the framework, the CDO (or manager in another area) can be relieved of routine tasks in the existing business through the justified delegation of control, decision-making and ordering authority to the AI, so that he or she can concentrate more on the innovation business.
- The framework can lead to an expansion of the CDO's (or manager's in another area) area of responsibility, who now acts as a rule maker and control authority for the formative creativity of an AI in the existing business.
- The framework can lead to a new positioning of the CDO (or manager in another area), who can now be interpreted as a user and controller for the transformative creativity of an AI in the innovation business.
- The framework can support the implementation of an AI in the company by the CDO (or manager in another area), in which the individual areas are considered one after the other (for example, first digital/artificial leadership in the area of exploitation, then digital/artificial leadership in the area of exploration).
- The framework can support the CDO's (or manager's in another area) analysis of AI in the company, looking at the origin, request and use of data under the different fora in each area in terms of cultural, regional, political, and ethical influences.

Overall, with this paper we have addressed the future influence of AI on data-driven decision-making in the context of corporate management, focusing on the field of digital transformation as an example, since this direct influence is obvious here due to the data as a basis for decision-making. We wanted to highlight the general importance of this topic area and illuminate it by means of the encounter between humans (in the form of a CDO) and a machine (in the form of an AI) in goals and tasks in this area. As a result, we differentiated between the associated decision-making and implementation by a CDO or an AI in the respective areas of existing and innovation business, considering the use of resources (exploitation and exploration). The result was a leadership model for digital transformation between digital leadership for innovative and artificial leadership for the existing business. Subject to empirical verification, researchers can use this model for a better structure of their future thinking in this area and consider effectiveness in the resulting fields under the different influences. Practitioners can use this framework to guide their implementation of AI.

Again, the Leadership Model for Digital Transformation between Digital Leadership for innovative and Artificial Leadership for the existing business - presented in this paper - can help to determine the application or reference point according to the different areas (existing vs. innovative business and operational vs. strategic leadership) and influences (exploitation vs. exploration). Overall, there will be many more questions associated with the use of AI in the context of business management that we do not have answers to today. But because AI has now arrived in society and business, at least since the hype surrounding Chat GPT, we need to address it. Among many legal, political and ethical questions, we count the following in particular: Is homo economicus being replaced by machina economica? Will there also be artificial followership by humans for artificial leadership by a machine? Who will finally take the responsibility for the consequences of a decision and/or instruction by an AI? The machine (if that is possible at all) or in the end the human who programmed it or who used it? It will be crucial that we deal with these questions and developments, both theoretically and practically, for the economy, society and politics - not at some point, but now!

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