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Understanding the interplay of artificial intelligence and strategic management: four decades of research in review

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Abstract

As artificial intelligence (AI) is enabling the automation of many facets of management and is increasingly used in a wide range of strategic tasks, it is necessary to better understand its relevance for strategic management. However, research on the interplay of AI and strategic management is unbalanced and lacks a coherent structure due to its multidisciplinarity. This article contributes to the emerging academic discussion by systematically reviewing and categorizing the substantial amount of research that has been conducted since the first article in the field was published in 1979. Furthermore, it introduces a comprehensive framework that integrates and synthesizes existing concepts. The framework displays the structure of the research field by classifying 58 relevant articles into two research scopes: condition-oriented research, which explores antecedents for leveraging the use of AI in strategic management, and outcome-oriented research, which studies the consequences of AI in strategic management at both the individual and the organizational level. Given the exponential potential of AI to reshape the field in its current form and the need for a realistic assessment of its impact, this review proposes promising research avenues for studying the quantifiable effects of the interplay of AI and strategic management based on the developed framework.

Keywords Artificial intelligence · Strategic management · Literature review · Algorithmic management

JEL Classification L2 · M15

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1 Introduction

AI, which can be defined as “a system’s capability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaption” (Kaplan and Haenlein 2019), has been in the focus of academia since the 1950s. In the years since, AI has experienced fragmented and unbalanced development in various research fields. Due to recent technological advances, which are facilitated by the availability of big data (BD) (George et al. 2014), the self-learning capacities of algorithms (Faraj et al. 2018) and the increasing power of computers (Ferràs-Hernández 2018), AI-based systems are becoming more effective (Brynjolfsson and McAfee 2016), less expensive (Agrawal et al. 2017) and increasingly used to solve business problems (Davenport and Ronanki 2018; Gunasekaran et al. 2017; Lee 2018; Phan et al. 2017). The application of AI is supposed to derive solutions to problems that would typically require the intervention of human intelligence (Kurzweil 1999; Mitchell 2019) or leadership (Wesche and Sonderegger 2019), and has accordingly induced a discussion about the future validity of traditional organizational assumptions (Jordan 2017) and the augmentation (Huang et al. 2019; Wilson and Daugherty 2018) or substitution of human managers by intelligent machines (Acemoglu and Restrepo 2018; Autor 2015; Brynjolfsson and Mitchell 2017).

From a strategic management perspective, the decisional situations that need human judgment and analysis regularly relate to issues where problems are far from being well-structured (Bettis 2017; Martínez-López and Casillas 2013; Reeves and Ueda 2016). This review adopts the definition of Nag et al. (2007) and understands strategic management as a field that “deals with the major intended and emergent initiatives taken by general managers on behalf of owners, involving utilization of resources, to enhance the performance of firms in their external environments.”

Research in the field has identified the knowledge base as the most significant factor for the success of strategic decision-making (Hickson et al. 2003) and has shown that algorithms outperform managers in various decision-making situations (Dawes 1979; Kahneman et al. 2016; Yeomans et al. 2019). According to Raghunathan (1999), decision-quality increases when decision-makers have more detailed knowledge of the connections between problem variables, thus shedding light on AI as a new knowledge source to reduce complexity by anticipatively addressing changes in the organizational environment (Barro and Davenport 2019; Jarrahi 2018) and calling for new models for managerial decision-making (Colson 2019; Lee 2018) and organizational culture (Fountaine et al. 2019; Ransbotham et al. 2018).

The use of intelligent systems is starting to increase in unstructured environments (Di Ciccio et al. 2015) for non-routine decisions (D’Acunto et al. 2019; Huang and Rust 2018; Schildt 2017; Tokic 2018) that are consequential for strategic outcomes (Ayoub and Payne 2016; Berman and Dalzell-Payne 2018; Kiron and Schrage 2019; Reeves and Ueda 2016; von Krogh 2018) and essential for the development of competitive advantages (Davenport 2016; Grover et al. 2018;

Lado and Zhang 1998). Intelligent decision systems that are supported by the entire organization outperform humans in accomplishing quantitative targets (Kolbjørnsrud et al. 2017) against measurable criteria (Parry et al. 2016) and help to reduce the degree of uncertainty in strategic decision-making in two ways in the period under review. While early studies indicate that AI could be used as a decision support system accumulating expert knowledge (Ashmore 1989) and guiding organizational action (e.g., Luconi et al. 1986; Merten 1991) with limitations at the strategic level (Edwards and Yanqing 2000), current research streams clarify that the real value of AI is to perform data analysis autonomously across various sorts of data, to access tacit knowledge and to create new knowledge by itself (Bani-Hani et al. 2018; Grover et al. 2018; Kaplan and Haenlein 2019; Uden and He 2017).

However, research related to the interplay of AI and strategic management lacks a coherent structure and consistent use of terminology (Duan et al. 2019) due to its multidisciplinarity. Despite the alleged maturity of the research field and the growing stream of literature on the business potential of AI, very little is known about what encompasses the concept within strategic management. In line with other researchers that consider systematic literature reviews particularly appropriate for emerging topics (Fosso Wamba et al. 2015; Snyder 2019), and the growing interest of both academia and practice (Davenport and Ronanki 2018), I argue that an integrative review is needed, to synthesize knowledge from earlier debates with the current scholarly discussion, in order to actuate recent excitement and to structure future research activities around the evolutionary phenomenon of AI in strategic management. Hence, this research is led by the following research question: What role does AI play in strategic management and how can existing concepts in the management literature be synthesized?

Therefore, the contribution of this systematic review is twofold. First, I provide a comprehensive presentation of the current state of scientific knowledge on the relevance of AI in the field of strategic management, by following the guidelines developed by Tranfield et al. (2003). Second, this review classifies the articles into a thematic “knowledge map” (Frank and Hatak 2014) to better understand the structure of existing literature. In particular, I distinguish between articles that focus on the antecedents of an organizational adoption of AI-based systems and those that investigate the consequences of AI on the individual as well as the organizational level of a firm. This thematic framework then subsequently serves as a basis for identifying promising research avenues in the emerging field of the interplay of AI and strategic management.

2 Research in artificial intelligence: a descriptive analysis

Since McCarthy coined the term “artificial intelligence” for the first time in 1955 at the Dartmouth conference, AI has been an ongoing important research topic in the intersection of computer science and psychology. However, initial successes such as the natural language-processing computer program ELIZA (Weizenbaum 1966) soon led to misjudgments as well as overoptimism regarding the performance capability and possible applications of AI. This resulted in recurring periods without significant research results, also known as AI winters (Russell and Norvig 2009). However, with advances in machine learning (ML), and by beating human players in multiple games (Jaderberg et al. 2019; Silver et al. 2016), AI is no longer seen as an "academic toy" (Holloway 1983) and has been described as having reached the tipping point for practical usefulness in other domains such as image recognition (Russakovsky et al. 2015).

In the context of strategic management, two main literature streams capture the concept of AI and provide different scopes. While early publications (1979–2005) understood AI as the underlying technology of rule-based expert systems to support and improve strategic decision-making in a top-down approach (e.g., Carlsson and Walden 1997), more recent articles about AI in strategic management (2015–2019) find their technological foundation in ML algorithms that recognize patterns in datasets with the help of statistical inferences and possess the potential capability to act autonomously in the area of cognitive tasks and process automation (Davenport and Ronanki 2018).

In line with the general trend within AI research, scientific publications on the subject of AI in strategic management are not consistent and unbalanced in the reviewed period. Despite the fact that a third of all considered studies have analyzed the role of AI before the era of big data, some actual controversies in the field, such as the substitution of humans by intelligent machines, falsely give the appearance of never having been discussed before and seem to be unaware of what happened before (Duan et al. 2019).

Given the time horizons between the publications, it is remarkable that the shortest and latest period in the years 2016–2019 has led not only to the most useful publications, but also to the highest quality of publications for this review. The recent advent of machine learning technology in strategic management has begun to move the discussion from information systems (IS) to the management literature and ensured that first sets of empirical work have emerged that show ambiguous effects on management practices with respect to algorithmic biases (D'Acunto et al. 2019; Lambrecht and Tucker 2019), algorithm aversion (Dietvorst et al. 2018; Prahl and Van Swol 2017) and algorithm appreciation (Logg et al. 2019). To illustrate the relevance of the subject in strategic management, the following figure (Fig. 1) illustrates the relevant articles for this review, sorted by publication date, place of publication and their quality according to the VHB-Jourqual 3.[1]

[1] The Jourqual 3 is a magazine ranking on the basis of the judgments of VHB members. It is published by the German Academic Association for Business Research (VHB) and can be accessed online at http://www.vhbonline.org (retrieved on November 15th, 2018).

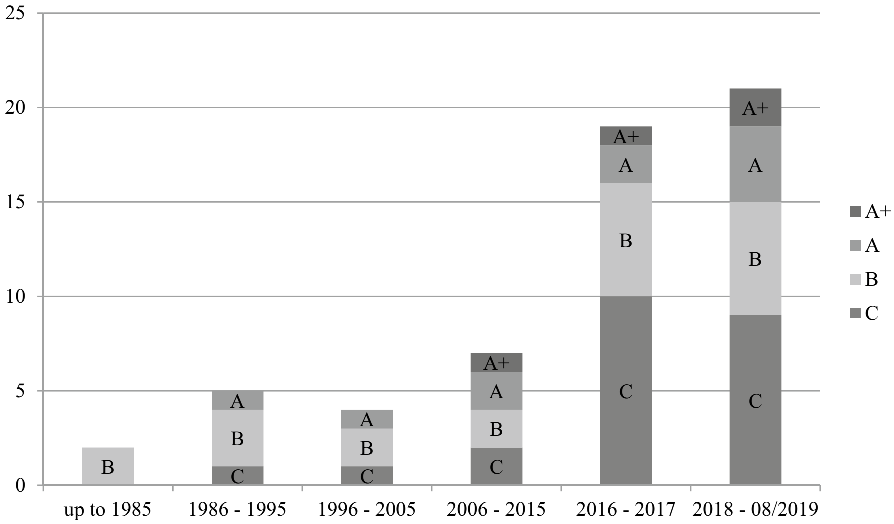

Fig. 1 Publication date and VHB ranking of literature in the research field

As the literature in the research field is fragmented at the intersection of information systems, management, and organizational studies, the number of distinct journals included in this review adds up to 35. Most articles (16) in the final sample were published in journals classified as B, followed by 8 A- journal publications. Likewise, C-categorized journal articles amount to 8, while the number of A + (3) publications remains relatively small. If the sub-categories are considered as the unit of analysis, it is noticeable that there is a disparity in the distribution of concepts and that all categories consist of mainly conceptual work. Table 1 provides a classification of the studies linked to their respective subcategories. As this systematic review followed a concept-centric approach, some studies appear in multiple categories.

Table 1 Categorization and number of articles per subcategory

	Theme	*Conceptual*	*Empirical*
Antecedents	Data-driven workflows	Constantiou and Kallinikos (2015), Davenport and Kirby (2015), Davenport and Mahidhar (2018), Grover et al. (2018), Kahneman et al. (2016), Lau et al. (2012), Mazzei and Noble (2017), Orsini (1986), Wright and Schultz (2018), Watson (2017)	Lambrecht and Tucker (2018), Davenport and Harris (2005), Janssen et al. (2017), Kowalczyk and Buxmann (2014), Merendino et al. (2018), Olszak (2016), Vidgen et al. (2017)
	Managerial willingness	Berman and Dalzell-Payne (2018), Constantiou and Kallinikos (2015), Davenport and Mahidhar (2018), Lichtenthaler (2018), Davenport and Kirby (2015), Davenport and Kirby (2016), Diakopoulos (2016), Epstein (2015), Geisler (1986), Lichtenthaler (2019), Parry et al. (2016), Phillips-Wren et al. (2009), Watson (2017), Wilson and Daugherty (2018), Wright and Schultz (2018)	Ghasemaghaei et al. (2018), Kolbjørnsrud et al. (2017), Prahl and van Swol (2017), Dietvorst et al. (2018), Logg et al. (2019), Schneider and Leyer (2019)
	Organizational determinants	Berman and Dalzell-Payne (2018), Bonczek et al. (1979), Davenport and Mahidhar (2018), Geisler (1986), Lau et al. (2012), Lawrence (1991), Merten (1991), Pinson and Moraltis (1997), Watson (2017)	Davenport and Harris (2005), Kolbjørnsrud et al. (2017)

Table 1 (continued)

	Theme	*Conceptual*	*Empirical*
Consequences	Managerial cognition	Agrawal et al. (2017), Berman and Dalzell-Payne (2018), Bettis (2017), Bonczek et al. (1979), Chi and Turban (1995), Davenport and Kirby (2016), Diakopoulos (2016), Garfinkel et al. (2017), Hoffman (2016), Intezari and Gressel (2017), Jarrahi (2018), Kahneman et al. (2016), Lawrence (1991), Orwig et al. (1997), Parry et al. (2016), Pomerol (1997), Wilson and Daugherty (2018), Wright and Schultz (2018)	Brynjolfsson and Mitchell (2017), Ghasemaghaei et al. (2018), Kowalczyk and Buxmann (2014), Lambrecht and Tucker (2018), Merendino et al. (2018)
	Value of complementary skills	Agrawal et al. (2017), Davenport (2016), Davenport and Kirby (2015), Davenport and Kirby (2016), Ferràs-Hernández (2018), Garfinkel et al. (2017), Geisler (1986), Jarrahi (2018), Lichtenthaler (2018), Plastino and Purdy (2018), Watson (2017), Wilson and Daugherty (2018)	Kolbjørnsrud et al. (2017), Wilson et al. (2017)
	Human-machine collaboration	Agrawal et al. (2017), Bettis (2017), Bonczek et al. (1979), Davenport and Kirby (2015), Ferràs-Hernández (2018), Geisler (1986), Holloway (1983), Huang and Rust (2018), Jarrahi (2018), Lichtenthaler (2018), Lichtenthaler (2019), Parry et al. (2016), Wilson and Daugherty (2018)	Bader and Kaiser (2019), Brynjolfsson and Mitchell (2017)
	Design of decision-making governance	Davenport (2013), Garfinkel et al. (2017), Hirsch (2018), Hoffman (2016), Holloway (1983), Parry et al. (2016), Shrestha et al. (2019), Watson (2017), Wright and Schultz (2018)	Davenport and Harris (2005), Kolbjørnsrud et al. (2017), Schneider and Leyer (2019)
	Agility and participation in strategy development	Berman and Dalzell-Payne (2018), Constantiou and Kallinikos (2015), Davenport (2016), Grover et al. (2018), Holloway (1983), Intezari and Gressel (2017), Mazzei and Noble (2017), Metcalf et al. (2019), Orsini (1986), Orwig et al. (1997), Pinson and Moraltis (1997)	Davenport and Harris (2005), Vidgen et al. (2017)
	Predictive logic in business models	Agrawal et al. (2017), Berman and Dalzell-Payne (2018), Constantiou and Kallinikos (2015), Dnport (2016), Davenport and Mahidhar (2018), Watson (2017)	

3 Research methodology

Drawing on the methodological framework of Tranfield et al. (2003) and the editorial of Fisch and Block (2018), this systematic literature review (SLR) is based on a multilevel process to systematically identify and synthesize the fragmented knowledge on the role of AI in strategic management. As suggested by Tranfield et al. (2003), this SLR can be subdivided into three phases, namely (1) planning, (2) conducting, and (3) reporting, to enable transparency and replicability.

After several pilot searches and exploratory readings, the most relevant keywords were identified in an iterative review approach and used to determine a systematic search strategy within an advanced database search utilizing Business Source Complete (EBSCO) and Scopus. I decided to apply two levels of broad keywords and used the search terms “artificial intelligence”, “AI” or “machine learning” in combination with the Boolean operator “AND” and the terms “strategic management” or “strategic planning” for matches in the titles, subjects, keywords and abstracts of academic papers, which yielded 658 articles. In line with similar reviews in the field (e.g., Akyuz and Gursoy 2019; Dias and Ferreira 2019), I used the term “strategic management” to define the search context. However, to account also for the changing of semantics in strategic management (Furrer et al. 2008; Ronda-Pupo and Guerras-Martin 2012) in the period under review, the synonymous use of the terms (Bowman et al. 2002; David and

David 2017) and the relevance of the term in IS literature (Barki et al. 1993), I also included "strategic planning" as a second search term, to enlarge the search context and integrate relevant concepts from the IS discipline. In accordance with other systematic reviews dealing with AI in adjacent research fields (Reis et al. 2019; Sousa et al. 2019), I followed an approach suggested by Brocke et al. (2015) and deliberately excluded more specific search terms and used "artificial intelligence", "AI" and "machine learning" as aggregated umbrellas, to keep the review focused on the general influence of AI on strategic management and to ensure a coherent synthesis of the articles.

I then excluded papers that were neither published in peer-reviewed academic journals nor written in English, to prevent inferior quality in the papers incorporated in this review. To cover the full range of literature for the research field, and to present its unbalanced development, I chose a far-reaching time frame from 1979, when the relationship between computer-based artificial support and strategic decision-making was first mentioned (Bonczek et al. 1979), until the finalization of the search for literature in August 2019.

In line with Tranfield et al. (2003), the suitability of the remaining 343 articles for the review was then assessed as part of a two-step content-screening process. If the title and abstract did not disclose the subject of the paper, the complete paper was analyzed to determine eligibility for this SLR. Reviews as well as studies without a managerial focus, in which the search terms were stated in the abstract or keywords but the authors did not discuss them in the full text, were excluded.

In line with previous SLRs (e.g., Ahn et al. 2018; Breitenmoser and Bader 2016; Gutmann 2019), and following an approach suggested by Levy and Ellis (2006), I considered the survey-based VHB-Jourqual 3 ranking fit as an additional quality threshold for the article selection process. Only articles from peer-reviewed journals possessing the minimum VHB-Jourqual 3 rating of "scientifically recognized" (C) were included in this SLR. Instead of assessing a journal's quality in relation to the quantity of citations, I deemed the internationally recognized (e.g., Li et al. 2019), expert-based VHB Jourqual-3 ranking particularly appropriate as a quality threshold (Eisend 2011) to relate the journals to their respective business research subdisciplines and also to mirror and integrate subdivisions of academic discussions (Schrader and Hennig-Thurau 2009).

In the final step, the number of relevant papers was further narrowed, based on an in-depth examination of the remaining 91 articles. By doing so, the further exclusion of 33 articles was driven by content, which (1) did not focus on strategic business activities (e.g., Levina et al. 2009), (2) only addressed the technological foundations of a particular AI (e.g., Lu et al. 2012) or (3) were only short editorials (e.g., Phan et al. 2017). Given the dynamics of the research field, I constantly tracked the relevant references of the articles that fulfilled our selection criteria in line with the guidelines for snowballing in systematic literature studies (Wohlin 2014) to add further concepts of relevance during the writing process. The systematic process, which is visualized in Fig. 2, resulted in a final literature base comprising a total of 58 articles (see Table 4), whose content was then consolidated and synthesized in a concept-centric approach as suggested by Webster and Watson (2002).

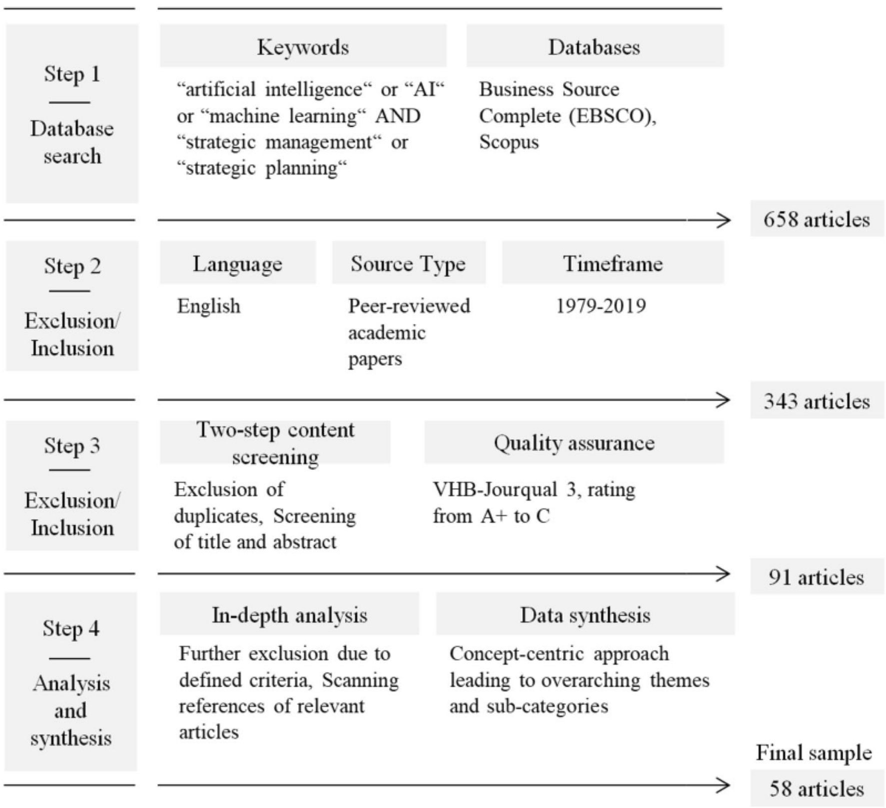

Fig. 2 Systematic approach to article selection

4 The role of artificial intelligence in strategic management literature: a thematic framework

This literature review identifies and maps knowledge by integrating and synthesizing concepts (Fisch and Block 2018) at the intersection of AI and strategic management. In line with Ginsberg and Venkatraman (1985), a concept-centric scheme has been designed for categorizing and systemically displaying the relevance of overarching themes and subcategories within the research field. An in-depth analysis of the body of the literature unveiled two categories of factors for understanding the interplay of AI and strategic management. Therefore, I developed a framework (Fig. 3) that not only displays the structure of the research field, but also classifies the relevant articles into two different research scopes: condition-oriented, i.e., research that explores antecedents for leveraging the use of AI in strategic management, and outcome-oriented, i.e., research that studies the consequences of AI in strategic management on both the individual and the organizational level.

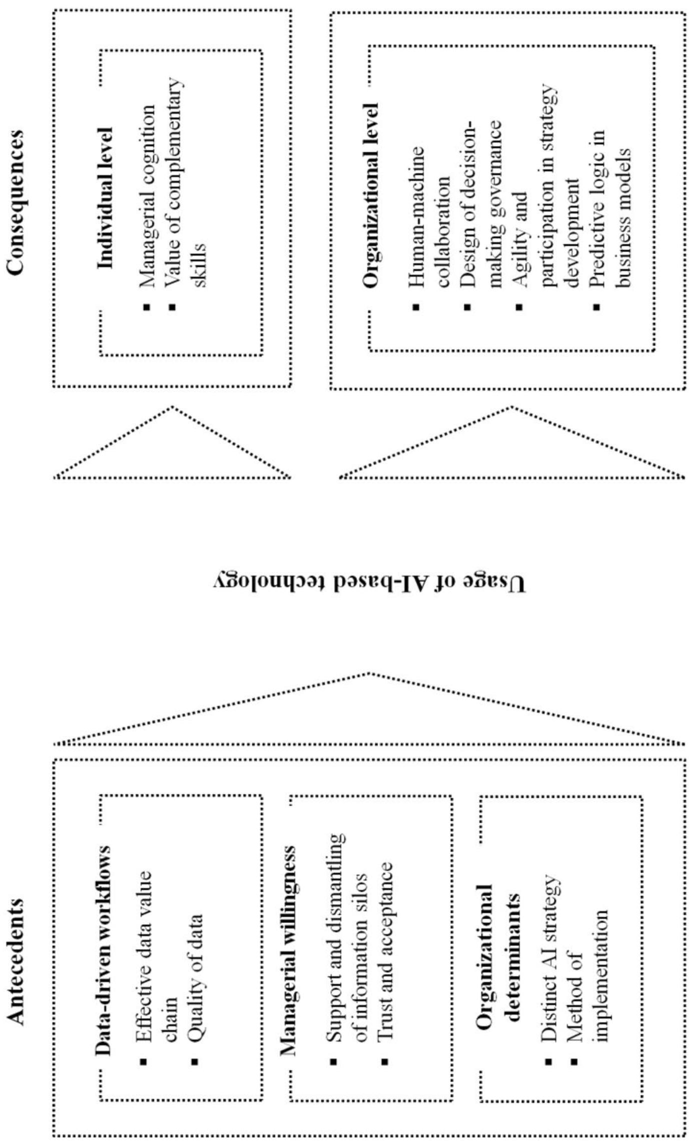

Fig. 3 Thematic framework of AI in strategic management based on the literature

4.1 Antecedents

4.1.1 Data-driven workflows

4.1.1.1 Effective data value chain Research in this category shows that sufficient data, experience and a routinized process to extract knowledge are preconditions for creating strategic value from AI. Accessing tacit knowledge with the help of cognitive technologies can be seen as an evolutionary process that builds on adaptive business intelligence (BI) as its precedent technology.

Recent literature shows that the importance of large amounts of datasets for strategic decision-making has found prevalence in many organizations (Merendino et al. 2018) and that the conversion of unstructured data into machine-readable data has developed into a crucial talent for organizational success (Olszak 2016). BD is thereby often associated with the use of predictive analytics, which consists of a variety of intelligent techniques to detect and predict relationships in data sets. However, leveraging BD to become a "strategic asset" (Grover et al. 2018) is not only a technical issue, but also requires organizations to align their analytics capability with their business strategy and match all related organizational (Vidgen et al. 2017) and human resources (Davenport and Harris 2005) within the scope of a mutual cognitive architecture. Data gathering, processing and utilization are not performed within a single department within the firm but usually require collaboration with partners from different disciplines (Janssen et al. 2017; Kowalczyk and Buxmann 2014).

Watson (2017) adds a temporal dimension to this discussion and posits that each generation of decision support inevitably builds on previous ones. This exemplifies the relevance of BD analytics in light of the growing importance of AI and shows that the current position of a company in BI influences not only its competitive position (Lau et al. 2012), but also its way forward. According to this proposition, the case study by Janssen et al. (2017) reveals that deriving benefits from BD is an evolutionary process in which the incremental understanding of the opportunities and the successive routinization of processes and constant updating (Constantiou and Kallinikos 2015) ultimately determine the success of the particular AI application.

4.1.1.2 Quality of data While generally the amount of data is an important factor for the performance of an AI system, the specific features of ill-structured problems in strategic management attach particular importance to the quality of data that underlies the algorithms and increasingly determines the success of actions within the scope of strategic management (Mazzei and Noble 2017).

Research shows that machine learning is empowered by data. More specifically, the precision of a derived analysis is positively correlated with the amount of data the AI system is fed (Davenport and Harris 2005; Davenport and Kirby 2015). In contrast, some scholars argue that more information, more variables and more data do not automatically lead to better results and strategic decisions (Orsini 1986; Wright and Schultz 2018). Applying data analytics techniques to generate new insights and knowledge for strategic management puts strong requirements on the data as well as the organizational workforce. Davenport and Mahidhar (2018)'s article extends this debate by stressing the value of information as a corporate asset, and discusses the risks of turning over content ownership to third parties even if “would-be users” are able to add significant value to what they receive.

As algorithms generally work with historical data, algorithmic decision-making can either amplify existing biases (Lambrecht and Tucker 2019) or mitigate human idiosyncrasies (Kahneman et al. 2016). Data governance practices should thus assist organizations in collecting and managing the availability, variety and quality of data with the help of refining loops, to enable real-time interpretation and applications for strategic management (Davenport and Kirby 2015).

4.1.2 Managerial willingness

4.1.2.1 Support and dismantling of information silos Leveraging the use of AI systems in strategic management places requirements on both the appropriate organizational infrastructure and the working methods of management teams. Research indicates that the organizational culture and the process of how AI is applied are decisive for organizational success. Instead of working in vertical customer-oriented business unit silos, the literature strengthens the role of AI as a horizontal facilitator by leveraging processes or improving or creating products.

Most of the studies in this research stream have identified organizational learning processes as being crucial for strategic renewal endeavors whilst emphasizing that suitable design of organizational structures facilitates the adaptation of technological advancement (e.g., Constantiou and Kallinikos 2015).

However, many companies lack adaption speed to avoid digital disruption in the future (Berman and Dalzell-Payne 2018; Lichtenthaler 2018) or oversteer the technological utilization of AI (Davenport and Mahidhar 2018). A study by Kolbjørnsrud et al. (2017) reveals that workforce support for the introduction of AI systems positively correlates with the rank and the level of management and is subjected to national and cultural differences. The authors show further that the willingness to trust AI systems is attached to a manager’s understanding, a proven track record (Prahl and Van Swol 2017) and the technology’s ability to provide reasoning for its advice. In line with this notion, Wilson and Daugherty (2018) suggest that the adoption of principles within the fields of employee commitment and experimentation can increase the speed, cost savings and revenues of AI initiatives. Other identified factors that foster the distribution and the success of AI in strategic management include the role of sharing knowledge, the vision of management (Davenport and Kirby 2016), the skills of current employees (Davenport and Mahidhar 2018; Watson 2017) and the organizational data analytics competency (Ghasemaghaei et al. 2018).

4.1.2.2 Trust and acceptance The themes of trust and algorithm acceptance have been the subject of several studies in the field, particularly in terms of how hierarchical layers are assigned with different levels of acceptability. While ethical considerations, public perception and the inexplicability of algorithmic decision-making are generally described as decelerating the deployment of AI in strategic management and burdening community relationships, executive support and leadership styles are seen as counterbalances.

The literature argues that the negative perception of AI (Epstein 2015; Lichtenthaler 2019), the lack of transparency (Davenport and Kirby 2016; Diakopoulos 2016) and the ethical issues of automation in business (Wright and Schultz 2018) diminish managerial trust in AI. For employees, trust issues can possibly be further increased, as autonomous AI systems could be used to justify immoral decision outcomes without a human-held veto, by maximizing certain parameters at all costs while ignoring firm-specific ethical standards (Parry et al. 2016). Enriching this discussion, Schneider and Leyer (2019), for example, examine factors influencing a manager's willingness to delegate strategic tasks to an AI, while Logg et al. (2019) challenge the prevalent assumption that humans prefer human to algorithmic judgment (Dietvorst et al. 2018; Prahl and Van Swol 2017). Their experiments show that laypeople trust algorithmic advice more than human advice in specific decision circumstances. Other studies show geographical and cultural differences regarding the willingness for and resistance to AI adoption, which necessitates adjusted approaches for a timely organizational distribution (Davenport and Kirby 2015) and clarifies the need for early ownership throughout the learning process, to promote familiarization with the intelligent systems (Kolbjørnsrud et al. 2017).

In addition, the literature stream also discusses measures to mitigate these challenges. Phillips-Wren et al. (2009), for example, note that the acceptance level could be elevated by personalizing the design. In a similar vein, Parry et al. (2016) propose a similar effect when increasing the degree of autonomy of such systems. Other identified factors are the level of support of executives (Geisler 1986) and the process transparency seen in how the intelligent agents reason and make decisions (Kolbjørnsrud et al. 2017).

4.1.3 Organizational determinants

4.1.3.1 Distinct AI strategy Implementing AI-based systems touches many elements of strategic management, as understood by Nag et al. (2007), and addresses a variety of issues, including content creation, technology components, people and change management (Davenport and Mahidhar 2018). Given the broad area of possible applications, managers must start tackling a manageable specific business problem with AI, before they generally deploy the technology within strategic management.

Research shows that the customized adoption of AI by organizations is on the rise, albeit adoption involves high upfront costs and rather long-term and unquantifiable benefits (Berman and Dalzell-Payne 2018). Davenport and Mahidhar (2018) see a clear AI strategy as the first step towards a distinct competitive advantage. Using cognitive technologies does not necessarily mean building a completely new strategy, but "[…] devis[ing] well-informed actions that align with existing business goals" (Davenport and Mahidhar 2018), which are driven by the specifics of the corporate strategy. Supporting the line of argumentation of other authors that emphasize integration with the help of trial-and-error approaches (e.g., Kolbjørnsrud et al. 2017), Davenport and Mahidhar (2018) consider a series of pilots with proofs of concept necessary for deploying the technology. To mitigate the workforce consequences of using AI in management, a study by Davenport and Harris (2005) underlines the importance of regular organizational communication and further training opportunities for employees at risk of losing their jobs.

As the use of AI technologies in management requires capabilities that can be either internalized externally or developed internally, Watson (2017) distinguishes the adoption of an organizational AI architecture in ten phases and notes that smaller and medium-sized organizations in particular will access AI as an analytics-as-service tool through cloud solutions.

4.1.3.2 Method of implementation While intelligent decision support systems (IDSS) in the form of expert systems have been the subject of academic discussions for almost 40 years, the scope of such systems has been confined to supporting managerial decision-making statically. However, more recent use cases in the literature refer to AI as a technological umbrella for a huge set of techniques and methods related to machine learning or fuzzy logic.

Despite the partial usefulness of early AI applications within IDSS for planning (Geisler 1986), knowledge management (Merten 1991) and organizational decision-making (Bonczek et al. 1979) most of the early expert systems fell into disuse due to managerial resistance (Davenport and Harris 2005) and the non-monotonous nature of reasoning in strategic management (Lawrence 1991). In the following years, scholars further evolved the systems into distributed planning systems supporting the top management in creating scenarios with the help of intelligent agents (Pinson and Moraltis 1997) attempting to replicate the cognitive process of human strategists. Before the era of BD, the main challenge in supporting strategic decision-making was understanding an executive as an individual user with domain-specific work and aligning the intelligence activities into the right context. Evolving this approach has led to the paradigm of cognitive support systems (Watson 2017) and resulted in a diversification of applications and more specific use cases for strategy formulation (e.g., Lau et al. 2012).

4.2 Consequences

4.2.1 Individual-level

4.2.1.1 Managerial cognition Strategic decision-makers with limited capacity for converting information are challenged by an increasing degree of volatility, uncertainty and complexity and have more data to analyze than ever before (Merendino et al. 2018). The literature indicates that the usage of AI in decision-making can offer aid to deal with this data overload and might enable managers to overcome cognitive limitations by mimicking rationality (Jarrahi 2018).

Numerous researchers have discussed and highlighted the potential of AI to augment managerial decision-making (Berman and Dalzell-Payne 2018; Bonczek et al. 1979; Davenport and Kirby 2016; Parry et al. 2016; Wilson and Daugherty 2018) and have shown its positive influence (Bettis 2017; Ghasemaghaei et al. 2018; Kowalczyk and Buxmann 2014) on the individual performance level of managers by increasing the amount of decision-relevant data (Chi and Turban 1995; Hoffman 2016; Intezari and Gressel 2017) as decision-inputs. This assumption has recently been challenged by Brynjolfsson and Mitchell (2017), who demonstrate that the competence of AI is highly context-specific and more fragile than the nature of human decision-making. In addition, the authors point out various tasks for which the algorithmic decision-making approach is completely ineffective.

The article by Pomerol (1997) underlines the interplay of human reasoning and AI and perceives the main strengths of AI in reducing the uncertainty in decision-making while criticizing the subjectivity of and the disregard for multi-attribute preferences at the same time. Another study states the high inter-subject reliability of using algorithmic decision-making, which can ultimately lead to consistent decision-making over time and increases the level of fairness (Kahneman et al. 2016). Other studies challenge the applicability of AI for strategic decisions that are novel and uncertain (Jarrahi 2018) or show that certain AI systems can also increase decisional complexity (Lawrence 1991) while enhancing the buy-in and legitimacy for decision outcomes (Orwig et al. 1997; Parry et al. 2016).

However, due to the fact that AI systems understand neither the inputs they process or the outputs they produce, research shows that pure data-driven rationality does not necessarily lead to the right decisions, as such decision agents might aim at maximizing specific parameters at all costs while ignoring morals, the firm's specific values and ethical standards (Agrawal et al. 2017; Wright and Schultz 2018). Learning with real-life data, algorithms retrospectively identify patterns to predict the future, which means that distrustful patterns of past decisions within the realms of sexism, racism and economic disadvantage may also be reflected and reinforced by algorithmic decision-making (Diakopoulos 2016; Merendino et al. 2018; Parry et al. 2016). Although studies have implied that machine judgment trained with historical data appears to be more accurate and less prone to biases than human judgment (Kahneman et al. 2016), other scholars have highlighted a number of negative examples of algorithmic bias from judicial decision-making (Garfinkel et al. 2017) and human resource management (Lambrecht and Tucker 2019).

4.2.1.2 Value of complementary skills The inclusion of AI modifies the strategic decision-making process and produces personal challenges for managers, in that it replaces tasks that are merely objective and therefore enables humans to focus on other activities such as judgment and more intuitive and empathetic areas within the realm of algorithmic management.

The segmentation of a strategic decision into its essential elements makes clear where the use of machine learning in strategic decision-making is of its most significant benefit: prediction (Agrawal et al. 2017). Although this is an integral part of every decision process under uncertainty, a prediction itself is not a decision. Agrawal et al. (2017) found that complementary skills to prediction are the most valuable in the future strategic co-creation of prediction-focused AI systems and judgment-focused managers. Strategic managers are required to develop what Wilson and Daugherty (2018) call "fusion skills" to collaborate effectively with intelligent machines (Jarrahi 2018; Lichtenthaler 2018; Watson 2017), and they need to take responsibility in the development and monitoring of the operations, depending on the degree of autonomy of such systems (Garfinkel et al. 2017).

Numerous studies argue that AI replaces managerial tasks that are predominantly objective and codifiable. As a consequence, the managerial role will evolve to focus on other activities requiring implicit knowledge, flexibility, judgment and creativity (e.g., Geisler 1986; Kolbjørnsrud et al. 2017). Moreover, Davenport (2016) not only points out that the cognitive capabilities of intelligent machines will need to be united with managerial intelligence in what he calls an “integrated strategy approach”, but he also develops five paths towards employability for knowledge workers in the era of intelligent machines (Davenport and Kirby 2015). In the same vein, Wilson et al. (2017) find and categorize three emerging human job roles, i.e. trainers, explainers and sustainers, that will need to be created to navigate the growing utilization of AI in management practices.

Further conceptual research in the field suggests that machines do not perform well at conceptually piecing together a big picture (Geisler 1986), while good human strategists excel on the narrative level of sense-making through a personal consideration of contexts and facts (Davenport 2016; Davenport and Kirby 2016). In line with this idea, other scholars argue that the introduction of AI will lead to an augmentation of management productivity and thus enable managers to focus on “high-value work” (Plastino and Purdy 2018), which will result in a premium on soft skills such as intuition (Ferràs-Hernández 2018) and human judgment (Agrawal et al. 2017).

4.2.2 Organizational level

4.2.2.1 Human–machine collaboration The degree to which tasks in strategic management can and will be substituted by AI has been the subject of various articles in the research field. Although some authors see the usage of AI in strategy overstated in the foresighted future, the majority of scholars anticipate the most beneficial impact for strategic management when AI augments managers (e.g., Agrawal et al. 2017; Wilson and Daugherty 2018) and focuses on strategy execution (Ferràs-Hernández 2018).

The concept of an artificial manager, meaning a machine replacing a human manager, is not an entirely new phenomenon but has not been able to live up scholarly expectations (Geisler 1986; Holloway 1983). Studies have examined the integration of human and algorithmic intelligence into work practices (Lichtenthaler 2018), the role of the interface of AI and human managers for user involvement (Bader and Kaiser 2019) and cognitive reasons for implementation barriers (Lichtenthaler 2019). Interdisciplinary research has shown that there are differences in the nature and the capabilities of humans and machines (e.g., Bettis 2017; Bonczek et al. 1979), which are the reasons why most scholars consider the relationship between machines and humans complementary (e.g., Jarrahi 2018; Parry et al. 2016) and contemplate that managerial tasks that cannot be automated will be supplemented by AI in the future (e.g., Davenport and Kirby 2015). Enriching this discussion, Brynjolfsson and Mitchell (2017) have developed a concept to assess the workforce implications for organizations, while Huang and

Rust (2018) map recommendations for managerial delegation within the field of analytical, intuitive and empathetic tasks.

4.2.2.2 Design of decision-making governance The advent of AI will further amplify the edge of analytics-based decision-making in strategic management. To establish smart decision-making processes and a more efficient and fact-based decision-making culture, research posits a rethinking of established leadership regularities.

The question surrounding the administration of an AI system in strategic management is a recurring theme in the research field (Holloway 1983; Parry et al. 2016) and becomes even more relevant with regard to the accountability (Garfinkel et al. 2017) and ethics (Wright and Schultz 2018) of autonomous decision systems. The framework produced by Shrestha et al. (2019) introduces three distinct categories in which collaborative decision structures can be classified: full delegation from manager to AI, sequential decision-making, and aggregated human-AI decision-making.

However, even if full automation of a decision-making process is possible, fiduciary, legal or ethical issues may still require the active role of a responsible human manager (Davenport and Harris 2005). While the delegation of decision-making authority to intelligent systems (Schneider and Leyer 2019) is associated with the dismantling of inefficient information structures, this at the same time poses new leadership challenges to managers in the realm of understanding the underlying principles and assumptions (Davenport 2013). Although there is no available AI technology that is completely able to incorporate the emotional, human and political contexts needed to automate strategic decisions, future AI-systems might enable a parting from top-down planning and imply a push to de-individualizing decision-making (Parry et al. 2016). This would require a rethinking of established leadership regularities and accountabilities (Garfinkel et al. 2017) without a human-held veto. In this context, studies were performed that indicate changes towards a more information-based leadership style in the era of algorithmic management. These studies further refer to the importance of defining tracking parameters, the tracking of potential abuse (Hirsch 2018) and the compliance of intelligent systems (e.g., Garfinkel et al. 2017; Kolbjørnsrud et al. 2017) with the help of accessing decision-support-related information through intelligent visualization systems (Hoffman 2016) or chatbots (Watson 2017).

4.2.2.3 Agility and participation in strategy development Research at the intersection of AI and strategic management considers traditional strategy approaches increasingly inadequate for business environments that are changed by emerging technologies. However, scholars are attributing to AI the potential to increase the variety of organizational knowledge integrated into the strategy development process.

To solve planning problems in strategic management, cooperation among several agents is needed (Pinson and Moraltis 1997). Early studies argue that each of the strategy formulation elements is subjected to repeated feedback and that no other planning system can be seen beyond the abilities of an AI concept which surpasses humans regarding knowledge and memory performance (Davenport 2016; Holloway 1983). As highlighted by Orwig et al. (1997), intelligent group support systems can decrease political friction in strategic decisions by providing a method to integrate many stakeholders (Orsini 1986) and objectives (Berman and Dalzell-Payne 2018) in the strategy process, thus leading to greater organizational buy-ins to decision outcomes by combining explicit and tactic knowledge (Metcalf et al. 2019). While Grover et al. (2018) describe the strategic value proposition of intelligent analytics, Berman and Dalzell-Payne (2018) call for an agile and IT-centric conceptualization of strategy in the context of AI. The authors attribute to various AI technologies the potential to detect and examine proactively driving forces of change with the help of sophisticated scenario-modeling (Constantiou and Kallinikos 2015).

While other researchers posit that AI systems can lead to faster (Davenport and Harris 2005) and more successful strategic decision-making (Intezari and Gressel 2017) when the role of the manager is limited to reviewing and confirming decisions (Davenport and Harris 2005), a small number of researchers considers special and inimitable organizational abilities more relevant than the pure ownership of marketable algorithms and data (Grover et al. 2018; Vidgen et al. 2017) and questions the long-term benefits and distinctive character of algorithms to create unique comparative advantages when the data and tools are available to all players in the market (Mazzei and Noble 2017).

4.2.2.4 Predictive logic in business models AI can display incremental shifts in demand and simplify the conversion of strategic opportunities into business model elements. Scholars in the field predict a change in the majority of value propositions due to the further dissemination of personalized products and services facilitated by the use of intelligent machines.

Agrawal et al. (2017) have recently developed the concept of an AI canvas and shown that data-driven services, as well as efficient operational processes based on complex prediction models, are the main pillars for digitized business models. To keep up with the pace of changes in the competition, companies will additionally need the capability to adapt their business models quickly. This can be done by deploying cognitive technologies that show incremental shifts in demand (Davenport 2016), or by utilizing natural language interfaces to reduce friction within the customer journey (Watson 2017). By continually scrutinizing whether existing business model elements still reflect current customer needs and place the focus on technological possibilities, managers are called first to explore and then utilize the knowledge to shape business models that will remain viable in the foreseeable future (Berman and Dalzell-Payne 2018).

With the arrival of the next generation of decision support services, the primary logic of business model design will shift to an understanding of how customers make decisions (Constantiou and Kallinikos 2015) and how this decision-making process can be used to generate revenue with personalized products and services (Davenport and Mahidhar 2018).

5 Discussion

Research on the role of AI in strategic management is not an entirely new phenomenon. Already in the 1980s, many promises were made about its managerial usefulness (e.g., Geisler 1986; Holloway 1983), but early forms in the shape of expert systems failed to achieve their value propositions on a strategic level (e.g., Edwards and Yanqing 2000), which led to a decline in publications and a temporary loss of the research field's significance. However, academic interested has increased again, as more recent articles (e.g., Jarrahi 2018; Wilson and Daugherty 2018) now find their technological foundation in sophisticated algorithms that are more powerful than ever before and are extending their reach into what would normally be seen as exclusively human domains in strategic management. Although AI is still at an early state of deployment in strategic management (Fountaine et al. 2019), recent publications have shifted the focus to the business potential of AI and consider the synergy of BD and AI being on the cusp of practical usefulness (e.g., Berman and Dalzell-Payne 2018; Ghasemaghaei et al. 2018). In contrast to earlier publications in the field, current studies assign AI a high degree of utility and more autonomy in the area of "thinking work" (Phan et al. 2017) within cognitive tasks and process automation (Davenport and Ronanki 2018).

This SLR contributes to the emerging discussion in strategic management literature by structuring and synthesizing concepts covering four decades of research and by deriving promising research opportunities in the area where AI and strategic management intersect. An in-depth analysis of the fragmented body of the literature yielded a range of themes (see: Fig. 3), which provides the first comprehensive assessment of the interplay of AI and strategic management and hence contributes to understanding the transition of the research field at the frontier of algorithmic management.

At the level of antecedents, research integrates technological suitability alongside a number of organizational-wide antecedents such as data-driven workflows, managerial willingness and other organizational determinants as one of many conditions in the context of AI adoption in strategic management. The literature shows that AI is not perceived as a plug-and-play technology with fast returns and that effective leverage of the technology's potential requires a clear and distinct deployment strategy involving multiple stakeholders. In the current state of many organizations, managers at the work-practice level are constrained by prevalent organizational models and insufficient interdisciplinary collaboration when approaching the utilization of BD and AI-based systems within different cognitive technologies. As the use of AI places requirements on the organizational infrastructure as well as managerial working methods, research indicates that the process by which it is implemented is decisive in its degree of trustworthiness and managerial acceptance.

At the level of consequences, AI-based systems are described as either supporting the human manager or replacing him in the realm of routine tasks that are objective and codifiable and enable managers to focus on more meaningful tasks. Literature shows that organizations that are capable of effectively addressing the challenges associated with the utilization of AI, including biased data sources, hidden imprecisions and ethical issues, are potentially able to achieve considerable strategic rewards. In this regard, studies indicate that the usage of AI in decision-making can help deal with data overload and might enable managers to overcome cognitive limitations. However, scholars have moved away from outdated concepts of AI-based systems replacing all managers (e.g., Holloway 1983), and now increasingly promote the concept of AI-enabled automation to mostly augment tasks within this human machine-partnership in strategic management. The prevailing view within academia still considers human managers best-suited for the role of central processor, due to their unique level of sense-making and judgemental competence. Given the predicted need for the transition of managerial working practices, distinct research streams in the field examine the degree to which strategic work can—and will—be affected by AI and how this human–machine collaboration will alter the decision-making governance and logic of business models.

With respect to the research question, concept synthesis shows that the extent of strategic value of AI-based systems on both the individual as well as the organizational level depends not solely on the power of the underlying algorithms, but it can only be enabled through effectively orchestrated organizational capabilities and the managerial willingness to utilize them. These conditions provided, AI promises to change the nature of strategic management and possesses the potential to transform how to generate competitive advantages—both by supporting managers with innovative ways to leverage knowledge in the process of strategic decision-making and by modifying the landscape of strategic capabilities through automation and the personalization of value propositions. However, the research field indicates that leveraging the technology's power to enhance strategic management practices is a learning process for both the individual manager and the organization. The roles within this learning process are described as gradually changing and prompting organizations to realign their structures, processes and cultural values continuously, in order to remain competitive in the era of intelligent management.

6 Avenues for future research

This review also points towards promising future research opportunities in the field to expand the scholarly discussion and contributes to theoretical advancement in the interdisciplinary area where AI and strategic management intersect. Drawing on the developed framework, I first outline the research opportunities within each identified research stream (Table 2). Subsequently, I then assess relevant cross-cutting research opportunities, to expand the scope of the identified research streams (Table 3), and discuss the research implications of the lack of theorization about the phenomenon of AI in strategic management in the current scholarly discussion.

A large body of the forward-looking research in the scattered field to date has been focused on conceptual issues such as the replacement versus augmentation debate without continuously substantiating claims with empirical evidence (e.g.,

Table 2 Research opportunities within each research stream

Research stream	Research opportunities
Antecedents	
Data-driven workflows	How should organizations structure their cognitive architecture and data governance to support AI-enabled systems in different departments? How do legal and ethical factors affect the use of BD as an input for AI-based systems? How can organizations ensure sufficient data quality for supporting managerial actions of strategic importance?
Managerial willingness	What are the psychological factors that drive managerial decision delegation to AI in a strategic context? Will managers allow autonomous AI systems to make and execute strategic decisions on their behalf? Will explainable AI-based systems affect the level of trustworthiness?
Organizational determinants	How do different AI implementation methods determine the concrete value added by intelligent technology? How can organizations assess the optimal use and distribution of AI in strategic management?
Consequences	
Managerial cognition	How does one organize the cognitive collaboration between human judgment and AI while minimizing the negative impact of the technology? How should managers deal with moral dilemmas and AI discrimination? How does the utilization of AI interplay with human biases in strategic decision-making processes? Will the utilization of AI-based systems lead to managerial over-reliance?
Value of complementary skills	What concrete leadership skills will remain important in management teams in the age of AI-enabled automation? How do AI-supported activities change the nature of strategic decision-making? What are the implications of an AI implementation for organizational training and future management education?
Human–machine collaboration	How can the human–machine partnership in strategic management be transformed into competitive advantages? How can one design the AI within organizational decision-making in line with different roles? What is the effect of AI on different levels of management?
Design of decision-making governance	How should organizations determine and assign the levels of authority and accountability for algorithms in strategic management? How can AI agency risks be administered? How does this choice affect the level of performance and motivation of human managers?
Agility and participation in strategy development	Will AI enable more equal relationships across different hierarchical levels? How will the utilization of AI redefine the boundaries of an organization? Which parts of the strategy development process are likely to be outsourced to AI, and what are the effects on organizational culture and performance?

Table 2 (continued)

Research stream	Research opportunities
Predictive logic in business models	What are concrete mechanisms through which organizations reconfigure their business models in the era of algorithmic management?

Davenport 2016; Jarrahi 2018; Parry et al. 2016). The accelerating deployment and relevance of AI in strategic management practices, however, create a growing need for more critical perspectives on the phenomenon in strategic management and a demand for more quantitative and qualitative research on the level of automation selection. A reasonable research approach could be experimental studies identifying the concrete causalities through which the collaboration of AI and human managers ultimately delivers the anticipated benefits, indicated by many conceptual studies. In light of the intriguing assumptions that a human–machine symbiosis is imminent, and that the quality of managerial actions will increase with the help of more inclusive data and the complementary skills of AI-based systems, further research should be undertaken to investigate how organizations can overcome the challenges of managerial resistance as well as manage the balance between the traditional objectives of human leadership and algorithmic optimization. Therefore, future research will need to study how AI may redesign business processes and create new forms of organizational design while also considering possible automation failures from a strategic management perspective by addressing the questions outlined in the following Table 3.

Table 3 Research opportunities beyond identified research streams

Research stream	Research opportunities
Organizational design	Which organizational design ensures that AI and human managers can work together effectively? What are the effects of an AI implementation on organizational governance and learning? How can organizations assess AI safety and take action to prevent data abuse? Is there an underlying cultural dimension to the logic of AI-based systems and their subsequent outcomes? What other organizational resources and capabilities do organizations need to invest for realizing performance enhancements through strategic AI applications?
Critical perspectives on AI discrimination and failure	How will organizations deal with failures and errors of strategic AI applications? Is the inexplicability of algorithms in itself compatible with the nature of strategic decision-making processes in organizations? Under what conditions do organizations require transparency of reasoning within strategic AI applications? What could be unintended consequences of AI-based systems that can produce downstream effects on management practices and markets?

From a theoretical perspective, AI is a domain with extensive opportunities for generating novel theory perspectives at the intersection of information systems and strategic management. Despite an initial set of empirical studies (e.g., Kolbjørnsrud et al. 2017; Schneider and Leyer 2019), there is still very limited theoretically-grounded research aiming at understanding the utility of the latest generation of AI from a technology-application perspective. While some articles in the field view the utilization of AI in strategic management through the theoretical lenses of the knowledge-based view (e.g. Intezari and Gressel 2017; Merendino et al. 2018), the agency theory (Pinson and Moraltis 1997) or theories in the sphere of the resource-based view (e.g., Olszak 2016; Vidgen et al. 2017), the most cited recent articles originate from practitioner-oriented journals such as *Harvard Business Review* or *MIT Sloan Management Review* that provide executives with guidelines on how to benefit and implement AI, without explicitly indicating the application of a theory to the research (e.g., Davenport and Ronanki 2018). Although this is due to the fact that in partially emerging fields early examinations generally seek to understand the phenomenon before applying theory (Hambrick 2007), further research is required to contemporarily theorize on new forms of management practices, to determine further the essentiality of AI as a resource. To develop a full picture of AI in strategic management, I encourage other researchers to shed light on the crucial relationship between AI and theory and build more systematic evidence on the question of whether the managerial use of AI requires modifying some assumptions of extant management and organizational theories.

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Appendix

See Table 4.

Table 4 Articles selected for review

Authors (Year)	Title	Journal	VHB-Jourqual 3	Categorization	Key findings
Agrawal et al. (2017)	What to expect from artificial intelligence	MIT Sloan Management Review	C	Conceptual	New managerial challenges ahead, due to focus on judgmental tasks. Based on the anatomy of a decision, a differentiation is made between automation and prediction
Bader and Kaiser (2019)	Algorithmic decision-making? The user interface and its role for human involvement in decisions supported by artificial intelligence	Organization	B	Empirical	User interfaces possess an ambiguous and meaning-ful function for human involvement in joint decision processes. The user interface is conceptualized a key role between the poles of human distance and attachment
Berman and Dalzell-Payne (2018)	The interaction of strategy and technology in an era of busi-ness re-invention	Strategy & Leadership	C	Conceptual	By proposing an innovative model for strategy develop-ment, it is shown that digital technology is a tool used for tactical advantage and, it is crucial for strategic renewal
Bettis (2017)	Organizationally intractable decision problems and the intellectual virtues of heuristics	Journal of Management	A	Conceptual	Drawing on heuristics AI provides opportunities to deal effectively with ill-structured and intractable decision envi-ronments
Bonczek et al. (1979)	Computer-based support of organizational decision making	Decision Sciences	B	Conceptual	Presentation of a framework for understanding the degree to which computer systems can be used to facilitate strategic planning processes beyond information retrieval

Table 4 (continued)

Authors (Year)	Title	Journal	VHB-Jourqual 3	Categorization	Key findings
Brynjolfsson and Mitchell (2017)	What can machine learning do? Workforce implications: profound change is coming, but roles for humans remain	Science	A+	Empirical	By assessing the suitability of ML for tasks, the increasing pace of automation is highlighted. ML will rarely automate whole jobs; in most cases, it will lead to a re-engineering the processes and reorganizing tasks
Chi and Turban (1995)	Distributed intelligent executive information systems	Decision Support Systems	B	Conceptual	Development of a framework (DIEIS). It illustrates how multiple resources can be merged for information processing in a strategic environment and how intelligent agents can cooperate in complex information processing
Constantiou and Kallinikos (2015)	New games, new rules: big data and the changing context of strategy	Journal of Information Technology	A	Conceptual	The usefulness of large data for strategizing depends on their ability to be constantly updated, which shortens the time span in which the information is relevant for strategy development and highlights contextual factors

Table 4 (continued)

Authors (Year)	Title	Journal	VHB-Jourqual 3	Categorization	Key findings
Davenport (2013)	Keep up with your quants	Harvard Business Review	C	Conceptual	The selection and handling of data analysts influence the success of intelligent analytics efforts. Managers need to understand the underlying principles of analytical decision-making for organizational success
Davenport (2016)	Rise of the strategy machines	MIT Sloan Management Review	C	Conceptual	Description of state-of-the-art machines that develop strategies for organizations. Nevertheless, only humans are able to make "big swing" strategic decisions, as machines are not very good at putting together the big picture
Davenport and Harris (2005)	Automated decision making comes of age	MIT Sloan Management Review	C	Empirical	Automatic decision-making capabilities are not equivalent to previous DSS and are embedded in the normal workflow with minimal human intervention

Table 4 (continued)

Authors (Year)	Title	Journal	VHB-Jourqual 3	Categorization	Key findings
Davenport and Kirby (2015)	Beyond automation	Harvard Business Review	C	Conceptual	Division of automation into three eras and the introduction of five paths to employability. Perception of automation as an opportunity to augment human abilities in creative problem-solving. Many managerial tasks, including empathy and storytelling, cannot be codified
Davenport and Kirby (2016)	Just how smart are smart machines?	MIT Sloan Management Review	C	Conceptual	The growing number of cognitive technologies is mapped in a framework that shows the degree of autonomy and what tasks they can perform
Davenport and Mahidhar (2018)	What's your cognitive strategy?	MIT Sloan Management Review	C	Conceptual	Mapping of recommendations, in order to develop and build a cognitive strategy. Understanding the key levers in a variety of topics such as the use of content, technology components, people, change management and organizational ambitions

Table 4 (continued)

Authors (Year)	Title	Journal	VHB-Jourqual 3	Categorization	Key findings
Diakopoulos (2016)	Accountability in algorithmic decision making	Communications of the ACM	B	Conceptual	Details on different types of algorithmic decision-making, such as prioritization, classification, allocation and filtering are presented. The need for regulation and standards (human participation, data, and modelling) is highlighted
Dietvorst et al. (2018)	Overcoming algorithm aversion: people will use imperfect algorithms if they can (even slightly) modify them	Management Science	A+	Empirical	Experimental studies show the option to mitigate algorithm aversion by giving users a small amount of control over the prediction of an imperfect algorithm
Epstein (2015)	Wanted: collaborative intelligence	Artificial Intelligence	B	Conceptual	Proposition of the development of collaborative intelligence as an alternative to autonomous systems that compete with managers, to improve both public perception and managerial acceptance
Ferràs-Hernández (2018)	The future of management in a world of electronic brains	Journal of Management Inquiry	B	Conceptual	Comparison of the advantages of both managers and machines along the value chain. Although machines outperform people in many cognitive tasks, human managers are uniquely capable of leading

Table 4 (continued)

Authors (Year)	Title	Journal	VHB-Jourqual 3	Categorization	Key findings
Garfinkel et al. (2017)	Toward algorithmic transparency and accountability	Communications of the ACM	B	Conceptual	AI cannot allow decision-makers to automatically overcome cognitive distortions, because these systems are not free of distortions by themselves, which creates new regulatory challenges
Geisler (1986)	Artificial management and the artificial manager	Business Horizons	C	Conceptual	Management by expert systems can take over predefined management tasks. Artificial managers possess advantages in the realm of technical and procedural decisions
Ghasemaghaei et al. (2018)	Data analytics competency for improving firm decision making performance	The Journal of Strategic Information Systems	A	Empirical	Development of a data analytics competency index from a resource-oriented perspective. Most dimensions of data analytics competency are described to improve decision quality, while the effect of the bigness of data remains ambivalent
Grover et al. (2018)	Creating strategic business value from big data analytics: a research framework	Journal of Management Information Systems	A	Conceptual	Development of a theoretical BD analytics framework to show how distinctive BDA components can become a strategic advantage for the company

Table 4 (continued)

Authors (Year)	Title	Journal	VHB-Jourqual 3	Categorization	Key findings
Hirsch (2018)	Tie me to the mast: artificial intelligence & reputation risk management	Journal of Business Strategy	C	Conceptual	The usefulness of AI in reputation risk management is assessed in two areas: ML to analyze employee emails to determine early signs of malpractice and to test business decisions for potential fraud
Hoffman (2016)	Using artificial intelligence to set information free	MIT Sloan Management Review	C	Conceptual	By focusing on the beneficial effects of AI in the way companies gather, analyze and act on knowledge, the study shows how AI will affect management practices in the areas of knowledge distribution, performance management and talent mobility
Holloway (1983)	Strategic management and artificial intelligence	Long Range Planning	B	Conceptual	The potential for "thinking" robots has a big impact on general management. By subdividing strategic planning problems, companies could benefit from massive knowledge storage within such systems

Table 4 (continued)

Authors (Year)	Title	Journal	VHB-Jourqual 3	Categorization	Key findings
Huang and Rust (2018)	Artificial intelligence in service	Journal of Service Research	A	Conceptual	A framework to cope with changes in the job structure induced by AI. According to four intelligences: mechanical, analytical, intuitive and empathetic. The article shows how companies should decide between humans and machines to perform these tasks
Intezari and Gressel (2017)	Information and reformation in KM systems: Big data and strategic decision-making	Journal of Knowledge Management	C	Conceptual	Typologization of different data-based decisions from a knowledge-based view. Characterizations of factors that help enable intelligent systems to handle BD and advanced analytics in strategic environments
Janssen et al. (2017)	Factors influencing big data decision-making quality	Journal of Business Research	B	Empirical	The use of BD is an evolutionary procedure in which the comprehension of the potential of BD and the routinization of practices play a pivotal role
Jarrahi (2018)	Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making	Business Horizons	C	Conceptual	AI can improve human cognition when confronted with managing complexity. However, human managers still offer more holistic and intuitive approaches to deal with uncertainty and ambiguity

Table 4 (continued)

Authors (Year)	Title	Journal	VHB-Jourqual 3	Categorization	Key findings
Kahneman et al. (2016)	Noise: how to overcome the high, hidden cost of inconsistent decision making	Harvard Business Review	C	Conceptual	The usage of AI in decision-making outperforms human managers in terms of consistency
Kolbjørnsrud et al. (2017)	Partnering with AI: how organizations can win over skeptical managers	Strategy & Leadership	C	Empirical	When managers are involved in AI development, they acquire a sense of ownership during the learning process. In addition, patterns for an effective introduction of AI are identified and described. The value of skills complementary to AI will increase
Kowalczyk and Buxmann (2014)	Big Data and information processing in organizational decision processes	Business & Information Systems Engineering	B	Empirical	Typologization of how large data processing mechanisms are used in various forms of BI to enable decision-making processes with an information-processing theory perspective
Lambrecht and Tucker (2019)	Algorithmic bias? An empirical study into apparent gender-based discrimination in the display of STEM career ads	Management Science	A+	Empirical	An algorithm that is supposed to optimize cost efficiency in a neutral task delivers discriminating results. This empirical result can be transferred to other decision environments and highlights the incoherence of decision objectives

Table 4 (continued)

Authors (Year)	Title	Journal	VHB-Jourqual 3	Categorization	Key findings
Lau et al. (2012)	Web 2.0 environmental scanning and adaptive decision support for business mergers and acquisitions	MIS Quarterly	A+	Conceptual	Market-based view operationalization of a scorecard model and development of a self-learning system for M&A decision support, based on a domain-specific sentiment and business relationship analysis
Lawrence (1991)	Impacts of artificial intelligence on organizational decision making	Journal of Behavioral Decision Making	B	Conceptual	The deployment of expert systems will produce less sophisticated and political decision-making processes, whereas the deployment of natural language systems will lead to divergent outcomes
Lichtenthaler (2018)	Substitute or Synthesis? The interplay between human and artificial intelligence	Research-Technology Management	C	Conceptual	The relationship between humans and AI is described in the form of a matrix that contains four quadrants to describe the different strengths in collaboration
Lichtenthaler (2019)	Extremes of acceptance: employee attitudes toward artificial intelligence	Journal of Business Strategy	C	Conceptual	Organizations experience barriers in the implementation of AI, due to the negative attitudes of their employees. A concept of no-human interaction settings is introduced to describe employees' preference for working with real colleagues

Table 4 (continued)

Authors (Year)	Title	Journal	VHB-Jourqual 3	Categorization	Key findings
Logg et al. (2019)	Algorithm appreciation: People prefer algorithmic to human judgment	Organizational Behavior and Human Decision Processes	A	Empirical	While calling for a theory of machines, they show that laymen are more likely to take advice when they originate from an algorithm rather than from a human. However, the level of algorithm appreciation decreases when a) users choose between utilizing an algorithm and their own decision and b) when users are experienced in that particular task
Mazzei and Noble (2017)	Big data dreams: a framework for corporate strategy	Business Horizons	C	Conceptual	Typologization of value creation layers with regard to the BD phenomenon. The framework shows how large amounts of data improve dynamic capabilities within companies and are becoming essential elements of disruptive strategies
Merendino et al. (2018)	Big data, big decisions: the impact of big data on board level decision-making	Journal of Business Research	B	Empirical	Demonstration of the limited cognitive abilities of decision-makers from a knowledge-based perspective. Subsequently, the potential benefits of BD and cohesion and control in leadership teams are discussed

Table 4 (continued)

Authors (Year)	Title	Journal	VHB-Jourqual 3	Categorization	Key findings
Merten (1991)	Loop-based strategic decision support systems	Strategic Management Journal	A	Conceptual	With the portfolio simulation model, the concept of continuous feedback loops is used to depict rule-based policy decisions made by companies that can increase quantitative knowledge in interaction processes
Metcalf et al. (2019)	Keeping humans in the loop: pooling knowledge through artificial swarm intelligence to improve business decision making	California Management Review	B	Conceptual	The concept of artificial swarm intelligence is presented. ASI is used by companies to increase collaboration by exploiting the different perspectives within groups and to enable the convergence of decisions
Olszak (2016)	Toward better understanding and use of business intelligence in organizations	Information Systems Management	C	Empirical	From a resource-based perspective, BI is a catalyst for making more impactful decisions, refining processes and outcomes and overcoming industrial barriers. Therefore, BI systems require continuous development and adaptation
Orsini (1986)	Artificial intelligence: a way through the strategic planning crisis?	Long Range Planning	B	Conceptual	Building on value theories the author identifies AI's recommendations as immediately relevant for strategic planning when they are implemented in useful hardware and software systems

Table 4 (continued)

Authors (Year)	Title	Journal	VHB-Jourqual 3	Categorization	Key findings
Orwig et al. (1997)	A multi-agent view of strategic planning using group support systems and artificial intelligence	Group Decision and Negotiation	B	Conceptual	Intelligent agents in the problem-solving process can both a) improve the quality of strategic plans by enabling greater participation of more members of the organization and b) increase complexity by enlarging the amount of textual information
Parry et al. (2016)	Rise of the machines: a critical consideration of automated leadership decision making in organizations	Group & Organization Management	B	Conceptual	AI provides opportunities to deal effectively with complex decision environments. The delegation of decisions to autonomous AI agents evokes both sociocultural and managerial challenges, depending on a human veto right
Phillips-Wren et al. (2009)	An integrative evaluation framework for intelligent decision support systems	European Journal of Operational Research	A	Conceptual	Development of an integrative, multicriteria IDSS assessment framework, which relates the decision value of an IDSS to both the outcome and the decision-making process
Pinson and Moraltis (1997)	An intelligent distributed system for strategic decision making	Group Decision and Negotiation	B	Conceptual	Development of a framework (ARISTOTE) drawing on agency theory, which facilitates coherence and simplifies coordination among stakeholders

Table 4 (continued)

Authors (Year)	Title	Journal	VHB-Jourqual 3	Categorization	Key findings
Plastino and Purdy (2018)	Game changing value from Artificial Intelligence: eight strategies	Strategy & Leadership	C	Conceptual	The unique characteristics of AI possess the ability to change management practices on a large scale and at a high speed and challenge companies to apply new approaches and methods in different functional areas
Pomerol (1997)	Artificial intelligence and human decision making	European Journal of Operational Research	A	Conceptual	Distinction between two aspects of decision-making according to decision theory: diagnosis and prediction. Study shows that AI has many relationships with diagnosis (expert systems, case-based thinking, etc.), but the field of predictive reasoning remains under-researched in the realm of AI
Prahl and van Swol (2017)	Understanding algorithm aversion: when is advice from automation discounted?	Journal of Forecasting	B	Empirical	Drawing on response-advice theory, the authors show that poor advice experiences diminish significantly the trust in automated advice. Decision-makers describe themselves as much more in common with human advisors than with automated counterparty, although there is no interpersonal relationship

Table 4 (continued)

Authors (Year)	Title	Journal	VHB-Jourqual 3	Categorization	Key findings
Schneider and Leyer (2019)	Me or information technology? Adoption of artificial intelligence in the delegation of personal strategic decisions	Managerial and Decision Economics	B	Empirical	The complexity of the decision situation does not influence the delegation decision, but humans with low situational awareness are more inclined to delegate decisions to AI in accordance with decision support theory
Shrestha et al. (2019)	Organizational decision-making structures in the age of Artificial Intelligence	California Management Review	B	Conceptual	Drawing on organizational theory, the authors differentiate three categories for how decision structures in organizations can be classified: full delegation from manager to AI, hybrid decision-making and aggregated decision-making between a manager and AI. Recommendations for strategic decision-making situations are derived
Vidgen et al. (2017)	Management challenges in creating value from business analytics	European Journal of Operational Research	A	Empirical	Building on the resource-based view of the firm, the authors state that organizations need a holistic data analysis strategy, appropriate workforce skills and cultural change when using data for developing competitive advantages

Table 4 (continued)

Authors (Year)	Title	Journal	VHB-Jourqual 3	Categorization	Key findings
Watson (2017)	Preparing for the cognitive generation of decision support	MIS Quarterly Executive	B	Conceptual	Managerial recommendations for the implementation of AI-based support systems in management, which the author considers as organizational resources
Wilson and Daugherty (2018)	Collaborative intelligence: humans and AI are joining forces	Harvard Business Review	C	Conceptual	While AI will radically change managerial responsibilities and the way work is done, the most beneficial impact thereof will be to augment human capabilities instead of replacing them
Wilson et al. (2017)	The jobs that artificial intelligence will create	MIT Sloan Management Review	C	Empirical	Conceptualization of three new types of jobs that will be created by the utilization of AI in management: trainers, explainers and supporters
Wright and Schultz (2018)	The rising tide of artificial intelligence and business automation: developing an ethical framework	Business Horizons	C	Conceptual	Assessment of the cultural and ethical impacts of business automation on stakeholders, ranging from workers to states. Holistic definition of business automation and introduction of a framework that integrates stakeholder and social contract theory

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