International Journal of Information Management 57 (2021) 102225

Contents lists available at ScienceDirect

International Journal of Information Management

journal homepage: www.elsevier.com/locate/ijinfomgt

The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions

Aline F.S. Borges [a,*], Fernando J.B. Laurindo [a], Mauro M. Spínola [a], Rodrigo F. Gonçalves [b], Claudia A. Mattos [c]

[a] *Universidade de São Paulo Escola Politécnica Departamento de Engenharia de Produção, São Paulo, Brazil*

[b] *Graduation Program in Production Engineering - Universidade Paulista, São Paulo, Brazil*

[c] *Fundação Educacional Inaciana Padre Sabóia de Medeiros, São Paulo, Brazil*

ARTICLE INFO

Keywords:
Artificial intelligence
Deep learning
Machine learning
Business strategy
Information technology
Literature review

ABSTRACT

Artificial Intelligence tools have attracted attention from the literature and business organizations in the last decade, especially by the advances in machine learning techniques. However, despite the great potential of AI technologies for solving problems, there are still issues involved in practical use and lack of knowledge as regards using AI in a strategic way, in order to create business value. In this context, the present study aims to fill this gap by: providing a critical literature review related to the integration of AI to organizational strategy; synthetizing the existing approaches and frameworks, highlighting the potential benefits, challenges and opportunities; presenting a discussion about future research directions. Through a systematic literature review, research articles were analyzed. Besides gaps for future studies, a conceptual framework is presented, discussed according to four sources of value creation: (i) decision support; (ii) customer and employee engagement; (iii) automation; and (iv) new products and services. These findings contribute to both theoretical and managerial perspectives, with extensive opportunities for generating novel theory and new forms of management practices.

1. Introduction

In the digital era, the business world has required shorter response times and more attention to the competitive landscapes, which can change more quickly than ever before (Venkatraman, 2017). In this background, many companies are embracing new technologies aiming to achieve high performance and competitive advantage (Weill & Woerner, 2017). Among these technologies, Artificial Intelligence has occupied a prominent position (Panetta, 2018) and has attracted attention from both the literature and business organizations. According to Davenport (2018), the AI may be the technological force with the greatest disruptive potential in evidence nowadays. Similarly, for Brynjolfsson and Mcafee (2017), AI is the most important general-purpose technology of our era, particularly with regards to machine learning techniques.

The term Artificial Intelligence was first coined in 1956 by McCarthy, which he referred to as “the science and engineering of making intelligent machines” (McCarthy, 1958). Since then, the history of AI has experienced success cycles and periods of mistaken optimism. From the beginning, based on interesting findings, AI researchers were confident with predictions of their successes in a near future (Russell & Norvig, 2010). Instead, the evolution of AI was slower than expected and relied on changes in researches directions over time, with phases of new approaches introduction and refinement of existing ones (Russell & Norvig, 2010).

However, in the last decade, the huge volume of data in diverse formats being generated faster than ever, demanded the development of new technologies, resulting in an acceleration of technological progress, which includes increasing the computational processing capacity and the development of new AI techniques (Brynjolfsson & McAfee, 2017; Bughin et al., 2017).

With these progresses, companies such as Netflix, Google, Airbnb, Amazon and Uber are able to process large amounts of data with AI and use the results to expand their scope with new products, markets and services (Iansiti & Lakhani, 2020; Venkatraman, 2017).

Considering the competitive scenario of the business world and with high volumes of data, scarce resources and the need for speed in decision-making, many organizations are motivated to adopt AI

* Corresponding author.
E-mail address: alinefsb@ime.usp.br (A.F.S. Borges).

https://doi.org/10.1016/j.ijinfomgt.2020.102225
Received 31 December 2019; Received in revised form 9 August 2020; Accepted 10 August 2020
Available online 14 September 2020
0268-4012/

technologies, mainly by their disruptive potential demonstrated by top digital corporations (Bean, 2019; Chakravorti, Bhalla, & Chaturvedi, 2019; Davenport, 2018; Venkatraman, 2017).

Aware that the disruption process requires a review of the business strategy, different leaders are reformulating their strategic plans for the insertion of AI technologies (Davenport, 2018). However, the literature suggests that more research is necessary to understand the impacts of AI in the business strategies planning and execution (Pappas, Mikalef, Giannakos, Krogstie, & Lekakos, 2018), since there is still little theoretical and empirical evidence on how to create business value with the adoption of AI technologies (Brynjolfsson & Mcafee, 2017; Davenport, 2018; Mikalef, Pappas, Krogstie, & Giannakos, 2018; Mikalef, Boura, Lekakos, & Krogstie, 2019; Pappas et al., 2018; Duan, Edwards, & Dwivedi, 2019; Wilson & Daugherty, 2018). Therefore, this article attempts to address the above research gaps by examining the intersection of the literature about artificial intelligence and business strategy, through a systematic literature review.

There are several researches that review the literature about AI linked with: medicine (D'Souza, Prema, & Balaji, 2020; Ebrahimighahnavieh, Luo, & Chiong, 2020; Foulquier et al., 2018; Kedra et al., 2019; Wang, Wang, & Lv, 2019; Orgeolet et al., 2020), accounting (Henrique, Sobreiro, & Kimura, 2019; Sezer, Gudelek, & Ozbayoglu, 2020); computer science (Moghekar & Ahuja, 2019; Zheng, Chien, & Wu, 2014; Wang, Chen, Li, & Vargas, 2019) telecommunication (Hassanien, Darwish, & Abdelghafar, 2019; Morocho-Cayamcela, Lee, & Lim, 2019); education (Alenezi & Faisal, 2020); sustainability (Nishant, Kennedy, & Corbett, 2020), impact on the future of industry and society (Dwivedi et al., 2019); and others (Carvalho et al., 2019; Guzman & Lewis, 2020; Li et al., 2019; McKinnel, Dargahi, Dehghantanha, & Choo, 2019; Sharma, Kamble, Gunasekaran, Kumar, & Kumar, 2020). In addition, few studies review the literature about AI from an organizational perspective, addressing information management (Pandl, Thiebes, Schmidt-Kraepelin, & Sunyaev, 2020; Zhu, Zhang, & Sun, 2019); decision-making (Duan, Xiu, & Yao, 2019; Ding et al., 2020); sustainable performance evaluation (Souza, Francisco, Piekarski, Prado, & Oliveira, 2019); and the future of work (Wang & Siau, 2019). Thus, to the best of our knowledge, this study differs from those already published by contributing with a systematic literature review that investigates the researches state of the relationship between AI and business strategy, theme not encompassed in the studies above mentioned.

The use of technology by organizations as a strategic tool is not a recent practice (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013; Laurindo, 2008; Venkatraman, 2017), but the connection of the AI technologies usage with business strategy becomes significantly more complex in relation to other technologies, since AI applications are able to perform tasks that require cognition and were formerly typically associated with humans (Bean, 2019; Brynjolfsson & Mitchell, 2017; Duan, Xiu et al., 2019; Lichtenthaler, 2020a; Norman, 2017; Wilson & Daugherty, 2018). In this sense, obtaining value from AI investments is more complex than expected, due the paradox that the same person may have negative or positive attitudes towards AI, depending on the specific situation (Lichtenthaler, 2019).

Thus, the present study aims to investigate and to analyze the literature regarding artificial intelligence and the connection of these technologies with concepts of business strategy in order to: (i) identify and describe the existing approaches and frameworks which deal with the relationship of AI technologies and business strategy; (ii) provide a synthesis of potential benefits, challenges and opportunities of the AI strategic usage aligned with business strategy; (iii) present a discussion about the future research directions.

2. Theoretical background

This section presents the literature review on the relevant studies related to AI and about the information technology alignment with business strategy, introducing the main definitions of fundamental concepts under the lens of different authors of these areas separately.

2.1. *Artificial intelligence*

Since the 1950s, when McCarthy introduced the term Artificial Intelligence, the AI field has developed in two dimensions: human-centered and rationalist approaches. The human-centered approaches involve hypothesis and experimental validation, being part of the empirical science (Bellman, 1978; Haugeland, 1985; Kurzweil, 1990; Rich & Knight, 1991). In turn, the rationalist approaches comprise a combination of engineering and mathematics (Charniak & McDermott, 1985; Luger & Stubblefield, 1993; Schalkoff, 1990; Winston, 1970).

Although AI has ideas, viewpoints and techniques from other areas, we here consider it a field which aims to develop software and hardware able to perform actions that can only be executed with the use of cognition (Bundy, Young, Burstall, & Weir, 1978; Russell & Norvig, 2010). Therefore, from the rationalist approaches perspective, the field of AI encompasses any technique which enable machines to act by simulating the human behavior to achieve the best result or, in uncertainty scenarios, the best result expected (Russell & Norvig, 2010).

In the early days of AI, the major challenge was (and still is) to perform tasks that are easily solved by a human being, but hard to describe formally in terms of mathematical rules (Abramson, Braverman, & Sebestyen, 1963; Goodfellow, Bengio, & Courville, 2016).

The difficulty in explaining this type of task by defining rules indicated that AI techniques needed the capability to extract patterns from data and to acquire their own knowledge (Abramson et al., 1963; Goodfellow et al., 2016; Michie, 1968; Solomonoff, 1985). This ability is known as machine learning (Goodfellow et al., 2016), which enable computer-based applications to automatically detect patterns in data and to act without explicitly being programmed (Murphy, 2012). Thus, the field of AI has advanced not just in the direction of process rules previously defined by human beings for simulating human behavior to make decisions (as in classical AI algorithms), but also aiming to mimic human learning.

The progress of AI with the development of machine learning algorithms demanded means to map the knowledge acquired from learning process to final predictions. This need drove the development of approaches categorized as representation learning, in which features are transformed into an intermediate representation containing useful information (Bengio, Courville, & Vincent, 2013; Witten & Frank, 2016).

When representations are expressed in terms of other representations, as in the case of complex concepts, it is necessary to employ deep learning techniques. Deep learning is a kind of representation learning that has the power and flexibility to represent the world through a hierarchy of concepts, in which each concept can be defined in relation to simpler concepts (Goodfellow et al., 2016). It means that deep learning allows computational models to learn representations with diverse levels of abstraction and these models are composed of multiple processing layers (LeCun, Bengio, & Hinton, 2015).

To summarize, Fig. 1 illustrates the relationship between the AI disciplines. The diagram shows how deep learning is a kind of representation learning, which is used for many but not all approaches of machine learning, which in turn is considered a kind of AI. The main difference among AI disciplines is the dependence of the human being on establishing rules or defining features to represent a problem. From the AI layer, human dependence on the learning process decreases towards inner layers.

To exemplify these differences, consider the problem of recommending products to a customer on an e-commerce platform. An example of classic AI algorithm would be to implement a program based on the rule: if the customer has already made a purchase, then recommend the products most purchased by him. Classic AI algorithms are built using hand-designed programs containing rules defined by a domain expert human (Goodfellow et al., 2016).

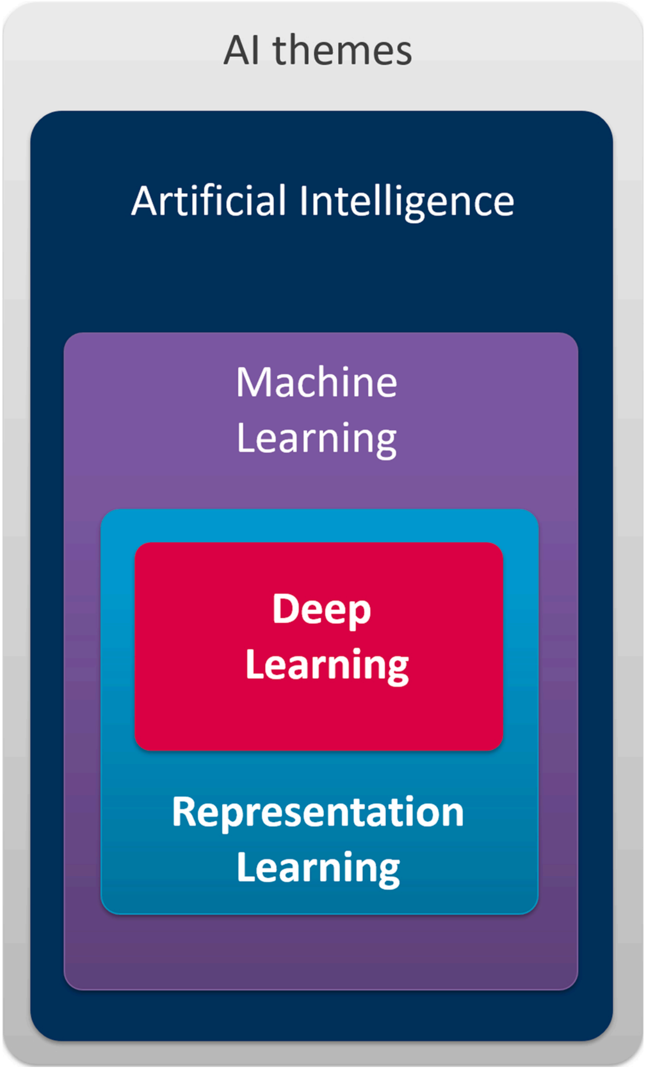

Fig. 1. Diagram representing the relationship between AI, machine learning, representation learning and deep learning.

Now, consider a customer that never bought on the platform. The defined rule will fail. A solution would be to use the age of the customer to perform recommendations based on product category. In this case, the age and product category are features defined by a human being. From these features, more rules could be established by a human specialist based on historical purchase data. But if the platform has diverse products and many customers, the definition of these rules becomes more difficult. Thus, a machine learning model could be trained from the historical data based on these features. Classic machine learning algorithms are a type of AI that needs a human to hand-design features which will be used by the algorithm to perform a mapping from features by extracting patterns and acquiring their own knowledge (Murphy, 2012).

Resuming the problem of product recommendation, besides the customer age, more features of customers can be important in real world scenarios. An approach generally used in this kind of problem is clustering the customers using representation learning algorithms. Representation learning algorithms are a kind of machine learning, but they start the learning process one step ahead of the classic machine learning algorithms. Representation learning methods have the capacity to learn from features inputted by a human and they are able to perform a mapping from features (Goodfellow et al., 2016). In the case of clustering the customers, representation learning models can decide the cluster of a client without the human being previously knowing it. However, due the number of features that exist in real-world contexts, the accuracy of the model could be improved if the features initially defined by the human being are used for the algorithm to map more abstract features. This is a capability of a deep learning algorithm.

Deep learning algorithms are a type of representation learning and they need the human being to define just simple features. From these simple features, they can define more abstract features in additional layers of learning and then perform a mapping from features (Goodfellow et al., 2016; LeCun et al., 2015). The term deep comes from these additional layers of learning.

2.2. *Artificial intelligence in organizations*

In the organizational perspective, the studies proposed in the early phases of AI began to assist the process of decision-making in the mid-1960s (Buchanan & O'Connell, 2006). At that moment, the AI field solved problems that could be described by a list of mathematical formulas (McCarthy & Hayes, 1981; Siklóssy, 1970).

AI has been used in business since the 1980s, being a target of investments and efforts from many companies to design and to implement computer vision systems, robots, expert systems, besides software and hardware for those purposes (Boden, 1984; Russell & Norvig, 2010). Moreover, at that time, AI had already begun to be cited as a strategic tool to improve organizational differentiation at a competitive scenario (Holloway, 1983; Porter & Millar, 1985).

Until the turn of the millennium, the studies on computer science in the AI field had focused on the algorithms, to create new approaches or to improve the existing ones (Zhuang, Wu, Chen, & Pan, 2017). Yet, since 2001, researchers have suggested that for many AI problems, the challenge was the volume of data, due to the existence of very large databases (Russell & Norvig, 2010). For this reason, new AI techniques were developed (Brynjolfsson & McAfee, 2017; Zhuang et al., 2017) enabled by the hardware evolution. This technological progress is attributed to the big data phenomenon, characterized by the interplay of technology, methodology and analysis capacity in order to search, aggregate, and cross-reference large data sets to identify patterns and to obtain insights (Boyd & Crawford, 2012).

In 2016, the Google DeepMind team presented to the world the real potential of AI technologies with AlphaGo, implemented with deep learning, which is one of the most important advances in machine learning throughout history (Hassabis, Suleyman, & Legg, 2017). AlphaGo is a computer program that plays the ancient game of Go and was trained from human experts moves and reinforcement learning from games of self-play (Silver et al., 2017). The AlphaGo was not built with rules and does not contain just moves planned by a human being, because the Go search space is enormous and it hinders the evaluation of board positions and moves to predict possibilities as in chess (Silver et al., 2016). Instead, it uses creativity and has the ability to identify and to share new insights about the game, showing how the AlphaGo algorithm is different from traditional AI (Silver et al., 2017). This ability made it possible for AlphaGo to beat the world champion Lee Sedol in a five-game match, with some moves that challenged millennia of Go wisdom (Hassabis et al., 2017).

The rise of AI in recent years and its development in many knowledge fields is due to three key factors: significant volume of data, improved algorithms, and substantially better computational hardware (Brynjolfsson & McAfee, 2017). This evolution has attracted the attention of large technology-oriented organizations to AI tools. Thus, companies such as Google, Amazon, Microsoft, Salesforce and IBM started to provide infrastructure for machine learning in the cloud, facilitating the access and use of cognitive technologies (Brynjolfsson & Mcafee, 2017; Davenport, 2018; Marr & Ward, 2019; Venkatraman, 2017).

Currently, in organizational contexts, AI can be considered a technology that has been introduced as a means of emulating human performance with the potential to draw its own conclusions through learning, which can aid human cognition or even replace human in tasks that require cognition (Chakravorti et al., 2019). In general, AI technologies can enable performance improvements in terms of speed, flexibility, customization, scale, innovation, and decision-making (Venkatraman, 2017; Wilson & Daugherty, 2018).

In addition, companies can benefit from the use of AI to generate value in different business dimensions: process automation; gaining insight through data for decision-making; engaging customers and employees; designing and delivering new products and services (Davenport & Harris, 2017; Davenport & Ronanki, 2018; Davenport, 2018; Lyall, Mercier, & Gstettner, 2018; Mikalef et al., 2019; Ransbotham, Gerbert, Reeves, Kiron, & Spira, 2018; Schrage & Kiron, 2018; Westerman, Bonnet, & McAfee, 2014).

2.3. The strategic use of technology

In this research context, AI tools are within the Information Technology (IT) field. IT involves human, organizational and administrative aspects, as well as encompassing information systems, data processing, software engineering, hardware and software (Keen, 1993; Porter & Millar, 1985).

Although a few scholars limit the concept of IT to technological factors, such as Alter (1992), we here consider the definition that also includes issues related to workflow, people and information, as understood by Porter and Millar (1985). Therefore, IT must be considered "broadly to encompass the information that businesses create and use as well as a wide spectrum of increasingly convergent and linked technologies that process the information" (Porter & Millar, 1985).

Despite the rise in the digital era, the role and impact of IT on the organizational context are not recent themes. In the late 1970s, researchers started to discuss the potential of IT to influence organizations competition (Benjamin, Rockart, Morton, & Wyman, 1983; Henderson & Venkatraman, 1992; Keen, 1991; King, 1978; McFarlan, 1984; Porter, 1979; Laurindo, 2008; Luftman, Lewis, & Oldach, 1993). In this direction, some scholars begun employing the term "strategic use" to refer to the potential of IT to shape new business strategies or to support existing ones, and to provide value to business (Frangou, Wan, Antony, & Kaye, 1998; Henderson & Venkatraman, 1999; Luftman et al., 1993; McFarlan, 1984; Philip, Gopalakrishnan, & Mawalkar, 1995; Porter & Millar, 1985). However, within this subject, there is a historical debate about the firms inability to generate value from investments in IT applications, which several authors attribute to the lack of alignment between the business and IT strategies (Bharadwaj et al., 2013; Cancino & Zurita, 2017; Chi, Huang, & George, 2020; Gerow, Grover, Thatcher, & Roth, 2014; Henderson & Venkatraman, 1999; Luftman et al., 1993; Masa'deh & Shannak, 2012; Mattos & Laurindo, 2017; Reich & Benbasat, 1996; Sabherwal & Chan, 2001; Shao, 2019).

Before proceeding with the explanation of the alignment between the business and IT strategies, it is important to understand what these concepts mean. Within the business domain, the conceptual frame of strategy consists of a large and growing body of multifaceted references that present heterogeneous approaches (Eisenhardt & McDonald, 2020; Hakansson & Snehota, 2006; Mintzberg & Lampel, 1999). The need for strategy is linked to the existence of competition, although there is a significant difference between natural competition and strategy. For Henderson (1989), natural competition is determined by probabilities and is evolutionary, while strategy is governed by reason and has a revolutionary character. Here, revolutionary means disrupting the natural course of events through deliberate interventions (Henderson, 1989).

From an organizational perspective, strategy focuses on accelerating the pace of change, aiming to modify the final result thus benefiting (or value) the firm that performed this intervention (Brandenburger & Stuart, 1996; Porter, 1996; Shimizu, Carvalho, & Laurindo, 2006). For some scholars, strategy is the planning of actions that generate competitive advantage for the business and the execution of these actions (Henderson, 1989). In other words, strategy involves the formulation of a well-structured plan about how to create value to business and its implementation (Campbell & Alexander, 1997). Besides the process of formulation and implementation, strategy can emerge in response to a situation (Mintzberg, 1987).

The plan formulation process, which results in the strategic plan (Campbell & Alexander, 1997), encompasses decisions related to competitive, product-market choices (Henderson & Venkatraman, 1999).

The implementation process, which means strategy execution or strategy implementation (Kaplan & Norton, 2000; Littler, Aisthorpe, Hudson, & Keasey, 2000; Neilson, Martin, & Powers, 2008; Bell, Dean, & Gottschalk, 2010), comprises the choices that concern the structure and capabilities of the enterprise to execute its product-market choices (Henderson & Venkatraman, 1999).

According to Porter (1996), the core of strategy is to achieve a unique and valuable position, encompassing the selection of a unique arrangement of activities to deliver a unique value arrangement, enabling the company to differentiate itself from its competitors. Thus, a well defined strategy must encompass these perspectives (Porter & Nohria, 2018).

The management and business literature also brings concepts pertaining to the strategy theory that categorizes it according to the diversification level of a company. For a diversified company, the strategy has two levels: corporate strategy and business strategy (Porter, 1987; Slack & Michael, 2002; Mintzberg, Ahlstrand, & Lampel, 2000). From a corporation perspective, corporate strategy concerns two questions: how the company should manage the range of business units and what businesses the corporation should be in (Porter, 1987). Business strategy is about how to compete in each business (Mintzberg et al., 2000).

Some scholars consider the concept of business strategy a synonym to competitive strategy, arguing that competitive strategy regards how to generate competitive advantage in each of the businesses in which a corporation competes (Andrews, 2005; Porter, 1987). However, the literature presents a series of studies that use the term business strategy to refer to strategy in a broad way, covering all the unfolding of the concept from an organizational perspective (Bharadwaj et al., 2013) and this is the definition adopted in this study. In this regard, business strategy can also be understood as an organizational strategy, which some authors define as the general direction in with the organization chooses to move to achieve its objectives and goals (Bharadwaj et al., 2013; King, 1978; Miles, Snow, Meyer, & Coleman, 1978).

The IT strategy has emerged as an unfolding of the business strategy at the functional level and should be expressed in terms of internal and external domains (Henderson & Venkatraman, 1999). The internal domain is related to how the information systems (IS) infrastructure should be designed and managed (Henderson & Venkatraman, 1999). The external domain concerns how the firm is positioned technologically in the market domain (Henderson & Venkatraman, 1999). The term IS strategy is also utilized with the same meaning as IT strategy (Chi et al., 2020; Shao, 2019).

According to Henderson and Venkatraman (1999), the alignment between the business and IT strategies is a process of continuous adaptation and transformation that encompasses not only business strategy and IT strategy, but also organization infrastructure and processes, and IT infrastructure and processes. Against this background, the strategic use of IT can enable the organization to keep up with changes in the competitive scenario (Laurindo, 2008).

Several models, theories and methodologies were proposed in the literature focusing on the use of IT aligned with the business strategy and operation (Gerow et al., 2014). Gradually, digital technologies have taken a leading position in the business strategies (Bharadwaj et al., 2013; Bughin & Catlin, 2019; Laurindo, 2008; Mattos, Kissimoto, & Laurindo, 2018; Venkatraman, 2017).

However, in the digital age, Bharadwaj et al. (2013) argue that it is necessary to rethink the role of IT strategy. Rather than being considered at the functional level and, in many cases, driven by a business strategy, as proposed by (Henderson & Venkatraman, 1992), the IT strategy must be integrated with the business strategy in a comprehensive phenomenon called digital business strategy (or digital strategy), which consists of an organizational strategy planned and executed to take advantage of the digital resources to obtain differential value (Bharadwaj et al., 2013; Venkatraman, 2017).

This view of the fusion of IT strategy with business strategy is also advocated by other authors of the literature, who believe that a dynamic synchronization between IT and business must occur to obtain a competitive advantage (Mithas, 2012; Prahalad & Krishnan, 2002; Mithas, Tafti, & Mithell, 2013). Prahalad and Krishnan (2008) highlight the importance of IT focused applications and of the analytic capacity provided by IT tools for building competitive advantages and innovations in the business strategy.

Despite the evolution of the theoretical and empirical contributions of studies that address the strategic use of digital technologies, when it comes to AI, it becomes significantly more complex because AI technologies are able to perform tasks that require cognition (Goodfellow et al., 2016; Hassabis et al., 2017). This capacity allows firms to radically change the scale, scope, and learning paradigms (Iansiti & Lakhani, 2020), which demonstrate the great potential of AI to provide value to business. Therefore, the strategic use of AI is related to harnessing this potential.

Despite the technological evolution in the last decade, academics and practitioners have discussed that technology is not the main challenge to adopting AI, but cultural obstacles, process and people (Bean, 2019; Duan, Xiu et al., 2019; Gursoy, Chi, Lu, & Nunkoo, 2019; Khakurel, Penzenstadler, Porras, Knutas, & Zhang, 2018). To address them, Davenport and Mahidhar (2018) argue that a strategy is necessary that properly includes information, technology components, people, management change and ambitions to transform the enterprise and the business. Naming the new generation of AI tools as cognitive technologies, the authors refer to that strategy as cognitive strategy (Davenport & Mahidhar, 2018).

The diagram in Fig. 2 illustrates the connection of IT and Strategy themes considered in this study, from an organizational point of view.

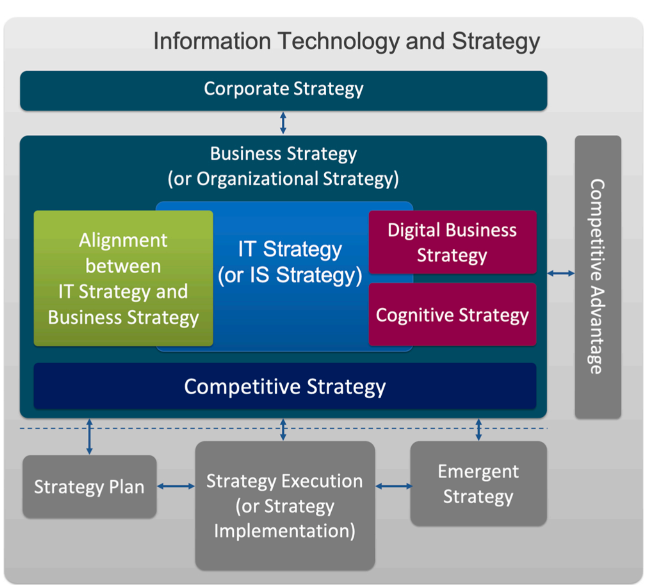

Fig. 2. Diagram representing the relationship between strategy concepts from organizational perspective.

3. Methodology

Given the changes occurred in the AI field in the last decade, the attention of top corporations for AI tools and the challenges involved in obtaining business value with the use of these type of technology, it is relevant to identify and to summarize the state of the literature about the relationship between AI and business strategy.

Thus, the following questions emerge:

RQ1 – Is there any evidence of the connection between the business strategy and the use of AI technologies?

RQ2 – What are the motivations to adopt AI strategically?

RQ3 – What potential advantages have been discussed regarding the strategic use of AI?

RQ4 – What impacts and benefits have enterprises received from using AI in the business strategy context?

RQ5 – What knowledge gaps exist in the current literature about the intersection between AI technologies and business strategy that future researches can investigate?

Considering these questions, this research was conducted using the systematic literature review method, following (Tranfield, Denyer, & Smart, 2003) in combination with Kitchenham (2004) and Kitchenham et al. (2009). As suggested by these authors, the literature review can be subdivided into three main phases: planning the review, conducing the review and reporting the review. The first two are detailed in this section. The final phase is presented in section 4.

This methodology has been used by several studies in the literature on information systems, technology applications and operational research (Al-Emran, Mezhuyev, Kamaludin, & Shaalan, 2018; Ali, Shrestha, Soar, & Wamba, 2018; Costa, Soares, & de Sousa, 2016; Gupta, Kar, Baabdullah, & Al-Khowaiter, 2018; Lepenioti, Bousdekis, Apostolou, & Mentzas, 2020; Martins, Gonçalves, & Petroni, 2019).

3.1. Planning the review

Based on the research questions and using the theoretical background of AI, information technology and business strategy domains, this study focused on the following meanings: "artificial intelligence", "machine learning", "deep learning", "representation learning", "strategic plan", "emergent strategy", "strategy execution", "competitive strategy", "competitive advantage", "digital strategy", "business strategy", "corporate strategy", "organizational strategy", "information technology strategy", "cognitive strategy" and "strategic use". In addition to the main concepts, its synonymous were defined.

The digital databases considered for this study were Web of Science and Scopus, which were used by multiple researches in the literature (Agarwal, Kumar, & Goel, 2019; Busalim & Hussin, 2016; Gupta et al., 2018; Rekik, Kallel, Casillas, & Alimi, 2018).

In line with Kitchenham et al. (2009) and Kitchenham (2004), to investigate the research questions, the following inclusion criteria were established: (i) journal and conference papers that addressed the intersection between AI and business strategy domain, containing the terms in title, abstract or keywords (ii) journal and conference papers written in English; (iii) journal and conference papers published since 2009, when the relationship between AI technologies and business strategy themes began to gain space in the literature (López-Robles, Otegi-Olaso, Porto Gómez, & Cobo, 2019). Moreover, the exclusion criterion was defined: (i) papers using the term strategy outside the organizational perspective (such as computational approach, for example). For the study quality assessment, the following exclusion criteria were applied: (i) papers with the terms just in abstract cited to present the study context; (ii) full article not available in electronic document.

As recommended by Kitchenham (2004) and Kitchenham et al. (2009), the data extraction process was planned based on the research questions and to highlight differences and similarities between studies' outcomes. Thus, the following elements were identified: source of publishing; year when the paper was published; author (s); AI technology function in organizational context addressed by paper; strategic aspects of the AI use discussed in the article; motivation of AI strategic use; classification of the AI technology used; research method; impacts and benefits from AI application; research target industry; challenges to AI adoption.

According to Tranfield et al. (2003), Kitchenham (2004) and Kitchenham et al. (2009), the step after the data extraction is the research synthesis. In this stage, methods for synthetizing, integrating and cumulating the findings of different studies can be used. Therefore, the intersection of the AI and business strategy themes was investigated in light on the perspective of the digital business strategy: the sources of business value creation and capture, proposed by Bharadwaj et al. (2013). For this, the papers were studied by means of the function exercised by AI application in an organizational context for generating or obtaining business value. In addition, AI applications were categorized according to their business dimensions: automation; decision support; customers' and employees' engagement; proposition of new products and services (Davenport & Harris, 2017; Davenport & Ronanki, 2018; Davenport, 2018; Lyall et al., 2018; Mikalef et al., 2019; Ransbotham et al., 2018; Schrage & Kiron, 2018; Westerman et al., 2014).

3.2. Conducing the review

The search was performed using the Web of Science and Scopus scientific databases using the final strings in Table 1. Drawing on the methodological frameworks of Tranfield et al. (2003); Kitchenham (2004) and Kitchenham et al. (2009), the systematic literature review was performed based on a multilevel process to systematically identify and summarize the fragmented literature about the strategic use of AI.

Therefore, the selection process comprehended the stages shown in Fig. 3 and followed the procedures described below:

- The terms were searched in abstracts, titles and keywords, without any other constraints. In this phase, the following articles information were exported: title, authors, abstract, publication year, keywords, source title, document type and language. Thus, the articles exported metadata were saved on Microsoft Excel spreadsheets and the duplicated studies were eliminated.

- The inclusion and exclusion criteria were applied. The full articles selected were exported and the quality criteria were applied.
- Based on the full content of each selected article, the data extraction was performed.

Table 1
Final Strings considering the search process strategy with inclusion and exclusion criteria.

Scientific database	Search String
Scopus	TITLE-ABS-KEY ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Represent* Learning") AND TITLE-ABS-KEY ("strateg* plan" OR "emergent* strateg*" OR "strateg* execution" OR "strateg* implementation" OR "competitive strateg*" OR "competitive advantage*" OR "digital strateg*" OR "business strateg*" OR "corporate strategy" OR "organi*ational strategy" OR "information technology strateg*" OR "IT*strategy" OR "IS*Strategy" OR "cognitive strateg*" OR "strategic use" OR "strategic usage")
Web of Science	TS= ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Represent* Learning") AND TS= ("strateg* plan" OR "emergent* strateg*" OR "strateg* execution" OR "strateg* implementation" OR "competitive strateg*" OR "competitive advantage*" OR "digital strateg*" OR "business strateg*" OR "corporate strategy" OR "organi*ational strategy" OR "information technology strateg*" OR "IT*strategy" OR "IS*Strategy" OR "cognitive strateg*" OR "strategic use" OR "strategic usage")

4. Reporting the review

This section presents the results of the literature review, which were obtained through an analysis process that considered the research methodology detailed in Section 3 (Kitchenham, 2004; Kitchenham et al., 2009; Tranfield et al., 2003).

As depicted in Fig. 4, the documents distribution throughout the years shows that there is an exponential growth of the number of papers published in the last two years. In addition, an analysis about the sources and authors showed that there is no specific editor, conference, research group or author in the sample examined.

4.1. AI tools and business strategy

RQ1 regards the existence of evidence about the connection between the business strategy and the use of AI technologies. Analysing the sample of selected articles from the business strategy perspective, papers considering general business strategy were the most numerous, representing 53.66 % (22). The use of AI to align IT strategy and business strategy were found in 21.95 % (9) of the articles. The IT strategy was discussed by 2.44 % (1), while the topic competitive strategy was addressed by 9.76 % (4). Regarding to digital strategy, the theme was cited by 12.2 % (5). Fig. 5 shows these percentages.

The literature review of the selected articles through the AI lens shows that techniques of *classic AI* (or *general AI)* were addressed by 58.54 % (24) of the selected articles. The theme *machine learning* was the focus of 24.39 % (10), while *representation learning* had the attention of 12.20 % (5). *Deep learning* was addressed by just 4.88 % (2) These percentages can be observed in Fig. 6.

The sample of selected articles was initially examined according to the themes of the studied fields separately. Therefore, Fig. 7 shows the number of papers mapped by each theme.

The analysis of the literature intersection between AI and business strategy allowed verifying that the sample selected articles addressed the strategic aspects of AI use to help the decision- making process in the perspective of **decision support**; to improve *stakeholder relationship* in both the **automation** and **customer and employee engagement** dimensions; and to enable *machine-to-machine* communication in the dimension of **new products and services offering**.

Table 2 presents the references belonging to each category, which are discussed in the following subsections.

From the perspective of the industry explored by the research works analyzed (Fig. 8), most of them addressed the strategic use of AI in multiple contexts and for assisting the decision making process. The papers that dealt with AI use without applying it to a specific organizational sector focused on AI applications design or implementation.

4.1.1. Decision making process

Although the use of AI technologies in the decision-making process is a practice that began in the 1960s, most research works presented in the studied literature sample still discuss or cite examples about this theme.

In this context, one challenge faced by organizations is related to decisions involved in planning the IT systems considering the business strategy goals. Cebeci (2009) and Ali and Xie (2011) proposed the use of AI tools to select the best alternative from a set of options for implementing enterprise resource planning (ERP) systems considering the business strategy perspective and goals. Cebeci (2009) contributed with the use of the Balanced Scorecard theory (Kaplan & Norton, 1996) to match the ERP package objectives with the business goals, while Ali and Xie (2011) provided critical factors to successfully implement ERP systems.

The design of decision support systems considering the principles of strategic information systems planning was proposed by Kitsios and Kamariotou (2016), through a conceptual framework that can help the decision process towards the business strategy. The authors implicitly argue about the use of AI for problem recognition tasks and prediction of

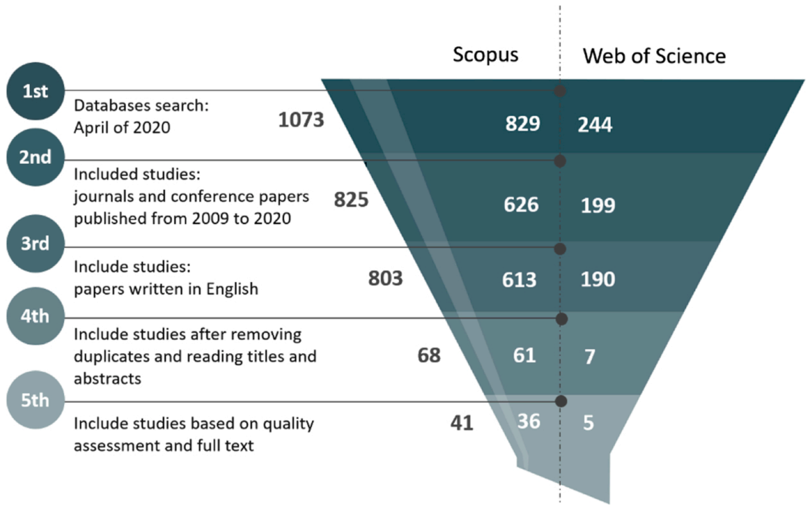

Fig. 3. Number of papers in each phase of the selection process.

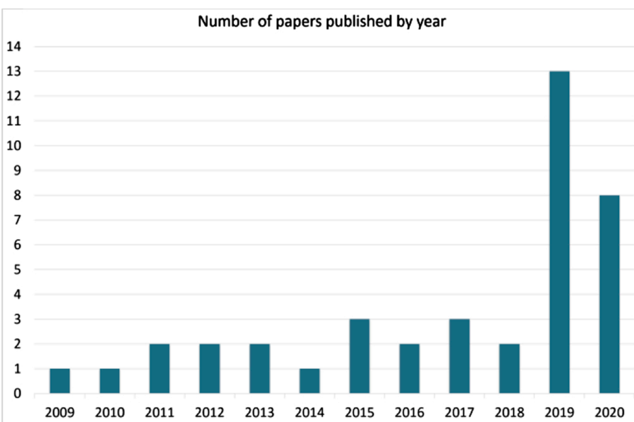

Fig. 4. Number of papers published by year.

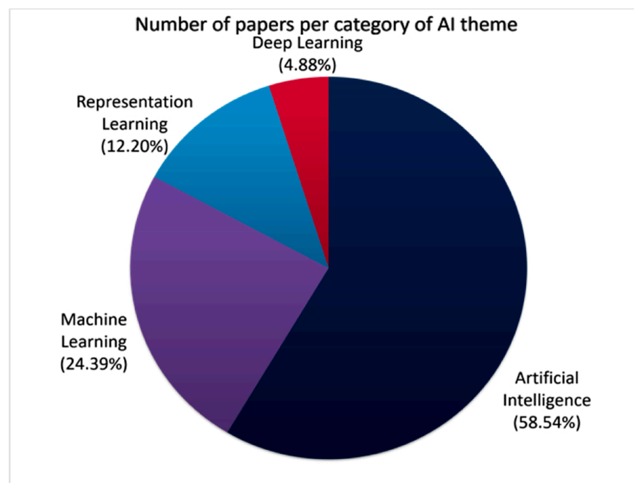

Fig. 6. Number of articles by category of AI discipline found in the sample studied.

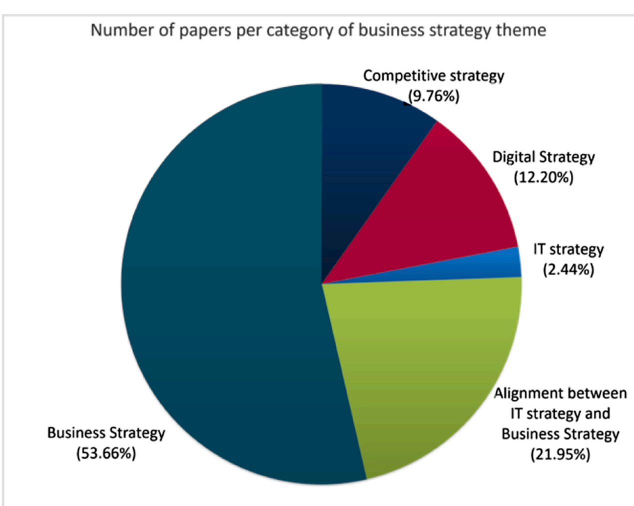

Fig. 5. Number of papers of sample studied per business strategy theme.

the most suitable alternative to be implemented.

Thompson, Ekman, Selby, and Whitaker (2014) presented a framework that uses AI to identify the most economically beneficial IT infrastructure configuration to ensure that design choices are consistent with the enterprise strategy.

Analytics tools based on AI are part of an important topic in the decision support theme, since they provide information and knowledge based on data (Kiron & Schrage, 2019). In this direction, Demirkan and Delen (2013) proposed a conceptual framework that helps the development and implementation of decision support systems in cloud, contributing to IT strategy. Alternatively, Dąbrowski (2017) idealized an adaptive conceptual framework that uses machine learning to facilitate data-driven decisions and promotes goal-modelling and reasoning as regards IT initiatives.

Analogously, the use of AI as part of advanced analytics solutions as a source of value to business was discussed in the literature. Nalchigar and Yu (2017) and Harlow (2018) idealized conceptual models that include AI technologies, representation learning and machine learning techniques to perform classification and prediction tasks with the promise of aligning analytics requirements with the business strategy. Boselli, Cesarini, Mercorio, and Mezzanzanica (2018) proposed the use of representation learning for monitoring and classifying online job advertisements and providing useful information to business to make better decisions about the labour market. Elacio, Balazon, and Lacatan (2020) proposed a model that uses machine learning to manage employee retention. Lichtenthaler (2020a) introduced a conceptual discussion about the organizational advantages in terms of competitiveness

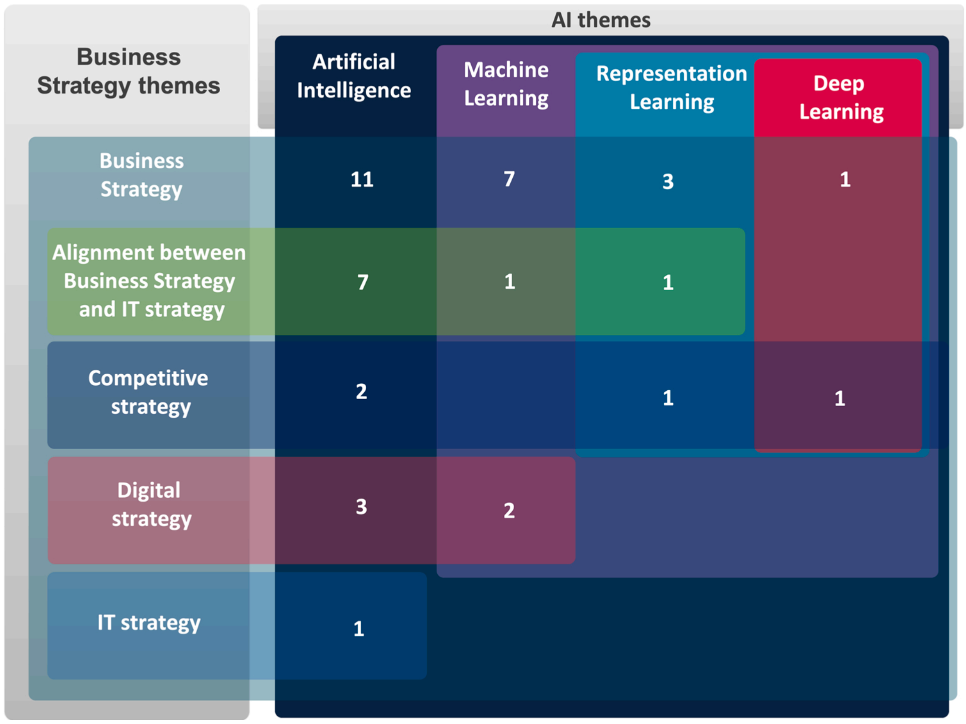

Fig. 7. Research map of the literature intersection between business strategy and AI.

Table 2
Classification of papers according to the dimension of AI application in organizational context.

Function of AI Application	References	Count
Decision Making Process	Song et al. (2017); Cannavacciuolo et al., 2015; Harlow, 2018; Boselli et al., 2018; Kiron & Schrage, 2019; Luo & Xu, 2019; Laínez et al., 2010; Ali & Xie, 2011; Demirkan & Delen, 2013; Thompson et al., 2014; Kitsios & Kamariotou, 2016; Nalchigar & Yu, 2017; Dąbrowski, 2017; Lee et al., 2012; Neshat & Amin-Naseri, 2015; Poplawska et al., 2015; Touati et al., 2017; Cebeci, 2009; Ching & De Dios Bulos, 2019; Arora et al., 2020; Bello-Orgaz et al., 2020; Hsu et al., 2020; Elacio et al., 2020; Choy et al., 2016; Janjua & Hussain, 2012;	25
Stakeholder Relationship	Black & van Esch, 2020; Tienkouw et al., 2011; Kreps & Neuhauser, 2013; Caputo et al., 2019; Duan, Xiu et al., 2019; Sujata, Aniket, and Mahasingh (2019); Bhãle, 2019; Lichtenthaler, 2019; van Esch & Black, 2019;	9
Machine-to-machine communication	Blitz & Kazi, 2019;	1
Decision Making Process ∩Stakeholder Relationship	Zaki, 2019; Miklosik et al., 2019; Gloor et al., 2020;	3
Decision Making Process ∩ Machine-to-machine communication ∩ Stakeholder Relationship	Brock & von Wangenheim, 2019; Lichtenthaler, 2020b, 2020a;	3

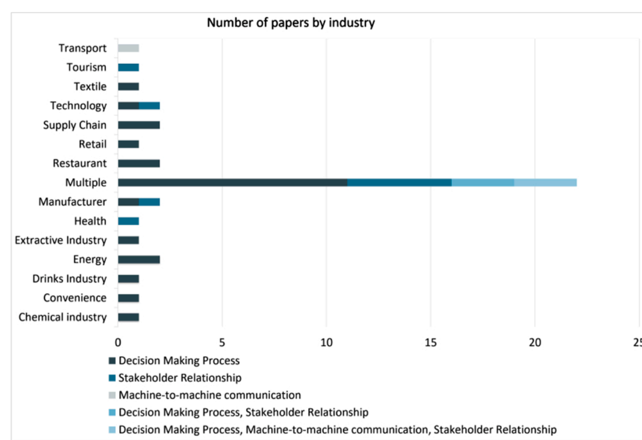

Fig. 8. Number of research works analyzed by industrial context.

obtained from advanced analytics, as a result of combining of human intelligence and artificial intelligence.

The importance of data-driven decision approaches was also addressed by Janjua and Hussain (2012). Using representation learning to resolve tasks of natural language processing and reasoning, the authors proposed a conceptual framework that can be used to develop decision support systems that reason over the data present across enterprise boundaries.

The predictive analytics field also was tackled by Lee, Shih, and Chen (2012) but focusing on the sales forecast problem. The researchers employed representation learning algorithms in a framework developed for producing daily sales fore casting, which can be a useful tool to enhance business strategies and to increase competitive advantages. Hsu, Chang, and Lin (2020) addressed the use of AI in predictive analytics applications for operating performance evaluation and forecasting.

Still in the direction of supporting decisions related to sales, but aiming to personalize the service and to recommend products, Song et al. (2017) explored the use of deep learning in a customer recognition application. The authors proposed a system, composed of software and cameras, which recognize customers in retail physical stores aiming to provide accordingly information to business strategy, enabling changes in sales strategy planning.

The decision support function of AI-based solutions was also discussed in social responsibility and sustainability themes. Poplawska, Labib, and Reed (2015) introduced a hybrid framework that uses classic AI techniques to guide the decisions about the priority alternative of the company social responsibility program to be implemented for incorporating it into the business strategy. Choy et al. (2016) focused on sustainability and used AI algorithms to define priorities and policies for establishing operation strategies from the identification of business strategies. These operation strategies optimize the chemical products production process conditions with the aiming to avoid unnecessary energy consumption.

Neshat and Amin-Naseri (2015) planned a multi-agent intelligence using a machine-learning algorithm in order to develop a suitable platform for sustainable energy systems planning that considers the market dynamics and the demand side interactions via an inter-temporal modification mechanism, contributing to the business strategy planning. Alternatively, Touati et al. (2017) proposed a model that uses machine learning to predict the output power from solar photovoltaic panels, which enables the strategic planning and management of the energy systems under diverse environmental conditions.

Suppliers management was another topic explored by the literature studied using AI in solutions to support decision. In this sense, Cannavacciuolo, Iandoli, Ponsiglione, and Zollo (2015) combined the use of AI and the aggregation of indicators related to business strategic needs to develop a system to guide companies in the evaluation of suppliers' portfolio. The authors adopted the resource-based view paradigm (Prahalad & Hamel, 1990) for enterprise competencies assessment and used an AI algorithm to calculate an indicator associated to all the assessed competencies.

In the same context of decision support, researches of the studied literature discuss about the use of AI to support marketing decisions. Laínez, Reklaitis, and Puigjaner (2010) proposed an approach using classic AI to assist managers in deciding the product pricing, the investments in advertising and other marketing strategies, also the production and distribution planning. Miklosik, Kuchta, Evans, and Zak (2019) discussed the important role of intelligent analytical tools in the development and execution of marketing strategies, but the study findings demonstrated the low level of adoption of the analytical applications based on machine learning to marketing management.

The use of social media was addressed by Arora, Srivastava, and Bansal (2020). The researchers designed and implemented a model using machine learning to detect if posts are promoted or organic in order to support marketing on monitoring and analyzing the social media behaviors of competitors (Arora et al., 2020).

Gloor, Fronzetti Colladon, de Oliveira, and Rovelli (2020) presented the system *Tribefinder*, an instrument implemented with deep learning, able to identify customers (or potential customers) tribes on Twitter. According to the authors, tribes are groups composed by heterogeneous individuals connected by a shared emotion. For Gloor et al. (2020), *Tribefinder* can contribute to improving firms' competitive advantage by offering a way to manage their marketing strategy and, consequently, their competitive strategy.

Also thinking of helping the marketing strategy formulation by using AI and data from Twitter, Bello-Orgaz et al. (2020) proposed a practical application to extract, model, and analyze collective behavior on Twitter activity, reflecting the responses of users to both the brand and other users' actions.

Still regarding marketing strategy, Ching and De Dios Bulos (2019) proposed the use of machine learning applications to assign customers sentiments to online restaurant reviews of the Yelp platform and use this information to suggest business strategies to improve customer experience. Similarly, Luo and Xu (2019) used the same platform and implemented an approach using machine learning to extract the main aspects from online restaurant reviews to assign customers sentiments to reviews. According to Luo and Xu (2019), the proposed approach can help restaurateurs better understand how to meet customers' needs and maintain competitive advantages.

4.1.2. Stakeholder relationship

The AI-based applications were also discussed within the (potential) customer relationship theme. Tienkouw et al. (2011) projected a system to help users to easily create their one-day trip schedule, using AI to optimize the time at each attraction considering the total travel time. The design of this system was planning based on Porter (1996) concepts of competitive strategy to obtain competitive advantages in terms of cost leadership, differentiation and market focus.

Within the medicine domain, Kreps and Neuhauser (2013) analyzed deficiencies in e-health communication programs and proposed the strategic use of general AI to engage patients and suppliers in the interaction with an application called *ChronologyMD*, which allows collecting observations of patients' daily living. For Kreps and Neuhauser (2013), this information is useful to increase consumer engagement and enhance health outcomes.

The use of AI tools to enhance customers experience by providing better personalization, quality of service and hassle-free service was discussed by Sujata, Aniket, and Mahasingh (2019) and Zaki (2019). The study of Sujata et al. (2019) introduced a conceptual model to help the alignment between IT strategy and business strategy. In the proposed model, the researchers included the strategic use of AI on applications such as sentiment analysis, emotion detection, virtual assistants, chatbots and content curation lead. Zaki (2019), on the other hand, presented a conceptual argumentation about the adoption of AI technologies motivated by the aims of customer experience improvement.

Considering the use of AI as a new advertising style for the product of e-channel, Duan, Xiu et al. (2019) investigated how the AI-push affects the profits of manufacturers and remanufacturers. Miklosik et al. (2019) also addressed the use of AI to automation applied to processes, such as reporting, creating and optimizing advertising campaigns, and communication with customers. However, neither study discussed the problems related to the consumers–AI interaction.

Bhāle (2019) explored the autonomous digital assistance theme using AI in chatbots and investigated customer satisfaction from the technology acceptance perspective. According to Bhāle (2019), although some researchers argue that customers do not like to realize that they are interacting with machines, it is possible to create value to business with digital assistance as well to improve customer experience.

Considering firms internal domain, the literature reviewed presented conceptual studies. Caputo, Cillo, Candelo, and Liu (2019) investigated the relations between technology and human resources soft skills in big data environments. They found that human resources competences, emotions, behaviors and motivations influence the strategic results of AI adoption. Moreover, Lichtenthaler (2019), argued that employee attitudes are crucial to obtain benefits from AI.

Still in the perspective of human resources management, van Esch and Black, 2019 and Black and van Esch (2020) evaluated the features that can influence prospective employees to engage with virtual assistant or chatbots, arguing that candidates recruitment f has moved from tactical human resources activity to a strategic business priority.

Regarding the relationship of AI and employees, Lichtenthaler (2020a) suggested that the value of AI applications can be acquired from the management of multiple types of intelligence in line with corporate strategy and business strategies: human intelligence, artificial intelligence and meta-intelligence. For Lichtenthaler (2020a), meta-intelligence involves the recombination and renewal of the different types of intelligence, which is similar to the intertemporal evolution of organizational innovation processes and capabilities.

4.1.3. Machine-to-machine communication

The use of AI tools in-product was conceptually presented by Blitz and Kazi (2019), describing the challenge of autonomous charging stations. In their vision, AI allows a smart grid to enable different new business opportunities related to hardware, software, operations, financial services and others. Although the authors discussed AI in a generic way and did not specify any technology in particular, for them, AI tools can be used to automatize station selection and scheduling; the recharge task itself; payment; and the communication of stations networks. For Blitz and Kazi (2019), strategists need to be prepared to the future of transportation and to take advantage of the AI technologies potential to create and to develop these new business opportunities.

In a more realistic way, Brock and von Wangenheim (2019) offered empirical evidences about the use of AI in smart products, but they focused on general AI. Alternatively, Zaki (2019) cited new products with virtual assistants using voice recognition technology as a way to enable interaction between humans and cognitive technologies.

4.2. Motivation of AI strategic adoption

Although some studies indicate that the overall use of AI is primarily driven by the technological potential and not by the real business needs (Bean, 2019; Davenport, 2018; Lichtenthaler, 2020a), **RQ2** concerns the motivation that leads to AI strategically usage. Thus, in the literature sample studied, most studies (65.85 %) were motivated by business needs, while 24.39 % focus on the technological potential to solve problems and less than 1% cited both. Table 3 presents these numbers along with references.

4.3. The impacts and benefits of AI strategic use

Seeking to investigate **RQ3** and **RQ4**, the research results evidence of each paper studied was categorized. Through the theoretical results found, potential advantages of the connection between AI technologies and business strategy were analyzed. Alternatively, in papers with empirical contributions, the (negative or positive) impacts and benefits that enterprises have received from the AI strategic use were identified. Table 4 presents the references for each research evidence category separated by function performed by AI application in the organizational domain.

Regarding theoretical research works from the studied literature, the following potential advantages were cited:

Table 3
References of the key motivation to AI adoption.

Key Motivation	References	Count
Business needs	Song et al., 2017; Tienkouw et al., 2011; Cannavacciuolo et al., 2015; Boselli et al., 2018; Kreps & Neuhauser, 2013; Caputo et al., 2019; Kiron & Schrage, 2019; Luo & Xu, 2019; Duan, Edwards et al., 2019; Laínez et al., 2010; Sujata et al., 2019; Ali & Xie, 2011; Thompson et al., 2014; Kitsios & Kamariotou, 2016; Lee et al., 2012; Dąbrowski, 2017; Neshat & Amin-Naseri, 2015; Poplawska et al., 2015; Touati et al., 2017; Cebeci, 2009; Ching & De Dios Bulos, 2019; Arora et al., 2020; Bello-Orgaz et al., 2020; Elacio et al., 2020; Hsu et al., 2020; Choy et al., 2016; Gloor et al., 2020;	27
Technological Potential	Black & van Esch, 2020; Blitz & Kazi, 2019; Harlow, 2018; Brock & von Wangenheim, 2019; Demirkan & Delen, 2013; Nalchigar & Yu, 2017; Bhäle, 2019; Lichtenthaler, 2019; van Esch & Black, 2019; Janjua & Hussain, 2012;	10
Business needs ∩ Technological Potential	Zaki, 2019; Miklosik et al., 2019; Lichtenthaler, 2020a, 2020b;	4

Table 4
References by category of research evidences.

Function of AI Application	Research Evidence Category	
	Theoretical	Empirical
Decision Making Process	Boselli et al., 2018; Kiron & Schrage, 2019; Luo & Xu, 2019; Ali & Xie, 2011; Thompson et al., 2014; Kitsios & Kamariotou, 2016; Neshat & Amin-Naseri, 2015; Poplawska et al., 2015; Cebeci, 2009; Ching & De Dios Bulos, 2019; Arora et al., 2020; Bello-Orgaz et al., 2020; Hsu et al., 2020; Elacio et al., 2020; Choy et al., 2016;	Song et al., 2017; Cannavacciuolo et al., 2015; Harlow, 2018; Laínez et al., 2010; Demirkan & Delen, 2013; Nalchigar & Yu, 2017; Dąbrowski, 2017; Lee et al., 2012; Touati et al., 2017; Janjua & Hussain, 2012;
Stakeholder Relationship	Kreps & Neuhauser, 2013; Duan, Xiu et al., 2019; Bhäle, 2019; van Esch & Black, 2019	Black & van Esch, 2020; Tienkouw et al., 2011; Caputo et al., 2019; Sujata et al., 2019; Lichtenthaler, 2019;
Machine-to-machine communication		Blitz & Kazi, 2019;
Decision Making Process ∩ Stakeholder Relationship	Miklosik et al., 2019; Gloor et al., 2020;	Zaki, 2019;
Decision Making Process ∩ Machine-to-machine communication ∩ Stakeholder Relationship	Brock & von Wangenheim, 2019;	Lichtenthaler, 2020b, 2020a;
Count	22	19

- Business strategy improvement with predictive analytics (Demirkan & Delen, 2013; Lee et al., 2012; Dąbrowski, 2017; Touati et al., 2017); by optimizing key performance indicators (Schrage & Kiron, 2018); and with image recognition to identify customer behavior (Song et al., 2017);
- Selection of the best alternative for IT infrastructure configuration plans according to future business conditions and its impacts on the need to make IT changes (Thompson et al., 2014);
- Effective implementation of decision support systems to guide strategic decision- making (Cannavacciuolo et al., 2015);
- Integration of corporate functional areas information to improve the management of supply and demand (Laínez et al., 2010);
- New business opportunities and capacity for innovation (Blitz & Kazi, 2019; Zaki, 2019);
- Competitive advantage with customer experience improvement (Tienkouw et al., 2011; Zaki, 2019);
- Producing actionable information present across organizational boundaries based on reasoning to assist business decision (Janjua & Hussain, 2012);
- Gaining advantage of segmenting populations to personalize actions and even replace or support human decision-making (Harlow, 2018);
- Allowing firms human resources to focus on the more productive processes (Caputo et al., 2019);
- Enhancing customer experience by providing better personalization, quality of service and hassle-free service (Sujata et al., 2019; Zaki, 2019).

According to the empirical results of the literature review, the implementation of AI applications considering business strategy within the decision support domain can benefit enterprises with:

- Planning IT systems with more accuracy (Ali & Xie, 2011; Cebeci, 2009);
- Strategic decision-making considering internal and external factors (Poplawska et al., 2015);
- Elimination of some difficulties regarding describing products attributes and machine settings (Choy et al., 2016);
- Products quality improvement (Choy et al., 2016);
- Market behavior classification (Neshat & Amin-Naseri, 2015);
- Reduction of the number of trials and materials in product development and production processes (Choy et al., 2016);
- Efficiency and effectiveness improvement of employees' recruitment (van Esch & Black, 2019);
- Enhancing business strategies based on sales forecast (Lee et al., 2012) and performance forecast (Hsu et al., 2020);
- Real-time labour market monitoring to drive the identification of strategic decisions to improve firms market share (Boselli et al., 2018);
- Monitoring users' responses to the brand actions from Twitter data to improve the marketing strategy formulation process (Bello-Orgaz et al., 2020);
- Providing useful information for human resources management to augment the retention of employees (Elacio et al., 2020);
- Better understanding how to meet customers' needs (Ching & De Dios Bulos, 2019; Luo & Xu, 2019);
- Providing insights related to a brand competitors behaviors and marketing strategies (Arora et al., 2020).

In the context of customer relationship, the empirical studies show that the strategic use of AI enables customer experience improvement by reducing the service resolution times with digital assistance and, consequently, decreasing churn in the contact centers (Bhāle, 2019). Moreover, the use of AI can provide sustainability business strategy alternatives, such as new advertising styles for e-channels (Duan, Xiu et al., 2019). Despite the positive impacts and benefits of AI, the use of cognitive technologies also involves negative implications (Davenport, 2018). However, these negative impacts were discussed just conceptually by the studied literature (Caputo et al., 2019; Lichtenthaler, 2020a, 2020b; Lichtenthaler, 2019).

5. Discussion, challenges and future research opportunities

Although the literature review shows the use of AI in connection with business needs and strategies, the results indicate that this intersection was little explored by the academy and still holds open questions and challenges. Therefore, this section presents the results of **RQ5** investigation. Fig. 9 shows the proposed framework based on findings, highlighting the gaps for future studies.

The new generation of AI (or cognitive technologies) which comprehend the technologies involving cognition, and little depend on or eliminate human beings to perform tasks was discussed just in specific contexts (Bhāle, 2019; Lee et al., 2012; Song et al., 2017); for applications with no focus on AI tool aspects (Janjua & Hussain, 2012; Nalchigar & Yu, 2017); or for introducing conceptually managerial implications (Caputo et al., 2019; Lichtenthaler, 2020a, 2020b; Lichtenthaler, 2019). Only two papers focused on the aware use of *deep learning* (Gloor et al., 2020; Song et al., 2017).

Considering the above mentioned, challenges and future research opportunities were established based on the literature review results. Thus, knowledge gaps and research propositions were defined in terms of sources of value creation with the user of AI and its connection with business strategy. These challenges and propositions are described below.

5.1. Decision support

According to the literature review results, the connection between AI and business strategy to decision support was addressed by most papers. However, recent advances in deep learning (Goodfellow et al., 2016) have not been well addressed yet. Likewise, no empirical evidence about the automation of the decision-making effectiveness was found. This result may be related to the complexity of the interaction between human and AI, which also affects decision-making automation (Barro & Davenport, 2019; Caputo et al., 2019; Lichtenthaler, 2019; Miklosik et al., 2019). Some AI technologies need a human expert in the problem domain to establish hypotheses and to select relevant features (Russell & Norvig, 2010), but the fear of job elimination can lead human beings not to provide useful information to AI model creation (Ransbotham et al., 2018). In turn, deep learning techniques can extract patterns from data by themselves (LeCun et al., 2015), but it is hard for humans to understand and to explain the results (Davenport, 2018). However, in the era

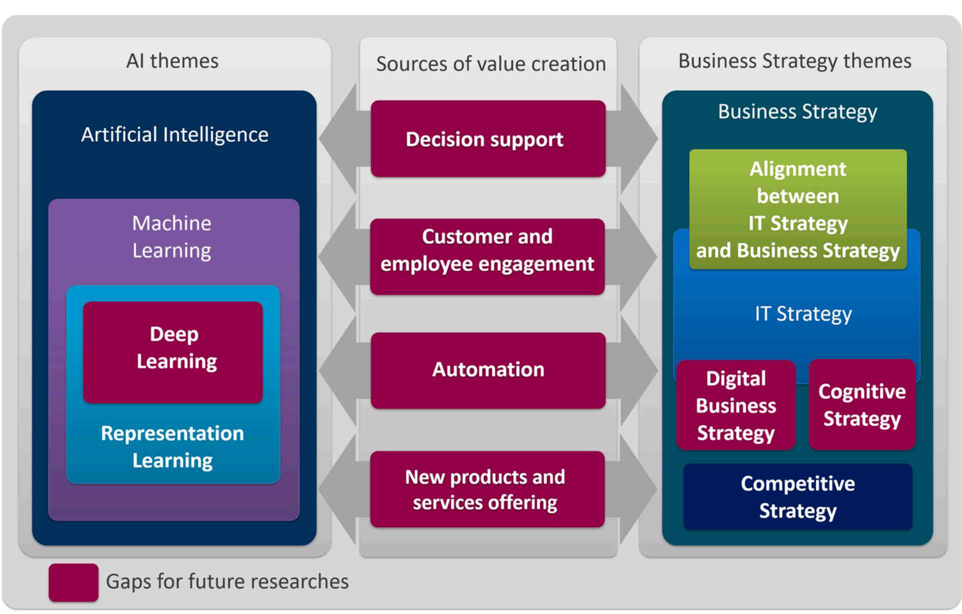

Fig. 9. State of the literature about the intersection between the use of AI tools and business strategy.

of big data and the need for speed to conduct business, AI technologies can make better decisions than humans in some contexts and human can decide better when judgment is required (Colson, 2019; Lichtenthaler, 2019). Thus, it is important to analyze how leaders formulate strategies to take advantage of the AI potential and to adjust the AI-human equation for generating value to business (Lichtenthaler, 2020a, 2019). Proposition1was outlined based on this context.

Proposition 1. . The adjustment of the AI-human equation in alignment with business needs and digital strategies is important for companies to successfully implement applications based on the new generation of AI technologies.

5.2. Customer and employee engagement

The literature review results show that the strategic use of AI technologies for customer and employee engagement has not been well exploited yet, since few papers discussed customer experience improvement. Although Bhāle (2019) and Duan, Xiu et al. (2019) showed that the use of AI in customer relationship generated value to business and Sujata et al. (2019) and Zaki (2019) presented a theoretical discussion about the use of AI to enhance the customer experience, the results are not generalizable because the use of AI interaction with humans is complex (Caputo et al., 2019). Among the reasons for this complexity, humans may not like to notice they are being served or understood by a machine (Bhāle, 2019). Thus, this type of reaction can negatively affect the business (Lichtenthaler, 2019). Therefore, the interaction of customers and AI applications using an appropriate digital strategy requires further research. In this context, the following proposition was e established:

Proposition 2. . The use of the new generation of AI technologies can create competitive advantages by improving customers' experience and engagement through the applications designed based on digital strategy.

The interface between employees and AI technologies was also addressed by the literature, indicating issues about the AI use in organizational contexts due to the possible deep change in workforce and consequent job reduction; the lack of confidence in AI decisions, recommendations and responses (Bean, 2019; Davenport, 2018; Khakurel et al., 2018; Ransbotham et al., 2018; Wilson & Daugherty, 2018; Barro & Davenport, 2019; Caputo et al., 2019; Lichtenthaler, 2019). Hence, there is a need for investigating digital strategies to reduce the negative impacts of AI use while improving employees' engagement (Duan, Xiu et al., 2019; Kiron & Schrage, 2019; Lichtenthaler, 2020a, 2020b). The proposition below was thus defined:

Proposition 3. . Enterprises can obtain competitive advantages by using the new generation of AI technologies with an appropriate digital business strategy to increase employees' engagement.

5.3. Automation

In the sample of articles studied, the theme automation was discussed in only a few papers (Caputo et al., 2019; Bhāle, 2019; Miklosik et al., 2019; van Esch & Black, 2019; Black & van Esch, 2020). This may be because, in the past, automation was typically associated with efficiency improvement to reduce costs rather than obtaining competitive advantage (Farbey, Land, & Targett, 1995; Laurindo, 2008; Satell, 2017).

Facing the digital era opportunities, some researchers found automation the most common type of AI application in organizations, due to its easy implementation and rapid return on investment (Davenport & Ronanki, 2018; Fountaine, McCarthy, & Saleh, 2019; Venkatraman, 2017). Perhaps because more recently there is an view that automation can create competitive advantage if used to automate tasks faster than competitors and a greater number of tasks (Venkatraman, 2017). For this reason, it is necessary a digital business strategy to achieve benefits through AI use in automation tasks (Jesuthasan & Boudreau, 2017). Moreover, it is necessary to establish and to develop capabilities that involve business rules to harness automation to obtain advantages (Davenport, 2019). More complex tasks require human resources to develop an adequate level of confidence with the technology (Caputo et al., 2019). Proposition 4 was thus defined.

Proposition 4. . The use of a new generation of AI tools in alignment with a well defined digital business strategy considering business needs and rules can enable automation and generate competitive advantage to the organization.

5.4. New products and services

As stated by the literature review results, the use of AI aligned with business strategy to create new products or services was covered just by three papers. Blitz and Kazi (2019) discussed the use of AI to enable machine-to-machine communication in new business opportunities, but they did not validate their ideas. In contrast, some studies argued that enterprises have received the benefits with the development of new products and offering of new services (Davenport & Ronanki, 2018; Davenport, 2018; Marr & Ward, 2019). For Barro and Davenport (2019), AI tools can drive innovation deeper into business and this is the greatest impact of intelligent technologies. Huang and Rust (2018) argue that artificial intelligence (AI) is increasingly reshaping the service, performing various tasks, constituting a major source of innovation ant creating opportunities for innovative human–machine integration.

Therefore, there is a need to understand how managers can create competitive and cognitive strategies aiming to innovate by using the potential of the new generation of AI. It is thus relevant to discover human emotions, behaviors and needs that drive the motivations to interact services and products based on cognitive technologies. Proposition 5 regards this challenge.

Proposition 5. . Competitive and cognitive strategies must be aligned to successfully use AI new generation in order to create innovative products and solutions.

6. Conclusion

AI technologies have occupied a prominent position in organizational contexts. This hype is partly due to its potential demonstrated by reports from leading consultancies or technology providers and white papers. In turn, great expectation is related to the business competitive scenario. For this reason, there is an increasing demand for researches on the strategic use of AI to obtain competitive advantages.

Thus, this paper aimed to investigate the connection between AI usage and business strategy through a systematic literature review. Hence, the relevant literature to the theme was analyzed to synthetize the results and to contribute to the current state; to identify benefits, challenges, knowledge gaps; and to indicate propositions to future researches (Table 5). This study also contributes with a conceptual framework (Fig. 9) that highlights these gaps for future works and helps to understand the interplay between the use of AI technologies and business strategy. In the framework, this interplay was expressed in terms of business value creation sources. In this direction, the strategic use of AI was addressed by the literature in the following ways: (i) to help the decision making process in the perspective of decision support; (ii) to improve customer relationship in the automation, customers and employees engagement dimensions; and (iii) to enable machine-to-machine communication in the dimension of new products and services offering.

These findings are relevant to both theoretical and managerial perspectives, with extensive opportunities for generating novel theory and new forms of management practices. As regard theoretical implications, the results indicated that the strategic use of AI technologies has not been well explored by literature yet, despite the appeal to digital and

Table 5
Summary of benefits, challenges and research opportunities.

Sources of Value Creation	Benefits	Challenges	Research opportunities
Decision support	Considering big data and the need for speed to conduct business, deep learning techniques can extract patterns from data a human being cannot, due to the volume and velocity of data generation. In addition, AI can make better decisions than humans in some contexts and humans can decide better when judgment is required.	Some AI technologies need a human expert in the problem domain to establish a hypothesis and to select relevant features, but the fear of job elimination can lead humans being unwilling to provide useful information to AI model creation. The cognitive AI technologies do not allow human beings to understand and to explain its behavior in many cases.	**Proposition 1.** The adjustment of the AI-human equation in alignment with business needs and digital strategies is important for companies to successfully implement applications based on the new generation of AI technologies.
Customer and employee engagement	AI technologies can create competitive advantages by improving customers' experience and engagement through the applications designed based on digital strategy	Possible deep changes in workforce and consequent job reduction; and the lack of confidence in AI decisions, recommendations and responses.	**Proposition 2.** Enterprises can obtain competitive advantages by using the new generation of AI technologies with an appropriate digital business strategy to increase employees' engagement. **Proposition 3.** The use of new generation of AI technologies can create competitive advantages by improving customers' experience and engagement through the applications designed based on the digital strategy.
Automation	The most common type of AI application in organizations, due to its ease of implementation and rapid return on investment. Allows firm human resources to focus their attention on the most productivity processes.	A digital business strategy is necessary to achieve benefits through AI use in automation. It is necessary to establish and to develop capabilities that involve business rules to harness automation to obtain advantages.	**Proposition 4.** The use of the new generation of AI tools in alignment with a well defined digital business strategy that considers business needs and rules can enable automation to generate competitive advantage for the organization.
New products and services offering	Deeper innovation in business with the development of new products and offer of new services based on the cognitive potential of the new generation of AI.	Discover the human beings' emotions, behaviors and needs that drive the motivations to interact with services and products based on cognitive technologies.	**Proposition 5.** Competitive and cognitive strategies must be aligned to successfully use the new generation of AI to create innovative products and solutions.

cognitive strategies to take competitive advantages of the AI working with humans. Therefore, given the rise of AI in the digital era, there is still plenty to investigate about the planning and management of the new generation of AI in different contexts at diverse scales and business scopes.

In relation to managerial implications, the proposed framework can be a guide to management and organizational practices, demanding new models for managerial decision-making and organizational culture reshaping. Furthermore, the demonstration of the AI and business strategy connection can help executives to adopt these new technologies with greater awareness about the opportunities, challenges and benefits that AI may bring to their organizations.

Although providing contributions, such as the current state of the literature and future research directions about the theme addressed, this paper also presents some limitations. The research was performed using the terms related to business strategy or IT strategy, not specifying other business strategy dimensions, such as operational strategy and financial strategy. Future studies may extend the search string and incorporate these perspectives. In addition, the dimensions presented in the conceptual model can trigger future research focusing on a specific direction. Hopefully, the questions and propositions arising from this study can be the focus of future field researches that can investigate these points.

CRediT author statement

Aline F. S. Borges: Conceptualization, Methodology, Formal analysis, Investigation, Data Curation, Writing- Original draft, Visualization, Writing- Reviewing and Editing

Fernando J. B. Laurindo: Validation, Investigation, Writing- Original draft, Visualization, Supervision, Project administration, Wrciting-Reviewing and Editing

Mauro M. Spínola: Validation, Writing-Original draft, Visualization, Supervision, Writing- Reviewing and Editing

Rodrigo F. Gonçalves: Validation, Writing-Original draft, Visualization, Supervision, Writing- Reviewing and Editing

Claudia A. Mattos: Validation, Investigation, Writing-Original draft, Visualization, Writing- Reviewing and Editing

References

Duan, C., Xiu, G., & Yao, F. (2019a). Multi-period E-closed-loop supply chain network considering consumers' preference for products and AI-push. *Sustainability (Switzerland), 11*(17).

Wang, J., Wang, Y., & Lv, Q. (2019a). Crowd-assisted machine learning: Current issues and future directions. *Computer, 52*(1), 46–53.

Abramson, N., Braverman, D., & Sebestyen, G. (1963). Pattern recognition and machine learning. *IEEE Transactions on Information Theory, 9*(4), 257–261.

Agarwal, S., Kumar, S., & Goel, U. (2019). Stock market response to information diffusion through internet sources: A literature review. *International Journal of Information Management, 45*, 118–131.

Al-Emran, M., Mezhuyev, V., Kamaludin, A., & Shaalan, K. (2018). The impact of knowledge management processes on information systems: A systematic review. *International Journal of Information Management, 43*, 173–187.

Alenezi, H. S., & Faisal, M. H. (2020). Utilizing crowdsourcing and machine learning in education: Literature review. *Education and Information Technologies*.

Ali, M., & Xie, Y. (2011). A decision support system for ERP systems implementation in Small Medium Enterprises (SMEs). *Communications in Computer and Information Science, 219*(1), 310–321.

Ali, O., Shrestha, A., Soar, J., & Wamba, S. F. (2018). Cloud computing-enabled healthcare opportunities, issues, and applications: A systematic review. *International Journal of Information Management, 43*, 146–158.

Alter, S. (1992). *Information Systems: A management perspective*. Boston, EUA: Addison-Wesley.

Andrews, K. R. (2005). *Resources, firms, and strategies: A reader in the resource-based perspective. Oxford Management Readers*.

Arora, A., Srivastava, A., & Bansal, S. (2020). Business competitive analysis using promoted post detection on social media. *Journal of Retailing and Consumer Services, 54*(September 2019), 101941. https://doi.org/10.1016/j.jretconser.2019.101941.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019b). Artificial intelligence for decision making in the era of Big Data: Evolution, challenges and research agenda. *International Journal of Information Management, 48*, 63–71.

Wang, L., Chen, M., Li, Q., & Vargas, H. A. (2019b). Artificial intelligence in prostate cancer imaging: State of the art and future directions. *Chinese Journal of Radiology, 53*(10), 804–807.

Barro, S., & Davenport, T. H. (2019). People and machines: Partners in innovation. *MIT Sloan Management Review, 60*(4), 22–28.

Bean, R. (2019). Why fear of disruption is driving investment in AI. *MIT Sloan Management Review*.

Bell, P., Dean, G., & Gottschalk, P. (2010). Information management in law enforcement: The case of police intelligence strategy implementation. *International Journal of Information Management, 30*(4), 343–349.

Bellman, R. E. (1978). *An introduction to Artificial Intelligence: Can computers think?* San Francisco: Boyd & Fraser Publishing Company.

Bello-Orgaz, G., Mesas, R. M., Zarco, C., Rodriguez, V., Cordón, O., & Camacho, D. (2020). *Marketing analysis of wineries using social collective behavior from users' temporal activity on Twitter. Information Processing and Management, February, 102220*. https://doi.org/10.1016/j.ipm.2020.102220.

Bengio, Y., Courville, A., & Vincent, P. (2013). Representation learning: A review and new perspectives. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 35*(8), 1798–1828.

Benjamin, R. I., Rockart, J. F., Morton, M. S. S., & Wyman, J. (1983). Information Technology: A strategic opportunity. *Sloan Management Review, 25*(3), 3–14.

Bhäle, S. (2019). *Enhancing value proposition through AI strategy: A case-study on a targeted application of AR in field support. Proceedings of the 10th International Conference on E-Education, E-Business, E-Management and E-Learning, ACM* (pp. 453–457).

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. *MIS Quarterly: Management Information Systems, 37*(2), 471–482.

Black, J. S., & van Esch, P. (2020). AI-enabled recruiting: What is it and how should a manager use it? *Business Horizons, 63*(2), 215–226. https://doi.org/10.1016/j.bushor.2019.12.001.

Blitz, A., & Kazi, K. (2019). Mapping technology roadblocks and opportunities in the transportation revolution. *Strategy and Leadership, 47*(4), 43–46.

Boden, M. A. (1984). Impacts of artificial intelligence. *Futures, 16*(1), 60–70.

Boselli, R., Cesarini, M., Mercorio, F., & Mezzanzanica, M. (2018). Classifying online job advertisements through machine learning. *Future Generation Computer Systems, 86*, 319–328. https://doi.org/10.1016/j.future.2018.03.035.

Boyd, D., & Crawford, K. (2012). Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon. *Information, Communication and Society, 15*(5), 662–679.

Brandenburger, A. M., & Stuart, H. W. (1996). Value-based strategy. *Journal of Economics & Management Strategy, 5*(1), 5–24.

Brock, J. K. U., & von Wangenheim, F. (2019). Demystifying Ai: What digital transformation leaders can teach you about realistic artificial intelligence. *California Management Review, 61*(4), 110–134. https://doi.org/10.1177/1536504219865226.

Brynjolfsson, E., & Mcafee, A. N. (2017). Artificial intelligence, for real. *Harvard Business Review*.

Brynjolfsson, E., & McAfee, A. N. (2017). What's driving the Machine Learning explosion? *Harvard Business Review, 18*.

Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications. *Science, 358*(6370), 1530–1534.

Buchanan, L., & O'Connell, A. (2006). Brief history of decision making. *Harvard Business Review, 84*(1), 32–41.

Bughin, J., & Catlin, T. (2019). 3 digital strategies for companies that have fallen behind. *Harvard Business Review*, 2–5.

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlström, P., et al. (2017). *Artificial intelligence: The next digital frontier. McKinsey Global Institute*.

Bundy, A., Young, R. M., Burstall, R. M., & Weir, S. (1978). *Artificial intelligence: An introductory course*. Edinburgh Univ. Press.

Busalim, A. H., & Hussin, A. R. C. (2016). Understanding social commerce: A systematic literature review and directions for further research. *International Journal of Information Management, 36*(6), 1075–1088.

Campbell, A., & Alexander, M. (1997). What's wrong with strategy? *Harvard Business Review, 75*(6), 42–50.

Cancino, C. A., & Zurita, G. N. (2017). A location-based service to support collaboration and strategic control in a real estate broker. In S. Ochoa, P. Singh, & J. Bravo (Eds.), *11th International Conference on ubiquitous computing and ambient intelligence, UCAmI 2017. Lecture notes in computer science, 10586*. Springer Verlag.

Cannavacciuolo, L., Iandoli, L., Ponsiglione, C., & Zollo, G. (2015). Knowledge elicitation and mapping in the design of a decision support system for the evaluation of suppliers' competencies. *VINE, 45*(4), 530–550.

Caputo, F., Cillo, V., Candelo, E., & Liu, Y. (2019). Innovating through digital revolution: The role of soft skills and Big Data in increasing firm performance. *Management Decision, 57*(8), 2032–2051. https://doi.org/10.1108/MD-07-2018-0833.

Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., Francisco, R. D. P., Basto, J. P., & Alcalá, S. G. S. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Computers & Industrial Engineering, 137*.

Cebeci, U. (2009). Fuzzy AHP-based decision support system for selecting ERP systems in textile industry by using balanced scorecard. *Expert Systems With Applications, 36*(5), 8900–8909.

Chakravorti, B., Bhalla, A., & Chaturvedi, R. S. (2019). Which countries ate leading the data economy? *Harvard Business Review*.

Charniak, E., & McDermott, D. (1985). *Introduction to artificial intelligence*. Boston, EUA: Addison-Wesley.

Chi, M., Huang, R., & George, J. F. (2020). Collaboration in demand-driven supply chain: Based on a perspective of governance and IT-business strategic alignment. *International Journal of Information Management, 52*, Article 102062.

Ching, M. R. D., & De Dios Bulos, R. (2019). Improving restaurants' business performance using yelp data sets through sentiment analysis. *ACM International Conference Proceeding Series, 2013*, 62–67. https://doi.org/10.1145/3340017.3340018.

Choy, K. L., Ho, G. T. S., Lee, C. K. H., Lam, H. Y., Cheng, S. W. Y., Siu, P. K. Y., et al. (2016). A recursive operations strategy model for managing sustainable chemical product development and production. *International Journal of Production Economics, 181*, 262–272.

Colson, E. (2019). *What AI-Driven decision making looks like. Harvard Business Review*.

Costa, E., Soares, A. L., & de Sousa, J. P. (2016). Information, knowledge and collaboration management in the internationalisation of SMEs: A systematic literature review. *International Journal of Information Management, 36*(4), 557–569.

D'Souza, S., Prema, K. V., & Balaji, S. (2020). *Machine learning in drug–Target interaction prediction: Current state and future directions. Drug Discovery Today*.

Dąbrowski, J. (2017). *Towards an adaptive framework for goal-oriented strategic decision-making. in: 2017 IEEE 25th International Requirements Engineering Conference, RE 2017* (pp. 538–543).

Davenport, T. H. (2018). *The AI Advantage: How to put the Artificial Intelligence revolution to work*. MIT Press.

Davenport, T. H. (2019). *How to tame "Automation sprawl". Harvard business review*.

Davenport, T., & Harris, J. (2017). Competing on analytics: Updated, with a new introduction: The new science of winning. *Harvard Business Review Press*.

Davenport, T. H., & Mahidhar, V. (2018). What's your cognitive strategy? *MIT Sloan Management Review, 59*(4), 19–23.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 108–116.

Demirkan, H., & Delen, D. (2013). Leveraging the capabilities of service-oriented decision support systems: Putting analytics and big data in cloud. *Decision Support Systems, 55*(1), 412–421.

Ding, R.-X., Palomares, I., Wang, X., Yang, G.-R., Liu, B., Dong, Y., et al. (2020). Large-Scale decision-making: Characterization, taxonomy, challenges and future directions from an Artificial Intelligence and applications perspective. *Information Fusion, 59*, 84–102.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., et al. (2019). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, Article 101994.

Ebrahimighahnavieh, M. A., Luo, S., & Chiong, R. (2020). Deep learning to detect Alzheimer's disease from neuroimaging: A systematic literature review. *Computer Methods and Programs in Biomedicine, 187*.

Eisenhardt, K., & McDonald, R. (2020). The New-Market conundrum. *Harvard Business Review*.

Elacio, A. A., Balazon, F. G., & Lacatan, L. L. (2020). Digital transformation in managing employee retention using agile and C4.5 algorithm. *Test Engineering and Management, 82*(March), 15217–15225.

Farbey, B., Land, F. F., & Targett, D. (1995). A taxonomy of information systems applications: The benefits' evaluation ladder. *European Journal of Information Systems, 4*(1), 41–50.

Foulquier, N., Redou, P., Le Gal, C., Rouvière, B., Pers, J.-O., & Saraux, A. (2018). Pathogenesis-based treatments in primary Sjogren's syndrome using artificial intelligence and advanced machine learning techniques: A systematic literature review. *Human Vaccines & Immunotherapeutics, 14*(11), 2553–2558.

Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-powered organization. *Harvard Business Review*.

Frangou, A. J., Wan, Y., Antony, J., & Kaye, M. (1998). ESAS: A case-based approach to business planning and monitoring. *Expert Systems, 15*(3), 182–196.

Gerow, J. E., Grover, V., Thatcher, J., & Roth, P. L. (2014). Looking toward the future of it–Business strategic alignment through the past: A meta-analysis. *MIS Quarterly: Management Information Systems, 38*(4), 1159–1185.

Gloor, P., Fronzetti Colladon, A., de Oliveira, J. M., & Rovelli, P. (2020). Put your money where your mouth is: Using deep learning to identify consumer tribes from word usage. *International Journal of Information Management, 51*(April 2019), 101924. https://doi.org/10.1016/j.ijinfomgt.2019.03.011.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning MIT press*.

Gupta, S., Kar, A. K., Baabdullah, A., & Al-Khowaiter, W. A. (2018). Big data with cognitive computing: A review for the future. *International Journal of Information Management, 42*, 78–89.

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management, 49*, 157–169.

Guzman, A. L., & Lewis, S. C. (2020). Artificial intelligence and communication: A Human–Machine Communication research agenda. *New Media & Society, 22*(1), 70–86.

Hakansson, H., & Snehota, I. (2006). No business is an island: The network concept of business strategy. *Scandinavian Journal of Management, 22*(3), 256–270.

Harlow, H. D. (2018). Developing a knowledge management strategy for data analytics and intellectual capital. *Meditari Accountancy Research, 26*(3), 400–419. https://doi.org/10.1108/MEDAR-09-2017-0217.

Hassabis, D., Suleyman, M., & Legg, S. (2017). *DeepMind's work in 2016: A round-up. DeepMind*.

Hassanien, A. E., Darwish, A., & Abdelghafar, S. (2019). Machine learning in telemetry data mining of space mission: Basics, challenging and future directions. *Artificial Intelligence Review*.

Haugeland, J. (1985). *Artificial Intelligence: The very idea*. Cambridge, Massachusetts: MIT Press.

Henderson, B. D. (1989). The origin of strategy. *Harvard Business Review*, 139–143. https://doi.org/10.1126/science.1089370.

Henderson, J. C., & Venkatraman, N. (1992). Strategic alignment: A model for organizational transformation through Information Technology. *Transforming Organizations*, 97–117.

Henderson, J. C., & Venkatraman, N. (1999). Strategic alignment: Leveraging Information Technology for transforming organizations. *IBM Systems Journal, 38*(2), 472–484.

Henrique, B. M., Sobreiro, V. A., & Kimura, H. (2019). Literature review: Machine learning techniques applied to financial market prediction. *Expert Systems With Applications, 124*, 226–251.

Holloway, C. (1983). Strategic management and artificial intelligence. *Long Range Planning, 16*(5), 89–93.

Hsu, M. F., Chang, T. M., & Lin, S. J. (2020). News-based soft information as a corporate competitive advantage. *Technological and Economic Development of Economy, 26*(1), 48–70. https://doi.org/10.3846/tede.2019.11328.
Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research, 21*(2), 155–172.
Iansiti, M., & Lakhani, K. R. (2020). Competing in the age of AI. *Harvard Business Review*.
Janjua, N. K., & Hussain, F. K. (2012). Web@ IDSS–Argumentation-enabled Web-based IDSS for reasoning over incomplete and conflicting information. *Knowledge-based Systems, 32*, 9–27.
Jesuthasan, R., & Boudreau, J. (2017). *Thinking through how automation will affect your workforce. Harvard Business Review*.
Kaplan, R. S., & Norton, D. P. (1996). The balanced scorecard: Measures that drive performance. *Harvard Business Review*, 71–79.
Kaplan, R. S., & Norton, D. P. (2000). Having trouble with your strategy? Then map it. *Harvard Business Review, 78*(5).
Kedra, J., Radstake, T., Pandit, A., Baraliakos, X., Berenbaum, F., Finckh, A., et al. (2019). Current status of use of big data and artificial intelligence in RMDs: A systematic literature review informing EULAR recommendations. *RMD Open, 5*(2).
Keen, P. G. W. (1991). *Shapping the future: Business design through information technology*. Harvard Business School Press.
Keen, P. G. W. (1993). Information Technology and the management difference: A fusion map. *IBM Systems Journal, 32*(1), 17–39.
Khakurel, J., Penzenstadler, B., Porras, J., Knutas, A., & Zhang, W. (2018). The Rise of Artificial Intelligence under the lens of sustainability. *Technologies, 6*(4), 100.
King, W. R. (1978). Strategic planning for management information systems. *MIS Quarterly: Management Information Systems, 24*(15), 1631–1641.
Kiron, D., & Schrage, M. (2019). Strategy for and with AI. *MIT Sloan Management Review, 60*(4), 30–35.
Kitchenham, B. (2004). Procedures for performing systematic reviews. *Keele, UK, Keele University, 33*(2004), 1–26.
Kitchenham, B., Brereton, O. P., Budgen, D., Turner, M., Bailey, J., & Linkman, S. (2009). Systematic literature reviews in software engineering: A systematic literature review. *Information and Software Technology, 51*(1), 7–15.
Kitsios, F., & Kamariotou, M. (2016). *Decision support systems and business strategy: A conceptual framework for strategic information systems planning. Proceedings of 6th IEEE international conference on IT convergence and security (ICITCS2016), Prague, Czech Republic, 149-153*.
Kreps, G. L., & Neuhauser, L. (2013). Artificial intelligence and immediacy: Designing health communication to personally engage consumers and providers. *Patient Education and Counseling, 92*(2), 205–210. https://doi.org/10.1016/j.pec.2013.04.014.
Kurzweil, R. (1990). *The age of intelligent machines*. Cambridge, Massachusetts: MIT Press.
Laínez, J. M., Reklaitis, G. V., & Puigjaner, L. (2010). Linking marketing and supply chain models for improved business strategic decision support. *Computers & Chemical Engineering, 34*(12), 2107–2117.
Laurindo, F. J. (2008). *Information technology: Planning and strategy management. São Paulo: Atlas*.
LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444.
Lee, W. I., Shih, B. Y., & Chen, C. Y. (2012). A hybrid artificial intelligence sales? Forecasting system in the convenience store industry. *Human Factors and Ergonomics in Manufacturing, 22*(3), 188–196.
Lepenioti, K., Bousdekis, A., Apostolou, D., & Mentzas, G. (2020). Prescriptive analytics: Literature review and research challenges. *International Journal of Information Management, 50*, 57–70.
Li, Z., Xu, K., Wang, X., Wang, H., Zhao, Y., & Shen, M. (2019). Machine-learning-based positioning: A survey and future directions. *IEEE Network, 33*(3), 96–101.
Lichtenthaler, U. (2019). Extremes of acceptance: Employee attitudes toward artificial intelligence. *The Journal of Business Strategy*. https://doi.org/10.1108/JBS-12-2018-0204.
Lichtenthaler, U. (2020a). Beyond artificial intelligence: Why companies need to go the extra step. *The Journal of Business Strategy, 41*(1), 19–26. https://doi.org/10.1108/JBS-05-2018-0086.
Lichtenthaler, U. (2020b). Building blocks of successful digital transformation: Complementing technology and market issues. *International Journal of Innovation and Technology Management, 17*(1), 1–14. https://doi.org/10.1142/S0219877020500042.
Littler, K., Aisthorpe, P., Hudson, R. S., & Keasey, K. (2000). New approach to linking strategy formulation and strategy implementation: An example from the UK banking sector. *International Journal of Information Management, 20*(6), 411–428.
López-Robles, J. R., Otegi-Olaso, J. R., Porto Gómez, I., & Cobo, M. J. (2019). 30 years of intelligence models in management and business: A bibliometric review. *International Journal of Information Management, 48*, 22–38.
Luftman, J. N., Lewis, P. R., & Oldach, S. H. (1993). Transforming the enterprise: The alignment of business and information technology strategies. *IBM Systems Journal, 32*(1), 198–221.
Luger, G. F., & Stubblefield, W. A. (1993). *Instructor's manual for Artificial Intelligence: Structures and strategies for complex problem solving*. São Francisco, EUA: Benjamin Cummings.
Luo, Y., & Xu, X. (2019). Predicting the helpfulness of online restaurant reviews using different machine learning algorithms: A case study of yelp. *Sustainability (Switzerland), 11*(19). https://doi.org/10.3390/su11195254.
Lyall, A., Mercier, P., & Gstettner, S. (2018). The death of supply chain management. *Harvard Business Review*, 1–4.
Marr, B., & Ward, M. (2019). *Artificial Intelligence in practice: How 50 successful companies used artificial intelligence to solve problems*. Hoboken, EUA: Wiley.
Martins, G. D., Gonçalves, R. F., & Petroni, B. C. (2019). Blockchain in manufacturing revolution based on machine to machine transaction: A systematic review. *Brazilian Journal of Operations & Production Management, 16*(2), 294–302.
Masa'deh, R., & Shannak, R. O. (2012). Intermediary effects of knowledge management strategy and learning orientation on strategic alignment and firm performance. *Research Journal of International Studies, 112*.
Mattos, C. A., & Laurindo, F. J. B. (2017). Information technology adoption and assimilation: Focus on the suppliers portal. *Computers in Industry, 85*, 48–57. https://doi.org/10.1016/j.compind.2016.12.009.
Mattos, C. A., Kissimoto, K. O., & Laurindo, F. J. B. (2018). The role of information technology for building virtual environments to integrate crowdsourcing mechanisms into the open innovation process. *Technological Forecasting and Social Change, 129*(December 2017), 143–153. https://doi.org/10.1016/j.techfore.2017.12.020.
McCarthy, J. (1958). *Programs with common sense* (pp. 77–84). *Proceedings of the Symposium on Mechanisation*, London.
McCarthy, J., & Hayes, P. J. (1981). *Some philosophical problems from the standpoint of artificial intelligence. in: Readings in artificial intelligence, 431-450. Morgan Kaufman*. n.
McFarlan, F. W. (1984). Information Technology changes the way you compete. *Harvard Business Review, 62*(3), 98–103.
McKinnel, D. R., Dargahi, T., Dehghantanha, A., & Choo, K.-K. R. (2019). A systematic literature review and meta-analysis on artificial intelligence in penetration testing and vulnerability assessment. *Computers & Electrical Engineering, 75*, 175–188.
Michie, D. (1968). "Memo" functions and machine learning. *Nature, 218*(5136), 19.
Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics and firm performance: Findings from a mixed-method approach. *Journal of Business Research, 98*, 261–276.
Mikalef, P., Pappas, I. O., Krogstie, J., & Giannakos, M. (2018). Big data analytics capabilities: A systematic literature review and research agenda. *Information Systems and E-Business Management, 16*(3), 547–578.
Miklosik, A., Kuchta, M., Evans, N., & Zak, S. (2019). Towards the adoption of machine learning-based analytical tools in digital marketing. *IEEE Access : Practical Innovations, Open Solutions, 7*, 85705–85718. https://doi.org/10.1109/ACCESS.2019.2924425.
Miles, R. E., Snow, C. C., Meyer, A. D., & Coleman, H. J. (1978). Organizational strategy, structure, and process. *Academy of Management, 3*(3), 546–562.
Mintzberg, H. (1987). *Crafting strategy. Harvard business review*.
Mintzberg, H., & Lampel, J. (1999). Reflecting on the strategy process. *MIT Sloan Management Review, 40*(3), 21–30.
Mintzberg, H., Ahlstrand, B., & Lampel, J. (2000). *Strategy safari*. Porto Alegre: Bookman.
Mithas, S. (2012). *Digital Intelligence: What every smart manager must have for success in an information age. Finerplanet*.
Mithas, S., Tafti, A., & Mithell, W. (2013). How a firm's competitive environment and digital strategic posture influence digital business strategy. *MIS Quarterly, 37*(2), 511–536.
Moghekar, R., & Ahuja, S. (2019). Face recognition: Literature review with emphasis on deep learning. *Journal of Theoretical and Applied Information Technology, 97*(12), 3332–3342.
Morocho-Cayamcela, M. E., Lee, H., & Lim, W. (2019). Machine learning for 5G/B5G mobile and wireless communications: Potential, limitations, and future directions. *IEEE Access : Practical Innovations, Open Solutions, 7*, 137184–137206.
Murphy, K. P. (2012). *Machine learning: A probabilistic perspective*. MIT Press.
Nalchigar, S., & Yu, E. (2017). *Conceptual modeling for business analytics: A framework and potential benefits. Procedings – 2017 IEEE 19th Conference on Business Informatics, CBI, 1, 369-378*.
Neilson, G. L., Martin, K. L., & Powers, E. (2008). The secrets to successful strategy execution. *Harvard Business Review, 86*(6).
Neshat, N., & Amin-Naseri, M. R. (2015). Cleaner power generation through market-driven generation expansion planning: An agent-based hybrid framework of game theory and particle swarm optimization. *Journal of Cleaner Production, 105*, 206–217.
Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *International Journal of Information Management, 53*, Article 102104.
Norman, D. (2017). Design, business models and human technology teamwork. *Research-Technology Management, 60*(1), 26–30.
Orgeolet, L., Foulquier, N., Misery, L., Redou, P., Pers, J.-O., Devauchelle-Pensec, V., et al. (2020). Can artificial intelligence replace manual search for systematic literature? Review on cutaneous manifestations in primary Sjögren's syndrome. *Rheumatology, 59*(4), 811–819.
Pandl, K. D., Thiebes, S., Schmidt-Kraepelin, M., & Sunyaev, A. (2020). On the convergence of Artificial Intelligence and distributed ledger technology: A scoping review and future research agenda. *IEEE Access : Practical Innovations, Open Solutions, 8*, 57075–57095.
Panetta, K. (2018). *5 trends emerge in the Gartner hype cycle for emerging technologies, 2018. Gartner*.
Pappas, I. O., Mikalef, P., Giannakos, M. N., Krogstie, J., & Lekakos, G. (2018). Big data and business analytics ecosystems: Paving the way towards digital transformation and sustainable societies. *Information Systems and E-Business Management, 16*(3), 479–491.
Philip, G., Gopalakrishnan, M., & Mawalkar, S. R. (1995). Technology management and information technology strategy: Preliminary results of an empirical study of Canadian organizations. *International Journal of Information Management, 15*(4), 303–315.
Poplawska, J., Labib, A., & Reed, D. M. (2015). A hybrid multiple-criteria decision analysis framework for corporate social responsibility implementation applied to an

extractive industry case study. *The Journal of the Operational Research Society, 66*(9), 1491–1505.
Porter, M. E. (1979). How competitive forces shape strategy. *Harvard Business Review*, 137–145.
Porter, M. E. (1987). *From competitive advantage to corporate strategy. Harvard Business Review*.
Porter, M. E. (1996). What is Strategy? *Harvard Business Review, 74*(6), 61–78.
Porter, M. E., & Millar, V. E. (1985). How information gives you competitive advantage. *Harvard Business Review, 63*(4), 149–160.
Porter, M. E., & Nohria, N. (2018). How CEOs manage time. *Harvard Business Review, 96*(4), 42–51.
Prahalad, C. K., & Hamel, G. (1990). The core competence of the corporation. *Harvard Business Review*.
Prahalad, C. K., & Krishnan, M. S. (2002). The dynamic synchronization of strategy and information technology. *MIT Sloan Management Review, 43*(4), 24–33.
Prahalad, C. K., & Krishnan, M. S. (2008). *The new age of innovation: Driving cocreated value through global networks*. McGraw-Hill Education.
Ransbotham, S., Gerbert, P., Reeves, M., Kiron, D., & Spira, M. (2018). *Artificial intelligence in business gets real. MIT sloan management review*.
Reich, B. H., & Benbasat, I. (1996). Measuring the linkage between business and information technology objectives. *MIS Quarterly: Management Information Systems, 20*(1), 55–77.
Rekik, R., Kallel, I., Casillas, J., & Alimi, A. M. (2018). Assessing web sites quality: A systematic literature review by text and association rules mining. *International Journal of Information Management, 38*(1), 201–216.
Rich, E., & Knight, K. (1991). *Introduction to artificial networks*. New York: Mac Graw-Hill.
Russell, S. J., & Norvig, P. (2010). *Artificial intelligence: A modern approach. Nova Jersey, EUA: PrenticeHall*.
Sabherwal, R., & Chan, Y. E. (2001). Alignment between Business and IS strategies: A study of prospectors, analyzers, and defenders. *Information Systems Research, 12*(1), 11–33.
Satell, G. (2017). *How to win with automation. Harvard business review*.
Schalkoff, R. J. (1990). *Artificial intelligence engine*. New York: Mac Graw-Hill.
Schrage, M., & Kiron, D. (2018). Leading with next-generation key performance indicators. *MIT Sloan Management Review, 16*.
Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2020). Financial time series forecasting with deep learning: A systematic literature review: 2005–2019. *Applied Soft Computing Journal, 90*.
Shao, Z. (2019). Interaction effect of strategic leadership behaviors and organizational culture on IS-Business strategic alignment and Enterprise Systems assimilation. *International Journal of Information Management, 44*(13), 96–108.
Sharma, R., Kamble, S. S., Gunasekaran, A., Kumar, V., & Kumar, A. (2020). A systematic literature review on machine learning applications for sustainable agriculture supply chain performance. *Computers & Operations Research, 119*.
Shimizu, T., Carvalho, M. M., & Laurindo, F. J. B. (2006). *Strategic alignment process and decision support systems*. Hershey: IRM Press (1), 357.
Siklóssy, L. (1970). On the evolution of artificial intelligence. *Information Sciences, 2*(4), 369–377.
Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., Van Den Driessche, G., et al. (2016). Mastering the game of go with deep neural networks and tree search. *Nature, 529*(7587), 484–489.
Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., et al. (2017). Mastering the game of Go without human knowledge. *Nature, 550*(7676), 354–359.
Slack, N., & Michael, L. (2002). *Operations strategy*. Pearson Education.
Solomonoff, R. J. (1985). The time scale of artificial intelligence: Reflections on social effects. *Human Systems Management, 5*(2), 149–153.
Song, Y., Xue, Y., Li, C., Zhao, X., Liu, S., Zhuo, X., et al. (2017). *Online cost efficient customer recognition system for retail analytics. in: 2017 IEEE Winter Applications of Computer Vision Workshops (WACVW)*.
Souza, J. T. D., Francisco, A. C. D., Piekarski, C. M., Prado, G. F. D., & Oliveira, L. G. D. (2019). Data mining and machine learning in the context of sustainable evaluation: A literature review. *IEEE Latin America Transactions, 17*(3), 372–382.
Sujata, J., Aniket, D., & Mahasingh, M. (2019). Artificial intelligence tools for enhancing customer experience. *International Journal of Recent Technology and Engineering, 8*(2 Special Issue 3), 700–706. https://doi.org/10.35940/ijrte.B1130.0782S319.
Thompson, S., Ekman, P., Selby, D., & Whitaker, J. (2014). A model to support IT infrastructure planning and the allocation of IT governance authority. *Decision Support Systems, 59*(1), 108–118.
Tienkouw, S., Wongtosrad, N., Tanwanont, P., Niraswan, R., Khlayprapha, C., Taesuwan, P., et al. (2011). *Technology-based strategic marketing planning for pi-pe. 2011 proceedings of PICMET'11: Technology management in the Energy Smart World (PICMET)*.
Touati, F., Chowdhury, N. A., Benhmed, K., Gonzales, A. J. S. P., Al-Hitmi, M. A., Benammar, M., et al. (2017). Long-term performance analysis and power prediction of PV technology in the State of Qatar. *Renewable Energy, 113*, 952–965.
Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management, 14*(3), 207–222.
van Esch, P., & Black, J. S. (2019). Factors that influence new generation candidates to engage with and complete digital, AI-enabled recruiting. *Business Horizons, 62*(6), 729–739. https://doi.org/10.1016/j.bushor.2019.07.004.
Venkatraman, V. (2017). *The digital matrix: New rules for business transformation through technology. EUA: LifeTree Media Ltd*.
Wang, W., & Siau, K. (2019). Artificial intelligence, machine learning, automation, robotics, future of work and future of humanity: A review and research agenda. *Journal of Database Management, 30*(1), 61–79.
Weill, P., & Woerner, S. (2017). Surviving in an increasingly digital ecosystem. *MIT Sloan Management Review, 59*(2), 26–28.
Westerman, G., Bonnet, D., & McAfee, A. (2014). The nine elements of digital transformation. *MIT Sloan Management Review, 55*(3), 1–6.
Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. *Harvard Business Review, 96*(4), 114–123.
Winston, P. H. (1970). *Learning structural descriptions from examples*. Cambridge, Massachusetts: Massachusetts Institute of Technology.
Witten, I. H., & Frank, E. (2016). *Data Mining: Practical machine learning tools and techniques*. Massachusetts, EUA: Morgan Kaufmann.
Zaki, M. (2019). Digital transformation: Harnessing digital technologies for the next generation of services. *Journal of Services Marketing, 33*(4), 429–435. https://doi.org/10.1108/JSM-01-2019-0034.
Zheng, J.-N., Chien, C.-F., & Wu, J.-Z. (2014). *Multi-objective demand fulfillment problem for solar cell industry to benefit revenue management. in: K. C., C. G., & U. O. (eds.). Joint international symposium on "'the social impacts of developments in information, manufacturing and service systems'". 44th international conference on computers and Industrial Engineering, CIE 2014 and 9th International Symposium on intelligent manufa, 1343-1356. Computers and industrial engineering*.
Zhu, X., Zhang, G., & Sun, B. (2019). A comprehensive literature review of the demand forecasting methods of emergency resources from the perspective of artificial intelligence. *Natural Hazards, 97*(1), 65–82.
Zhuang, Y. T., Wu, F., Chen, C., & Pan, Y. H. (2017). Challenges and opportunities: From big data to knowledge in AI 2.0. *Frontiers of Information Technology & Electronic Engineering, 18*(1), 3–14.