AI and its Opportunities for Decision-Making in Organizations: A Systematic Review of the Influencing Factors on the Intention to use AI

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Abstract: One domain of application of artificial intelligence (AI) is decision support, particularly in management. Although there are already research streams examining the interaction of AI and humans (e.g. the stream on "hybrid intelligence"), there are still numerous open research gaps – for example, a comprehensive overview of which factors favor the intention to use AI is missing. By conducting a systematic literature review, we identify the factors that potentially positively influence AI usage intentions for decision-making processes in organizations. From this, we create a framework that both provides practical implications for the successful use of AI in organizational decision-making processes and delivers further research approaches, for example, on the validity/ usability of proven IS adoption models in the present context.

Keywords: artificial intelligence, decision-making, management, systematic review

Potenziale Künstlicher Intelligenz (KI) für Entscheidungsprozesse in Organisationen: Eine systematische Analyse relevanter Einflussfaktoren auf die Bereitschaft, KI als Hilfsmittel zu nutzen

Zusammenfassung: Ein Anwendungsbereich Künstlicher Intelligenz (KI) ist die Entscheidungsunterstützung, insbesondere im Management. Obwohl einzelne Forschungsbereiche das Zusammenspiel von KI und Mensch bereits untersuchen (z.B. die Forschung im Bereich "hybrider Intelligenz"), gibt es noch zahlreiche offene Forschungslücken – so fehlt z.B. ein umfassender Überblick darüber, welche Faktoren die Absicht, KI zu nutzen, begünstigen. Mittels einer systematischen Literatur-Analyse ermitteln wir eben diese Faktoren, die die Nutzungsbereitschaft von AI in organisationalen Entscheidungsprozessen potenziell positiv beeinflussen. Hieraus erstellen wir ein Framework, welches sowohl praktische Implikationen zur erfolgreichen Nutzung von AI in Entscheidungsprozessen in Organisationen als auch weitere Forschungsansätze liefert, beispielsweise zur Gültigkeit/ Nutzbarkeit erprobter IS-Adaptions-Modelle im vorliegenden Kontext.

Stichwörter: Künstliche Intelligenz, Entscheidungsfindung, Management, systematische Übersichtsarbeit

1 Introduction

The use of and discussion regarding artificial intelligence (AI), which we define as a self-learning technology that delivers recommendations for the human decision-maker (e.g., *Jarrahi* 2018; *Kolbjørnsrud et al.* 2017), has been around since the 1950s, however, nowadays the opportunities for its use are rising (*Anderson et al.* 2018; *Davenport* 2018; *Davenport/Kirby* 2016; *Liebowitz* 2001; *Min* 2010; *Stoica et al.* 2017). A McKinsey study suggested that AI might raise the global GDP by 1.3 % by 2030 (*McKinsey Global Institute* 2018). Due to recent advances in technology, AI has inherited new opportunities for companies and their employees; for example, the opportunity to perform different and difficult tasks in a human-like way, and even act as noteworthy support to the organizational decision-maker (*Davenport/Kirby* 2016; *Jarrahi* 2018; *Parry et al.* 2016). Therefore, the technology is considered to be one of the most disruptive forces in business (*Jarrahi* 2018), although the practical use of analytically-based technologies, like AI, is still in its initial phase (*Lismont et al.* 2017). The above-mentioned advances can be attributed to three developments, (1) the huge amounts of data that are produced and stored, (2) the increasing scalability and performance of computers and software, and (3) the broad accessibility of both (*Duan et al.* 2019; *Stoica et al.* 2017) – all three can be summarized under the term or are traits of “Big Data” (e.g., *Abbasi et al.* 2016; *Davenport* 2018).

Not only, but particularly these large amounts of data lead to complexity in decision-making in organizations. Therefore, one promising case for AI-use is to reduce this complexity by providing decision support (*Duan et al.* 2019; *Jarrahi* 2018; *Stoica et al.* 2017). With its expected rationality and other “algorithmic competencies” like speed, efficiency, and accuracy (*Bader/Kaiser* 2019), AI can help managers to base their decisions on hard facts instead of “making them from the gut” (*Faraj et al.* 2018; *Kim et al.* 2008; *Kolbjørnsrud et al.* 2017; *Moskowitz et al.* 2011).

Although there are already research streams examining the interaction of AI and humans (e.g. the stream on "hybrid intelligence"; see Antretter et al. *2020*; Dellermann et al. *2019*), up to now, there is still a lack of sufficient investigation and understanding of the specific interaction of AI and decision-makers in organizations (*Duan et al.* 2019). Among other things, appropriate definitions for AI in this context are lacking, the interaction between humans and AI has not yet been conceptualized, and the factors influencing the intention to use the technology are unknown (*Duan et al.* 2019; *Jarrahi* 2018). By conducting a comprehensive systematic review, we aim to close these research gaps. While other recent research findings regarding AI and organizational management take a more general approach (*Keding* 2020, for example, uses a systematic review to examine the fundamental role of AI in strategic management), we give an answer to the specific question on what influences an organization’s (or their employees’) intention to use AI in its decision-making; a research question that has already been mentioned many times as urgent to be answered (e.g., *Duan et al.* 2019; *Keding* 2020). We provide a framework of relevant factors that need to be considered to successfully use the technology in this specific context. This framework aims to identify a scientifically proven status quo, research gaps and further research directions. Prior to this, we develop a possible definition of AI and conceptualize the interaction between the technology and the human decision-maker.

To examine the acceptance of IT systems, various IT adoption models and theories exist, such as the Technology Acceptance Model (TAM, *Davis* 1989), the Value-Based Adoption Model (VAM, *Kim et al.* 2007) or the Theory of Planned Behavior (TPB, *Ajzen*

1991). Recent studies like *Sohn/Kwon* (2020) or *Quentin et al.* (2018) investigate their suitability to explain the user acceptance of AI. However, these studies consider the user as customer and refer to AI within products such as smart speakers and home appliances, not to AI in decision-making processes in an organizational context, which is what we focus on. Therefore, we try to assign the identified influencing factors – as far as possible – to the existing IS-adoption models and thus to suggest appropriate approaches for further investigations.

Our systematic review consists of keyword searches and snowball samplings, followed by a bibliometric and content analysis. Following *Webster/Watson* (2002), our systematic review uses a concept-centric approach. The review resulted in 267 papers, which were examined in more detail. Of these 267 papers, 42 contained relevant results on the answer to our research questions.

The course of our paper is as follows: First, we briefly explain the procedure and the methodology of our systematic review, following which we explain the results of the individual steps. Second, we present various descriptive and bibliometric data that help to classify the subsequent answers to our research questions in a proper context. Third, we begin the prescriptive part of our paper with the necessary definition of AI, which is the basis for further research procedures. We conclude by answering our research question based on the results of the content analysis. Finally, we summarize our results by providing concrete implications for management, research suggestions, and by explaining the limitations of our research.

2 Systematic review

2.1 Approach and research questions

Our approach. We conduct a systematic review of the existing research in the field of AI and decision-making; a systematic review informs both scholarship and practice (*Briner/Denyer* 2012). Different to other kinds of reviews, the systematic review uses a replicable and transparent approach, allowing us to answer our research questions in the most scientific way (*Briner/Denyer* 2012; *Rousseau et al.* 2008). Our approach follows *Briner/Denyer* (2012); *Kitchenham/Brereton* (2013) and *Roetzel* (2019). In accordance with *Briner/Denyer* (2012), our structured review mainly consists the following five steps: Planning the structured review, locating studies, evaluating their individual research contribution, analyzing and synthesizing the findings from the studies and merging and generalizing the review findings. The subsequent content analysis – based on the systematic review – uses a concept-centric approach and follows *Webster/Watson* (2002).

To identify all relevant studies, we apply the following search strategy (as examples of this strategy or parts of it, see *Kitchenham/Brereton* 2013; *Roetzel* 2019; *Schaltegger et al.* 2013): In step 1, we list all known papers that deal with AI and decision-making in organizations and identify the journals publishing these papers. In step 2, we define keywords to conduct a manual search on other relevant papers within the identified journals. In step 3, we define a set of (here) 9 of the most important of the known papers. Subsequently, we search for all papers that referenced one of the papers of the set (forward snowballing). Up to here, we assess the relevance based on the title and abstract of the paper. In step 4, after defining a list of unique papers, we read the full versions of the papers and apply our inclusion/ exclusion criteria (which were defined before conducting the systematic review). To ensure that we did not miss any relevant papers, in step 5, we finally check the references of all the identified papers for possible gaps (backward snowballing). *Figure 1* outlines this process.

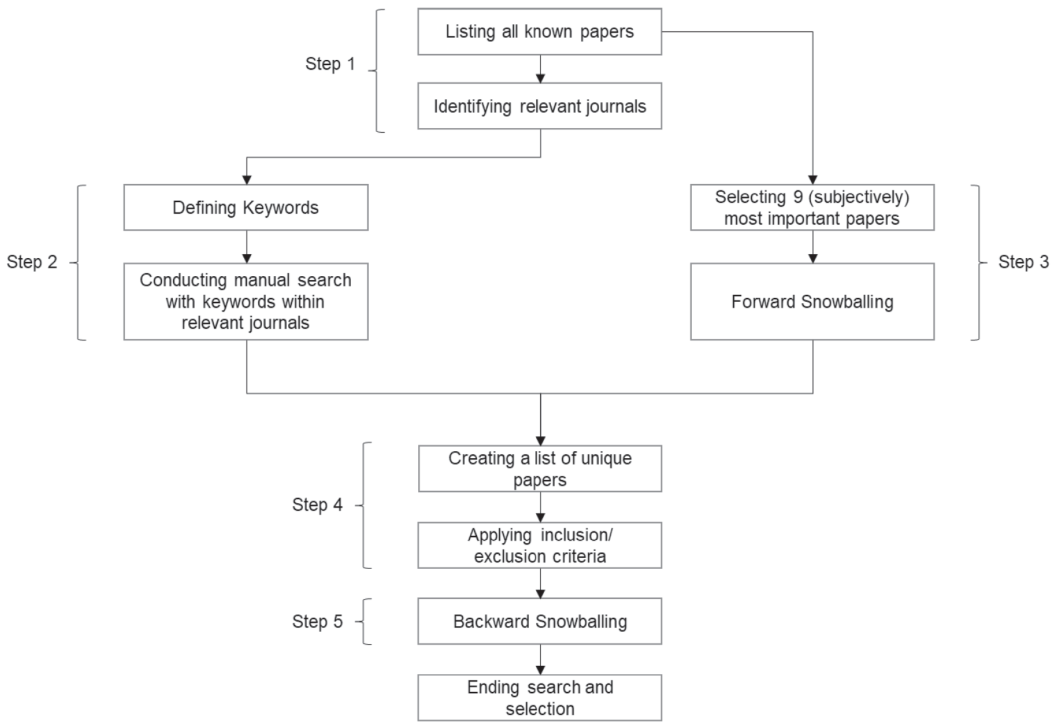

Figure 1. Search and selection process

Research Question. Regarding AI, various recent papers and fragmented studies put forth propositions and questions to be answered in the areas of AI implementation, AI-human interaction, or its theoretical development *(Duan et al.* 2019; *Stoica et al.* 2017). Initial theoretical approaches explain how AI can assist humans in decision-making. *Duan et al.* (2019) present an overview of the possible approaches within scientific literature and, in addition, state that the use of AI for decision-making is "[…] one of the most important applications in AI history." *Jarrahi* (2018) provides an example of AI dealing with three challenges in decision-making: AI can reduce uncertainty by, for example, providing access to real time data from anywhere inside a company. It can flatten complexities by analyzing or structuring data, and it can eliminate equivocality by analyzing sentiments.

Overall, the influence of AI on decision-making (in organizations) has not yet been sufficiently investigated (*Duan et al.* 2019). While – following e.g. *Edwards et al.* (2000); *Faraj et al.* (2018) or *Jarrahi* (2018) – a positive influence of AI on decision-making can be assumed, the question remains open as to what influences the actual usage of AI. It is assumed that AI users' personal traits, their values, different cultures, etc. have an influence on the intention to use the technology (*Duan et al.* 2019). To close this research gap, we investigate these propositions along our main research question and combine the results in a framework. This framework is both intended to support the practitioner in the implementation of AI and to provide approaches for further research. Therefore, our main research question is: *What influences the intention to use (and hereby the actual usage of) AI in the decision-making process in organizations?*

2.2 Execution and numerical results

In the following section we describe the execution of our structured review and demonstrate the main results. The following steps refer to the search and selection process in *Figure 1*.

Step 1: Listing known papers and identifying relevant journals.

In a first step, we collected the papers known to us that dealt with AI and decision-making. To ensure quality, we listed only papers that have been published in qualified journals. To identify these journals, we used the VHB-JOURQUAL3—a ranking of journals relevant to business research based on evaluations by members of the German Academic Association for Business Research. Following *Roetzel* (2019), we excluded papers published in journals that are either not listed in the VHB-JOURQUAL3, listed in category D or ranked as “no academic journal”. Additionally, we excluded papers that were published before 1997. We chose this date as it is widely regarded as the end of the last AI winter, with Deep Blue’s victory over Garry Kasparov. In addition, even older publications did not seem relevant in the context of a rapidly developing technology. Our collection resulted in 25 known papers, which served as our starting point for further systematic search. The journals that published the papers also served as reference journals for our keyword search. As our topic of research is closely related to practice, we added the MIS Quarterly Executive as a reference for our subsequent keyword search. In addition, we have added three more journals that are not included in the initial collection, but which experts, with whom we have discussed our research, suggest may contain relevant papers. Therefore, the journals for our search process are listed in the following:

- Business Horizons
- Communications of the ACM
- Computers Operations Research
- Decision Sciences
- Decision Support Systems
- European Journal of Information Systems
- European Journal of Operational Research
- Group Organization Management
- Harvard Business Review
- Information and Organization
- Information Systems Research
- Interfaces
- International Journal of Information Management
- International Journal of Logistics Research and Applications
- Journal of the Association for Information Systems
- Journal of Business Analytics
- Journal of Business Research
- Journal of Information Technology

- MIS Quarterly Executive
- MIS Quarterly
- MIT Sloan Management Review and Science

Step 2: Defining keywords and keyword clusters.

Within the 25 papers, we identified 88 keywords. We analyzed the frequency of the different keywords and considered all keywords with a frequency greater than one to be relevant, since they appear to be replicable. The identified keywords are “Artificial Intelligence”, “Decision-making”, “Decision Support Systems”, “Expert Systems”, “Knowledge Management”, “Machine Learning”.

Afterwards, we examined existing dependencies within the keywords. For example, the keywords "artificial intelligence" and "decision-making" are often used together. These two keywords must be differentiated. The first describes the technique (or the general term for underlying techniques): artificial intelligence. The second is the relevant use case for this technique we focus on: decision-making. We identified the relevant combinations and used them for our search. In combination with our results, they are listed in *Table* 1. To ensure that we do not miss any relevant papers, we have also considered frequently used abbreviations for the subsequent searches (e.g., “AI” for “artificial intelligence”). Using the composite keyword combinations and after removing duplicate results, we identified 87 additional papers.

Keyword 1 (AI Technique)	*Keyword 2 (AI Application)*	*Results*
Artificial Intelligence	Decision Support Systems	52
AI	Decision Support Systems	43
Artificial Intelligence	Decision-making	19
AI	Decision-making	22
After removing duplicate results (before)		*87 (136)*

Table 1: Initial keyword combinations

Search term “Artificial Intelligence”. As stated above, a common understanding of AI is still missing. This leads to a major challenge in locating relevant studies, as the keywords are inconsistent. Over the last decades, different terms for AI-related technologies were used. What we presently call “AI” can also be referred to in earlier (but also recent) studies as, for example, knowledge-based systems (KBS), decision support systems (DSS), expert systems (ES), intelligent agents (IA), or knowledge management systems (KMS) (*Duan et al.* 2019, *Gregor/Benbasat* 1999; *Liao* 2003). AI itself can be seen as a collective term for different techniques, such as rule-based inference, semantic linguistic analysis, and others (*Duan et al.* 2019). We solve this problem by applying the most relevant of these different terms as keywords (and combinations) in all steps of our search strategy. *Table* 2 lists the keyword-combinations and the results of the additional search.

Keyword 1 (AI Technique)	*Keyword 2 (AI Application)*	*Results*
Machine Learning	Decision-making	25
Expert Systems	Decision-making	30
Knowledge Management Systems	Decision-making	10
Intelligent Agents	Decision-making	8
Intelligent Systems	Decision-making	7
Knowledge Based Systems	Decision-making	6
Deep Learning	Decision-making	3
After removing duplicate results (before)		*81 (89)*

Table 2: Additional keyword combinations

To ensure that we did not miss any important keyword/s, we also compared the chosen keywords with the results and lists of keywords of *Sutton et al.* (2016) and *Watson* (2017).

Step 3: Forward snowballing.

Following our strategy in *Figure 1*, we selected the papers we felt were most relevant to our research and used them as a starting point for forward snowballing. These papers are *Abbasi et al.* (2016), *Constantiou/Kallinikos* (2015), *Davenport* (2018), *Dhar* (2013), *Nemati et al.* (2002), *Gregor/Benbasat* (1999), *Jarrahi* (2018), *Min* (2010) and *Sharma et al.* (2014). We found 136 papers that might have been relevant at first sight, but after more intensive examination, 74 papers remained. Combined with the results of the keyword searches and the initial data set, 267 papers remained unique for a subsequent, more detailed analysis (25 initial papers, 87 and 81 papers from the keyword searches and 74 papers from the forward snowballing).

Step 4: Applying inclusion and exclusion criteria.

Following *Briner/Denyer* (2012), we defined our inclusion and exclusion criteria before conducting the search and selection process. The aim of this systematic review was to obtain a comprehensive overview of the papers related to AI and decision-making in organizations and, most importantly, to our research questions. Therefore, our inclusion criteria were as follows:

1. The main objective of the paper contributes to our research question.
2. To keep our study at manageable levels, the scope was restricted to papers that deal with AI and decision-making in a business context. Therefore, for example, we excluded studies which focus on AI in other contexts, like medicine.
3. The paper must be written in English. We do not believe that many relevant studies would be published in languages other than English (see also the selected journals).

Our exclusion criteria were as follows:

1. Papers that do not clearly indicate whether they refer to AI. We learned that in the field of AI research, many different terms are used for the same things. For example, terms like "expert system" are equated with "AI," and vice versa. Simultaneously, not every technology referred to as "AI" is actually "intelligent" and in line with our definition of AI, which we present below. Therefore, unambiguity was essential at this point.
2. Mathematical approaches that present technological details of a certain AI technique and particularly its algorithms. The results of these studies do not support our research goals.
3. The content is not scientific but an introduction, glossary, etc. However, as there are not too many studies on our topic, we accepted, for example, opinion papers in scientific journals.

As will be seen subsequently, a broad range of methodological approaches was used within the identified studies; for instance, a lot of papers used conceptual approaches. Therefore, we have consciously not excluded individual types of studies (e.g., conceptual papers). We believe that the selection of our inclusion and exclusion criteria allows for sufficient relevant studies, yet simultaneously offers adequate filtering possibilities. Applying these criteria to our list of unique papers rendered 43 papers remaining.

Step 5: Backward snowballing.

To ensure that we did not miss any important papers, we conducted backward snowballing with some newer papers that cite a lot of relevant research in our context: *Duan et al.* (2019) and *Mahroof* (2019). Thus, we identified nine additional papers, four of which were relevant to our research.

List of papers for bibliometric and content analysis.

Finally, according to our initial database, we excluded papers older than 1997. This resulted in a final number of 42 remaining papers to conduct the subsequent analyses.

2.3 Descriptive bibliometrics

Number of Relevant Papers per Journal. The assignment of the papers to their publishing journals in *Figure 2* shows a distinct figure. With a share of 17 %, most of the papers relevant for our research can be found in the "Decision Support Systems". The "European Journal of Operational Research" follows with 12 %. It should be noted that the initial number of papers found in this journal was significantly higher. However, it was mainly reduced due to our exclusion criteria, the exclusion of purely mathematical approaches.

Used Methods. The used methodology was explicitly not applied as an inclusion or exclusion criterion in the search and selection process. This was to ensure that no relevant statements and assessments were lost in an area that has been little researched to date, such as AI in the context of decision-making in organizations. The analysis of the methods used in the studies included confirms this assumption (see *Figure 3*). Conceptual papers with a 40 % share, namely those that present individual (but mostly justified) assessments and propositions or introduce new concepts or theories, were the leading category. Experiments and literature reviews followed with 17 % each. Since the approach of a systematic review may well differ from that of a (simple) review, the categories have been separated. Surveys followed at a 12 % share.

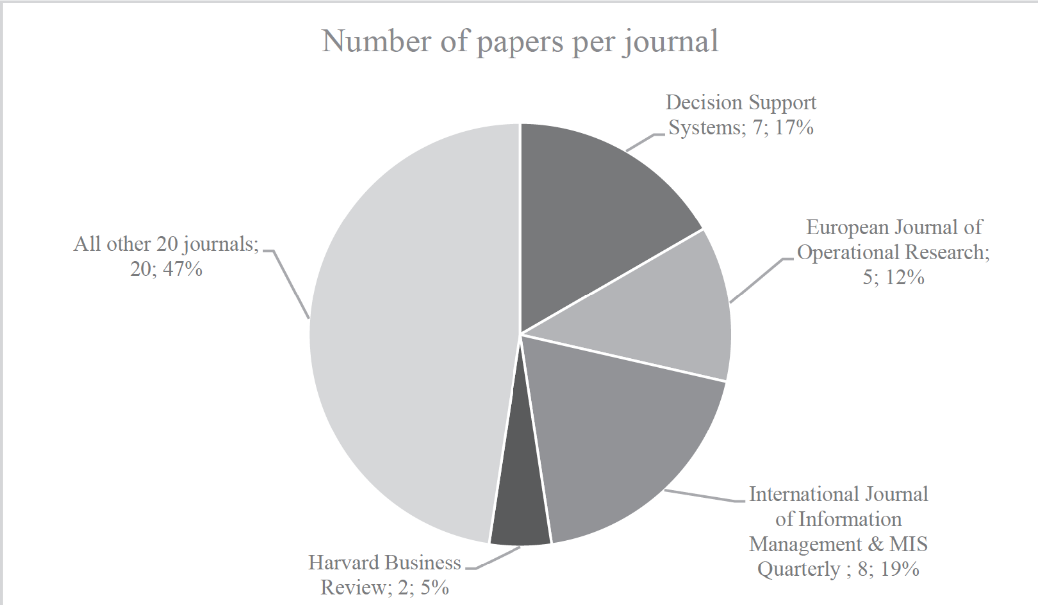

Figure 2: Number of papers per journal

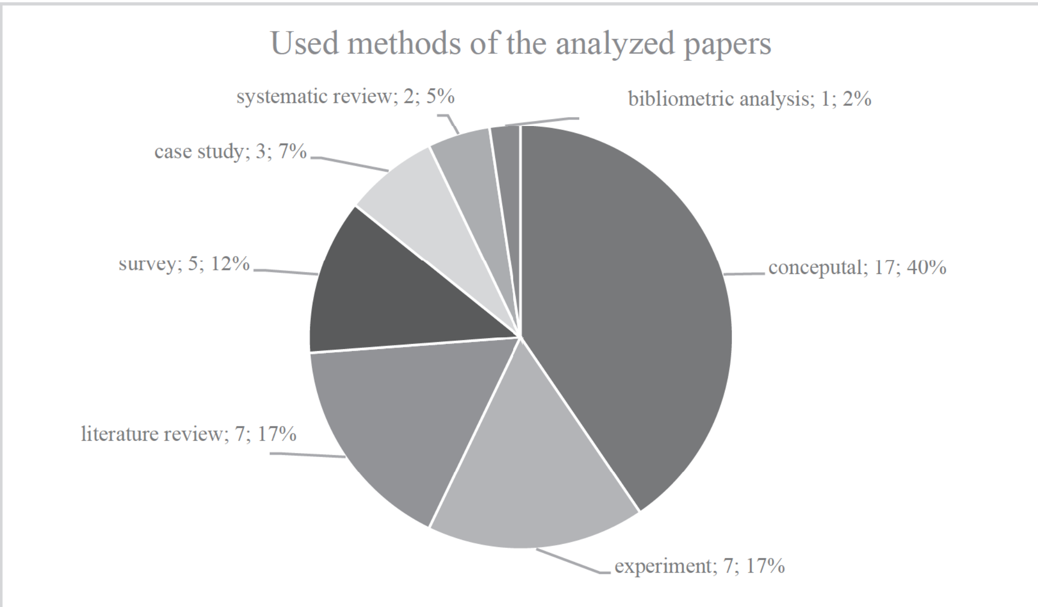

Figure 3: Used methods of the analyzed papers

3 Content analysis results

3.1 AI and decision-making in organizations

To be able to give profound answers about what influences the intention to use AI in decision-making processes within organizations, some preliminary work must be done. First, individual decision-making needs to be delimited from the context of organizational decision-making. Second, based on the results of our research, we provide a working definition for AI. Third, with the help of an abstract model of a decision process, we bring together the previous results and explain where AI can augment the human decision-maker and what it might look like in decision-making processes within organizations, when humans and machines work together.

3.1.1 Differentiating decision-making at an individual and organizational level

Decision-making at an individual and organizational level are two different research streams. The former relates particularly to the perspective of behavioral decision theory, whose roots go back to 1954 (*Shapira* 2010) and which has led to very well-known work in the context of individual decision behavior, for example the prospect theory by *Kahneman/Tversky* (1979). The roots of work on decision-making in organizations go back to Simon in 1947 and 1955 (*Shapira* 2010). Individual and organizational decision-making are strongly related to each other and overlap greatly (*Shapira* 2010).[1] Therefore it is not always easy to view the two streams separately.

We focus on AI and decision-making at the individual level; and, therefore, behavioral aspects need to be considered. This means that we investigate what influences individuals (humans) to use AI as a support tool for their (daily) decision-making processes. This refers to the decision-making processes they perform within their organizational environment – for example in their daily job.

3.1.2 Definition of AI for decision-making

As AI technology evolves and the terms for AI-based systems change, there is still no generally accepted definition for AI (*Duan et al.* 2019); however, different prominent definitions exist (*Duan et al.* 2019; *Jacob et al.* 1988; *Min* 2010; *Moser* 1986; *Russell/Norvig* 1995). The underlying AI-based technologies and the underlying stage of technical development seem to account for most of these differences. Although they differ in some respects, most of the definitions indicate a consensus on two major characteristic of AI – first, the imitation of human behavior in analyzing data and, second, the ability to self-improve. We will discuss these characteristics in detail.

A suitable definition is essential to our research. Thus, as a first step, we propose a working definition of AI for the specific context of decision-making in organizations. Therefore, we merged the different understandings to a unique and comprehensive working definition. To be accepted and useful for other researchers, a definition needs to be based on existing research. Therefore, we analyzed each definition within the identified papers, extracted the most relevant keywords and terms and formed clusters of defining traits from these, to which we have assigned the papers in *Table 3*.[2]

1 *Shapira* (2010) provides a broad overview of the history and interplay of both streams of research.
2 Not all analyzed papers define AI; accordingly, these are not included.

Reference AI…	…is self-learning and infers decision-rules by using large amounts of data	…generates predictions (as input for the human decision-maker)	…offers algorithmic competencies (Speed/ Efficiency/ Accuracy)	…is self-improving
Arnold et al. 2006		x		
Bader/Kaiser 2019			x	
Bhatt/Zaveri 2002	x		x	
Chuang/Yadav 1998				x
Faraj et al. 2018	x	x		
Gregor/Benbasat 1999	x			
Hall 1999				x
Jarrahi 2018	x			x
Kolbjørnsrud et al. 2017	x	x		x
Kratzwald et al. 2018	x			x
Mahroof 2019	x			x
Min 2010	x			x
Nunes/Jannach 2017		x		
Phillips-Wren et al. 2009		x		
Pieters 2011	x			
Pomerol 1997	x			
SHAO 1998	x			
Shreshta et al. 2019			x	
	11	*5*	*3*	*7*

Table 3: Defining traits of AI

By combining the results, we propose the following working definition of AI in decision-making processes within organizations, the components of which are explained in further detail below:

Artificial Intelligence (AI) is a self-learning technology that infers decision-rules by processing large amounts of data. With speed and accuracy, it delivers recommendations for the human decision-maker, who makes the final decision. At the same time, AI constantly improves itself by refining its initial solutions. AI can thus play an important role in the decision-making process (of organizations), namely the preparation of decisions to improve the speed and quality of decision-making processes in organizations.

Following *Jarrahi* (2018), we consider AI as a kind of umbrella that includes specific AI technologies like Natural Language Processing or Deep Learning.

Discussion of relevant defining traits.

…is self-learning and infers decision-rules by using large amounts of data.

One of the most important differences between AI and related technologies (e.g., expert systems, robotic process automation, etc.) is the AI's ability to learn on its own (which means to infer decision-rules on its own, to use these for future recommendations). This is the only way to significantly reduce complexity in decision-making situations (*Jarrahi* 2018; *Min* 2010). Otherwise, humans would have to completely overcome the complexity and design the algorithm accordingly to reduce the complexity in the next step, and that is not what we understand as AI. Following *Moualek* (1997), complexity can be characterized as uncertainty about the decision outcomes, multiple or even conflicting objectives within a group of decision-makers and a huge number of options and decision-alternatives.

To be trained (or to make it capable of inferring decision-rules on its own), AI requires a huge number of datasets (*Bhatt/Zaveri* 2002; *Faraj et al.* 2018; *Kratzwald et al.* 2018). However, this does not mean that no human is needed. A human decision-maker confirms or rejects the rules identified by AI, enabling its training, and further learning each time. The availability of the required computing capacity of an AI algorithm can be attributed to the three developments mentioned in the introductory section, in particular, the increasing scalability and performance of computer and software to process those data.

…generates predictions (as input for the human decision-maker)

A proven application of DSS in general, of which we also count AI as a functional sub-form, is the augmentation of human decision-makers in their decision-making processes. Nowadays, some opinions suggest that AI can play an even broader role, that is, to fully replace the decision-maker (e.g., *Edwards et al.* 2000; *Faraj et al.* 2018). Whether such a scenario is realistic or hypothetical can be critically questioned (*Parry et al.* 2016). We try to answer this question by assigning the different studies and papers analyzed to the two functions (augmentation and replacement). The definitions of the roles are as follows: The AI in an augmenting role supports experts or non-experts in their decision-making. As a tool that replaces the human, AI makes the final decision instead of the end-user (*Edwards et al.* 2000). Every analyzed study in our systematic review has considered AI as augmentation of human decision-makers or as both an opportunity to augment as well as replace humans. But we found no examples of AI being purely described as a tool to replace humans. *Parry et al.* (2016) also saw machines substituting the human skills required for decision-making but not for the decision-making itself. According to the authors, this final step should be left to humans. *Faraj et al.* (2018) state that highly consequential situations require humans to be the final decision-makers.

We follow the results and define AI as a tool to augment the – in the end responsible – human decision-maker by providing recommendations (*Kolbjørnsrud et al.* 2017). Those recommendations are predictions that are based on rules the AI-algorithm has inferred before – often the classification of those large amounts of data analyzed (*Faraj et al.* 2018). Thereby, the technology can structure organizational knowledge and make it usable for decision-making processes in organizations (*Arnold et al.* 2006).

Often attempts are made to compare AI's abilities with those of a human being. For example, AI, following *Faraj et al.* (2018), tries to imitate knowledge workers. *Kolbjørnsrud et al.* (2017) even describes AI as a technology that "feels", "perceives" and "understands". *Mahroof* (2019) describes AI as a technology that imitates human behavior. In our opinion, these are adjectives that are not initially attributed to a technology in the actual understanding. It can be critically questioned whether these attempts to equate (or at least compare) AI with humans should be pursued further against the background of ongoing ethical debates in the context of AI (see e.g., *Awad et al.* 2018; *Cath et al.* 2018), or whether they lead in the wrong direction. This is a debate that should not be deepened further at this point.

…offers algorithmic competencies (Speed/ Efficiency/ Accuracy)

Following *Bader/Kaiser* (2019) and *Bhatt/Zaveri* (2002), we understand AI's algorithmic competencies to be the ability to analyze and structure large amounts of data quickly, efficiently, and accurately, to derive patterns and generate recommendations for decisions. When a human decision-maker prepares his decision, he regularly finds himself in a trade-off between speed and accuracy (*Shreshta et al.* 2019). As a rule of thumb, accuracy decreases with increasing speed of decision-making and vice versa. This is not necessarily bad. There are enough decisions in which accurate decisions can be made in a very short time. However, most of the time these are decisions in which the decision-maker either needs only little information for a decision (and has it already available) or follows very precise rules (in the latter case it can be discussed whether this can be called a decision at all. In our opinion, a decision that runs completely according to predefined rules is no longer a decision in the true sense).

A possible fourth algorithmic competence is the generation of consistent and replicable decisions (*Shreshta et al.* 2019). We deliberately do not include this as a defining trait, because: If we assume the ability of self-learning and continuous improvement, it must be assumed that different decision recommendations are generated over time, even if the data from which the recommendation is generated is the same.

…is self-improving.

First, self-improving should not be confused with self-learning by inferring decision-rules, a defining trait we discussed earlier. But these two traits go hand in hand. Once arrived in a trained status, to learn on its own also implies the ability to further improve itself in the course of time (*Chuang/Yadav* 1998; *Jarrahi* 2018). By "improving" we refer to the improvement of the AI's recommendations, that become more precise and better in the end.

For this purpose, the algorithm continuously improves its ability to correctly recognize patterns (*Min* 2010). The question arises as to how the improvement proceeds in detail. Basically, there are two methods that can be considered: First, supervised learning. Here the AI algorithm makes a recommendation based on its previous training. The human decision-maker examines whether the recommendation was right or wrong and provides feedback to the AI system. The system then learns from this feedback and improves the accuracy of its recommendations. Additionally, the datasets for training are usually pre-labeled by humans. Second, unsupervised learning. The algorithm recognizes patterns and structures almost independently, without having to rely on pre-labeled data. Also, the subsequent improvement works basically without human intervention (see e.g., *Bao et al.* 2019).

3.1.3 Interplay of human and AI in decision-making processes of organizations

To be able to provide a suitable model of the interplay of human and AI, we examine in which steps of a typical decision-making process AI can be used. For this purpose, we rely on a model given by *Martin* (2016). He divides the typical decision-making process (of a human decision-maker) into five steps: Situational analysis, challenge framing and causal analysis, solution generation, solution choice, and solution implementation. We understand AI as a decision support tool. Thus, to be able to discuss an AI-augmented decision-making process, we modified the process as displayed in *Figure 4*. Particularly, AI does not generate solution ideas, but it generates predictions (step 3). Afterwards, AI can provide recommendations (step 4) for a final decision by a human decision-maker (step 5).

Of the analyzed papers in our review, 6 % have considered AI as a tool to support the analysis of the initial situation, thereby identifying that a change in the current situation is required; 9 % have stated that AI can be used to support the framing of the decision situation (the challenge) and the conduction of a causal analysis to find out which factors determine the current state to be changed; 35 % see AI as a tool to generate predictions; and 50 % see the strength of AI in providing recommendations for the decision-maker. The final decision is usually left to the human decision-maker. The identification of the need for change (Step 1) usually occurs before any decision support tool is consulted. This situation analysis and the following challenge framing – the definition and framing of the decision to be made – is typically done by a human. Against the background of the massive expansion of computing capacities, as described in the Introduction, the question of whether, in the future, “activated” AI-based tools could be permanently used to indicate the need for change (and, thus, promote the initiation of necessary decisions) can be asked.

Summarized, the most important area of use of AI can be found in steps 3 and 4 – the generation of predictions and the providing of recommendations for a final decision by a human (step 5).

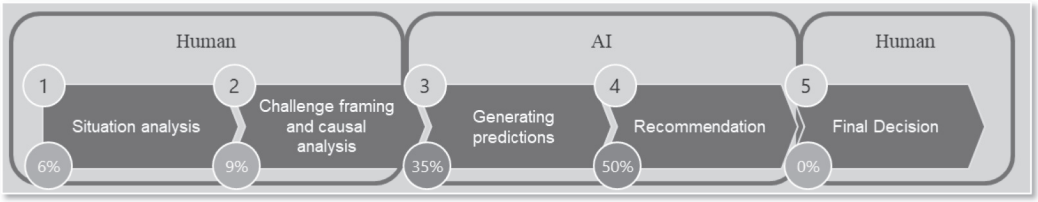

Figure 4: Steps involved in the decision-making process (modified according to *Martin*, 2016).

The process shown describes decisions that are typically made by humans. AI supports but does not make any decisions of its own. Thus, what exactly does this support look like? AI can provide probabilities and predictions on the basis of which a (human) decision-maker makes the final decisions. Let us take a credit process as an example, in which a human decision-maker decides whether a customer receives a loan or not. Based on existing data and comprehensive training, an AI tool can now generate scenarios, each of which results in a corresponding repayment probability (or vice versa: a default probability) of the loan (step 3, whereby no "creative" solutions are necessary in the chosen example, only a decision between yes and no). Based on the consolidated repayment probability, a recommendation can be taken from the AI tool (step 4), based on which the human employee then makes the final decision.

3.2 Factors that influence the intention to use AI

3.2.1 Overview of results

Our main research question asks about the factors that influence the intention to use AI in decision-making processes within organizations. To provide a suitable answer, we extracted the factors that, following the results of our identified papers, influence the use of AI, in particular, the intention or ability to use it. One of the most used theories to explain the influencing factors on the intention to use a technology (or the actual system use) is the Technology Acceptance Model (TAM) by *Davis* (1989). We use this well-known model and two of its relatives to explain some of the factors we identified to influence the intention to use AI.

To extract the relevant factors, we used principles of the content-centric approach of a literature review (e.g., *Webster/Watson* 2002). In detail, we first identified the influencing characteristics in all relevant studies and clustered them into eight categories. We assigned these categories to three dimensions, visualized in *Figure 5*. Through this aggregation we try to increase transparency and, hereby, to add value for a better understanding of the relevant factors to influence the intention to use AI.

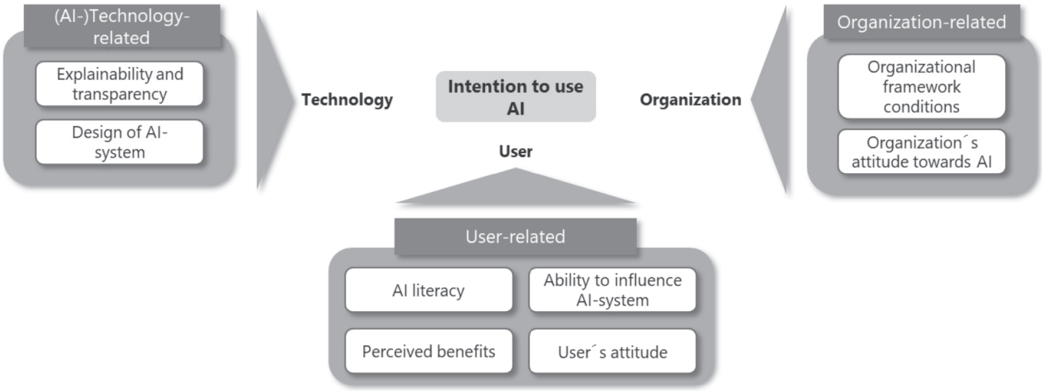

Figure 5: Framework of the three dimensions that influence the intention to use AI.

The first dimension is labeled "Technology" and includes characteristics of the individual AI-solutions itself. The second dimension "User" comprises factors that are user-related. This means, the factors concern individuals, for example, the employees of an organization which make use of AI-tools. The third dimension contains identified organizational factors that influence the use of AI. By "Organization," we refer to an institution, for example, a company. *Table* 4 lists the identified factors and their respective references.

	Factors to influence the intention to use AI							
	AI-Technology-related		Organization-related		User-related			
	Explainability and Transparency	Design of AI-System	Organizational framework	Organization's attitude	AI Literacy	Possibility of influence	Perceived benefits	User's attitude
Arnold et al. 2006	x							
Bader/Kaiser 2019		x						
Burton et al. 2020			x		x		x	
Clark et al. 2007				x	x	x	x	x
Davenport 2018			x	x	x			
Druckenmiller/Acar 2009		x	x					
Edwards et al. 2000			x					
Fountain et al. 2019	x				x	x		
Giboney et al. 2015	x							
Gregor/Benbasat 1999	x							
Jensen et al. 2010								x
Kim et al. 2008		x						
Kolbjørnsrud et al. 2017			x	x	x	x		
Kuechler/Vaishnavi 2006	x							
Limayem/DeSanctis 2000	x							
Lismont et al. 2017				x				

	Factors to influence the intention to use AI							
	AI-Technology-related		*Organization-related*		*User-related*			
	Explainability and Transparency	*Design of AI-System*	*Organizational framework*	*Organization's attitude*	*AI Literacy*	*Possibility of influence*	*Perceived benefits*	*User's attitude*
Miller 2019	x							
Nunes/Jannach 2017	x							
Pieters 2011	x							
SHAO 1998				x				
Shreshta 2019			x					
Sutton et al. 2016					x	x		
Workman 2005						x		x
	9	3	6	5	6	5	2	3

Table 4: Influencing Factors on the intention to use AI

3.2.2 Discussion

Explainability and Transparency

The factor “explainability and transparency” relates to the system itself and its technical design and, therefore, belongs to the dimension “Technology”. According to the literature analyzed, it can be assumed that the more comprehensible (and, thus, transparent) the analyses and recommendations (see steps 3 and 4, *Figure 4*) of the AI tool are, the more likely employees are to accept the tool as a support option. Explainability and a high degree of transparency, for example, an explanation of the recommendation process of the AI tool, are helpful in achieving this comprehensibility. From a quantitative perspective, explainability[3] seems to be the most important factor influencing the use of AI. Several studies examined the different influences of explainability, meanwhile, these studies are not always related to AI but also to other technologies like DSS or ES (see *Table* 4 for an overview). Additionally, some of these studies examined explainability in particular (e.g., *Arnold et al.* 2006; *Giboney et al.* 2015).

Referring to AI, explanations can provide information on why certain actions are taken by the AI system and they help users understand what the system does (*Gregor/Benbasat* 1999; *Pieters* 2011). Thus, the main goal of explanations is to generate transparency and to promote trust in a technology (*Nunes/Jannach* 2017; *Pieters* 2011). Referring to cognitive fit theory and the person-environment fit paradigm, *Giboney et al.* (2015) show how the user’s acceptance of a system can be positively influenced by explanations, in particular, when explanations cognitively fit the user. *Nunes/Jannach* (2017) use a comprehensive systematic review to examine how explanations promote trust in a system, and thereby in AI. Referring to the quantitative and qualitative results, we assume that the explainability of a system or technology is one of the most relevant influencing factors on the intention and ability to use AI. As explainability promotes trust and AI still lacks trust (*Giboney et al.* 2015; *SHAO* 1998), a lot of confidence building work is required to reduce these retentions, for example, by improving the explainability of AI (thus, creating a better understanding of the technology). This allows the enthusiasm for AI that already exists in the C-levels (*Kolbjørnsrud et al.* 2017) to be transferred to lower management levels, and thus, to the entire organization (this also affects the organization's and thus the user's attitude towards AI, as we will discuss below).

AI inherits the risk of a “black-box-feeling" for its users (*Bader/ Kaiser* 2019; *Shreshta et al.* 2019) when interacting with AI. This means, algorithms often use other, more rational logics than humans on the way to a decision recommendation ("rational distancing" and "cognitive displacement" of the human is possible). Expressed in simple terms: The decision-maker does not know why the algorithm recommends the proposed solution to him or her. Explainability and transparency are characteristics to avoid this possible “black-box-feeling”.

Design of AI-System

The design of the AI technology in use is the second factor that is AI-technology-related. The design is especially the interface that connects human and AI system as a kind of mediator (*Bader/Kaiser* 2019; *Druckenmiller/Acar* 2009). The design of this interface can

3 We assume here and below that the terms “explanation” and “explainability” express the same thing.

promote the intention of the decision-maker to use AI. This can be assumed if it supports, for example, the traceability of recommendations (*Kolbjørnsrud et al.* 2017) – the connection to explainability. Such a design leads to an attachment of the human decision-maker to the decision process that is supported by AI (*Bader/Kaiser* 2019). If an appropriate design is missing, humans can become unattached to the process which, following *Bader/Kaiser* 2019, leads to deferred decisions, workarounds, and (data) manipulations – all of them negative effects in decision-making and technology usage.

A suitable theoretical model to explain the relationship between the design of the AI-system and the intention to use it is the above mentioned TAM, the most used model for this purpose (*Sohn/Kwon* 2020). Following the implications of the TAM, an improvement of the design of the system can lead to an improvement in the perceived ease of use. This in turn increases the intention to use the technology and – in the end – its actual use.

Transferring the results of *Kim et al.* (2008), another aspect in improving the intention to use an AI-system by a suitable design of the technology is to adapt the AI-system (which is a software or piece of code) to the type of decision-making situation it should be used for. This means, for example, that one AI-software could be more suitable to provide recommendations in a strategic decision-making situation, another one could be more suitable for operational ones.

Organizational framework

The organizational framework is the first component of the organization-related factors that influence the intention to use AI in the decision-making process. A suitable organizational framework is needed to improve the intention to use AI (we elaborate this below). With this "organizational framework" we are referring to two things: First, we are focusing on the organization's individual decision-making process. This can differ from organization to organization, but also within the organization between different departments or management levels (e.g., *Burton et al.* 2020). Second, with the organizational framework we also refer to the organization's capabilities in terms of using AI (e.g., *Davenport* 2018).

1. When designing an AI-human-integrated decision-making process, an organization should ensure that the algorithmic support works for the human decision-maker and not vice versa (*Burton et al.* 2020). This also means that the chosen algorithm should respect the requirements and boundaries of the already existing decision-making policies and processes of the organization. No decision process should have to be adjusted too much in order not to lose the acceptance of the employees (and thus AI users). However, a certain degree of adaptation of such organization-specific conditions can still make sense to ensure the fit between AI and organizational framework conditions referring to the design of the decision-making process and, thus, the acceptance of AI as a decision aid (*Davenport* 2018; *Druckenmiller/Acar* 2009). *Kolbjørnsrud et al.* (2017) recommend a strong interaction between AI and the decision-maker. The greater this interaction, the higher the acceptance of the technology and thus the intention to use it. We can assume that this interaction is similar to the (also positive related) possibility of influencing the technology, a characteristic that will be discussed later in the category "Users".
2. To be accepted as a decision aid, an AI-tool must fit into the context of the organization's current capabilities (*Davenport* 2018). These capabilities are, for example, the company culture, the analytics capabilities and the data and technology capabilities.

Take, for example, an organization that has not yet dealt with topics such as analytics, big data or robotics (i.e., rule-based process automation). We can assume that this organization lacks the skills to use AI profitably. In the same way, it probably lacks belief in and understanding of such a technology. These capabilities may differ within organizations. *Kolbjørnsrud et al.* (2017) show that there exist regional differences and that organizations should adapt their AI adoption strategies to local conditions to achieve the greatest possible acceptance and thus success. Another aspect to be considered is the existing IT system landscape of the organization. This must be "capable of absorbing" AI, that is, it must be possible to integrate artificial intelligence as a system into the existing landscape without causing too many breaks (*Edwards et al.* 2000).

Organization's attitude

The second factor within the dimension "organization" is the organization's attitude. Based on the literature reviewed, it can be assumed that an AI-positive corporate attitude also promotes a more positive attitude towards AI among employees; and thereby a greater intention to use. By this we understand the fundamental attitude of an organization or its employees towards AI. In many cases, this particularly refers to managers who, in their role, determine the attitude towards (new) technologies and who can influence the attitude of their employees, as studies have shown (e.g., *Clark et al.* 2007; *SHAO* 1998). It follows that first and foremost the management level of an organization must develop a positive attitude towards the use of AI to support decision-making. For this purpose, it is advisable to promote an AI-open corporate culture (*Davenport* 2018), for example to develop and propagate a positive, open-minded attitude towards the technology. In order not to arouse rejection among employees, management must consider the preferences, wishes, but also the concerns and fears of employees regarding AI (*Kolbjørnsrud et al.* 2017).

Now let us assume that the organization, through a positive AI culture, manages to create so-called subjective norms[4] within the workforce that promote the acceptance of AI. We can then refer to the Theory of Planned Behavior (TPB). Like the TAM, the TPB can also be used to explain factors influencing the intention to use a technology. The TPB was developed at about the same time as the TAM and can be used specially to measure social influences on the use of innovative technologies (*Sohn/Kwon* 2020).

AI Literacy

We identified four user-related factors that have the potential to positively influence the intention to use AI. The first is what we call "AI Literacy". The more developed this empowerment of employees is, the more likely it is that there will be a higher intention to use it among these employees. By this we refer to the ability of a user to handle AI appropriately. This includes different aspects: First, we refer to the technical ability to use the AI-software (*Clark et al.* 2007; *Sutton et al.* 2016). Second, AI literacy also includes an appropriate expectation management of what AI can and cannot do (*Burton et al.* 2020). Third, AI users must understand to some degree how the recommendations for

4 The term "subjective norms" refers to the importance of social influences on the acceptance of (here) a technology that influence individual behavior (*Ajzen/Fishbein* 1973).

their decisions are made to be able to evaluate them, thus, they need AI-knowledge (*Clark et al.* 2007; *Sutton et al.* 2016).

These individual capabilities do not necessarily have to be available to users from the very beginning. Rather, they can be acquired through training (*Davenport* 2018) and experience. In the end, this allows the user to become empowered to use AI profitably in their own environment and decision-making process. Thus, the AI literacy created promotes the acceptance of a collaboration with AI.

Ability to influence AI-system

The second user-related aspect is the possibility of user's influence on the AI system or algorithm. Following the relevant studies in *Table* 4: The wider the possibility of influence, the potentially greater is the intention to use. Two dimensions of influence are relevant here: First, the influence before actually using the AI solution (*Clark et al.* 2007). It makes sense to involve the users already in the selection process for a specific AI solution or algorithm. This ensures that the needs of the users are sufficiently considered, which in turn ensures later acceptance. Second, just as important for this is the possibility of influencing the system during the later usage (*Fountain et al.* 2019; *Workman* 2005). That is, when the appropriate solution has already been selected and is in operation. Such an influence can take place in form of the determination of parameters, the surface, etc. by the user. To promote user involvement with the system, *Sutton et al.* (2016) recommend promoting an experimental approach to the AI solution by users (in the form of learning and exploring). The possibility of influencing the system provides a "perceived control" for the user. Again, following the TPB, a subsequent intention to use and thus actual usage can be concluded (*Sohn/Kwon* 2020).

Perceived benefits

The third aspect of user-related factors that influences the intention to use AI is the perceived benefits, that is, the benefits the user obtains when using AI in their decision-making process. Such benefits can significantly promote user commitment to AI (*Clark et al.* 2007). A further proven IS adoption model can be used to explain this in detail: The Value-based Adoption Model (VAM), which goes back to (*Kim et al.* 2007). It offers an alternative to the TAM by taking more account of the effects of exogenous factors to explain the intention to use newer information communication technologies (*Sohn/Kwon* 2020). According to the VAM, the "benefits" consist of the two variables usefulness and enjoyment by using a technology. These perceived benefits then positively influence the perceived value of the technology use and, hereby, its adoption. Thus, an organization that wants to increase the intention of its employees to use AI in their decision-making, must find ways to increase the perceived benefits of an AI-usage. Some possibilities have already been discussed (for example, suitable AI user interfaces). Another, not yet discussed, but as *Burton et al.* (2020) show, a promising option is incentivation. Following *Burton et al.* (2020), there are two types of incentivation prevalent: First, economic incentives (usually monetary ones). To positively influence the use of AI in decision-making, it may be appropriate to reward employees for the use of AI (e.g., in monetary terms). Second: social incentives, for example, social norms and maintaining reputation within the organization. This aspect forms a bridge to the influencing factor "organization's attitude" already discussed above, which can also influence the intention to use AI through social norms.

So far, when discussing the benefits of AI, we implicitly compare the two situations of "using AI" with "not using AI". What is missing is the comparison of an AI use with the use of another technology for decision support. In our view, it is quite imaginable that the perceived benefits of AI also increase when the use of AI delivers a greater benefit than the use of other decision support solutions. To our knowledge, such a comparison has not yet been conducted and offers potential for further research.

User's attitude

The last factor in the dimension "user" is the user's attitude. Based on our review, it is also positively related to the intention to use AI (e.g., *Workman* 2005). The user's attitude is significantly influenced by the organization's attitude (see above and *Clark et al.* 2007). But the latter is not the only affecting factor. *Jensen et al.* (2010) show, for example, that inexperienced employees have fewer reservations about a new technology like AI than experienced ones ("experts"), which suggests intrinsic motivation. The individual user's attitude can also be classified based on a theoretical model. The TPB can again be used for this purpose, according to which the user's attitude is a factor influencing the intention to use.

4 Summary of findings

4.1 Practical implications

The call for a stronger AI orientation and use by companies is growing (e.g., *Davenport* 2018). To achieve this, the intention of the users within these organizations to use AI is a decisive factor. By means of a systematic review, we have identified three categories with a total of eight factors that can influence this intention: AI-technology-, organization- and user-related influencing factors.

Technology-related implications:

Based on our research, the factor explainability and transparency appears to be the most important, at least quantitatively. Thus, to ensure an active AI-use of employees within their decision-making, organization's management should pay attention to the ease of use of the AI-software and, particularly, the design of its user interface. The latter forms the mediator between human and machine and appears to be a decisive factor for the acceptance of AI. Additionally: The chosen AI-system or -software must match its projected use case.

As discussed above, AI inherits the risk of a "black-box-feeling" for its users (*Bader/Kaiser* 2019; *Shreshta et al.* 2019). Transparency and explainability have a positive effect on the intention to use AI, according to the results of the analysis. Thus, the black box risk can be countered positively by improving explainability and transparency.

Organization-related implications:

An organizational framework that promotes human-AI-interaction should take the needs of the organization's employees into account. Therefore, sufficient thought on the interaction between human and AI is needed and, if necessary, the framework conditions must be adjusted accordingly. Following *Davenport* (2018), these (adjusted) framework conditions could be summarized in an individual AI-strategy. This strategy should include AI-goals, an integration plan with an appropriate timeline and implementation partners. Additionally, in our opinion, such a strategy has the potential to promote the organization's attitude towards AI and, thus, the user's attitude – as shown before.

To promote the latter, managers must become role models and use AI in their own decision-making processes, support their employees in trying it out and using it later, and represent an open-minded attitude.

User-related implications:

Combined with appropriate training (how to interact with AI, how to interpret results, core concepts of statistics, etc.; see *Burton et al.* 2020), this results in an empowerment; employees can and want to use AI (that they are allowed to do so is assumed here as a necessary condition): A level that we call AI-literacy.[5]

To ensure acceptance, it is advisable to involve the prospective users in the AI software selection process. Furthermore, the users should have sufficient possibilities to influence the algorithm during use, i.e., to determine parameter settings, etc.

Benefits be they monetary, social, or completely different, can form a further building block in the creation of an organization-wide positive intention to use AI.

4.2 Limitations and suggestions for further research

There are several limitations to our research. We have deliberately not restricted ourselves to certain methods to do justice to the young and non-extensive state of research on the interplay between AI and decision-making processes (or behavior) in organizations. Instead, we have limited the initial stock of papers and keyword searches to a certain selection of ranked journals. Therefore, individual papers in journals that were not relevant for this study were not included in our analysis. The initial stock of papers also significantly influenced the subsequent search results as we initially conducted our searches within this stock. Through forward and backward snowballing (for which we have deliberately removed the journal restriction), we tried to mitigate the restrictions and identify all relevant papers.

Another limitation was that the literature only went as far back as the year 1997, but in our opinion, older studies would not have taken account of the technological progress made in the meantime. Further research could help verify this assumption. Moreover, to keep our study at a manageable level, we did not analyze the citation network behind the papers in our sample. The different terms used for AI presented the risk of missing out on some relevant papers. However, due to our use of various search terms and combinations, we assume to have considered all the relevant papers. We assigned various technologies and designations to the generic term of AI even though the authors had not done so at the time of publishing their respective papers. Using our definition of AI, we tried to make an appropriate assignment. However, we do not eliminate the possibility that this may have caused some degree of ambiguity.

The suitability of the different IS adoption models for the intention to use the AI technology appears to be a promising stream for further research, which we could only scratch at the edges in our analysis in order to remain focused. When it comes to the adaptation of information systems, a relevant stream of research has developed over the

5 *Burton et al. (*2020) use the similar term „algorithmic literacy".

years. Well-known models to explain the readiness for use, the IS-adoption, are the TAM, the TPB or the VAM. Our results show that some of the influencing factors can be found as variables in these models; for example, the perceived ease of use. This suggests that the IS-adoption models are basically suitable to explain AI-adoption (or at least the intention to use AI). *Sohn/Kwon* (2020) investigate the suitability of different IS adoption models in relation to the intention to use AI-based products (smart speaker, home appliances, etc.), but from a consumer perspective. Their study prefers the VAM for that context. Which model is best suited to explain the intention to use in the context of decision-making processes within organizations needs to be further investigated. Based on our results, we can conclude that the most important variables of the TAM (perceived ease of use and usefulness) and TPB (attitude, subjective norms, perceived behavioral control) are also our identified variables or influencing factors that positively favor the intention to use AI. At this point, we can make the hypothesis (yet to be proven) that the TAM and the TPB are basically suitable to explain the intention to use AI. Thus, we call for further research to confirm the suitability of these theoretical models for AI-adoption.

One aspect that has not yet been investigated in previous research is the costs associated with a use of AI. How high are these? How do they differ between different AI systems? Are other decision support solutions better suited from a cost-benefit perspective? These questions are open and should be urgently investigated and answered from a scientific perspective.

Additionally, so far, only a few of the identified influencing factors on the intention to use AI for decision-making processes within organizations have been extensively examined through a sufficient number of different studies. Therefore, we call for further research to both confirm the presumed effects and search for additional ones.

We limited our surveyed literature to 1997. In the environment of rapidly evolving technologies like AI, this is a long time period. Thus, it might be worth comparing the earlier possibilities that AI offered to decision-making in organizations with today's and working out the differences.

As a result of our review, *Figure 4* shows how the interaction between humans and AI can work along a decision-making process. If we take this result as an "improved" decision-making process, the next step could be to examine the extent to which an adapted (AI-enhanced) decision-making process in turn favors the adaptation of AI. An examination of this could provide an integrated framework as a result and, thereby, make an original and important theoretical contribution.

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