Artificial Intelligence in Business: State of the Art and Future Research Agenda

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Abstract

This study provides an overview of state-of-the-art research on Artificial Intelligence in the business context and proposes an agenda for future research. First, by analyzing 404 relevant articles collected through Web of Science and Scopus, this article presents the evolution of research on AI in business over time, highlighting seminal works in the field, and the leading publication venues. Next, using a text-mining approach based on Latent Dirichlet Allocation, latent topics were extracted from the literature and comprehensively analyzed. The findings reveal 18 topics classified into four main clusters*: societal impact of AI, organizational impact of AI, AI systems,* and *AI methodologies.* This study then presents several main developmental trends and the resulting challenges, including robots and automated systems, Internet-of-Things and AI integration, law, and ethics, among others. Finally, a research agenda is proposed to guide the directions of future AI research in business addressing the identified trends and challenges.

Keywords: Artificial Intelligence, intelligent agent, business applications, text mining, research agenda, future trends

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Artificial Intelligence in Business: State of the Art and Future Research Agenda

1. Introduction

Artificial intelligence (AI) is reshaping business, economy, and society by transforming experiences and relationships amongst stakeholders and citizens. The roots of AI may lie in ancient cultures of Greek (e.g., the mythological robot Talos), Chinese (e.g., Yueying Huang' dogs) and other mythologies (Nahodil & Vitku, 2013), where automatons were believed to be imbued with real minds, capable of wisdom and emotion. Yet, the term emerged in a workshop at Dartmouth College (United States) in 1956 (Nilsson, 2010), which is dubbed the birth of AI.

Since then, research on AI has stemmed from different fields of knowledge. Social scientists have been discussing ethical and legal implications of AI (Cath, 2018), computer scientists have developed advanced deep learning algorithms (LeCun, Bengio, & Hinton, 2015), while researchers in business management have studied the impacts of AI on customers, firms, and stakeholders in an increasingly automated and interrelated business world (Huang & Rust, 2018). However, such advances in AI research have mainly been done in isolated silos with few interdisciplinary exchanges. Similarly, a unique and consensual definition of AI has been hard to get. Recently, Russell and Norvig (2016) summarize the various definitions of AI systems into four categories along two dimensions: reasoning–behavior dimension and human performance–rationality dimension. These are: (1) systems that think like humans, (2) systems that act like humans, (3) systems that think rationally, and (4) systems that act rationally. AI systems should have the following capabilities: *natural language processing* to communicate in a natural language, *knowledge representation* to store information, *automated reasoning* - the use of the stored information to answer questions and to draw new conclusions, and *machine learning* to adapt to new circumstances and to detect and extrapolate patterns (e.g., Russell & Norvig, 2016; Huang & Rust, 2018). Yet, the lack of a consensual definition has not prevented the spread of research for new applications of AI in the world.

The worldwide spending on cognitive and AI systems has been growing steadily for the past years with $24.0 billion being spent in 2018. Such investment is expected to grow to $77.6 billion in 2022 (IDC, 2019). In order to encourage further advancements in research on business applications of AI, which often require a multidisciplinary perspective, AI practitioners and researchers will benefit from a comprehensive knowledge about what has been investigated and applied in different business domains (i.e., from manufacturing to services) and in different disciplinary fields, such as marketing, tourism, management, sociology, psychology, and so on. Such a comprehensive knowledge will provide researchers a foundation to prioritize research foci and practitioners to guide effective investment in important aspects of AI for business.

Notably, several researchers have attempted to conduct a comprehensive literature review on the use of AI in business. For example, Côrte-Real, Ruivo, and Oliveira (2014) perform a systematic mapping of the diffusion stages of business intelligence and analytics (BI&A) implementation, proposing a future research in the then rather neglected post-adoption stages. Moro, Cortez and Rita (2015) conduct a literature analysis between 2002 and 2013 focused in Business Intelligence (which uses some AI algorithms for predictive analysis) in Banking. Tkáč and Verner (2016) review two decades of research on the application of artificial neural network in business and found most of the examined articles discussing expert systems with applications. Finally, Duan, Edwards, and Dwivedi (2019) analyze relevant articles published in *International Journal of Information Management* to identify issues and challenges around AI for decision making in the era of big data, proposing theoretical development and AI implementation. While these efforts present useful knowledge about the advancements in AI and business research, they focus either on specific applications (e.g., artificial neural network, BI&A) or domains (e.g., decision support system). To address this gap, the current paper aims at providing an overview of extant research on AI in business by comprehensively analyzing the evolution and state-of-the-art research on AI, as well as identifying future trends in order to provide useful directions for future research in the field. Specifically, the current study uses (1) a graph mining analysis to map citations of prominent studies in the relevant literature and (2) a text mining approach similar to the ones used by Loureiro et al. (2018), Guerreiro et al. (2016), Moro et al. (2017) and Cortez et al. (2018) to classify the extant studies into latent topics and evaluate how such research has evolved over time. Furthermore, this study discusses the main trends in research and business implementation of AI and proposes a research agenda to address future trends and challenges.

The remainder of this paper is organized as follows. The next section describes the methods of collecting and managing data, followed by topic analyses, where insights into the information revealed from the data are discussed. The last two sections are devoted to discussions on future trends in AI and presentation of major questions for future research.

2. Method

In order to identify the most relevant literature for this review, a set of articles discussing AI was collected from both Web of Science and Scopus online libraries. Papers that had the terms "artificial intelligence" or "artificial-intelligence" in their title, abstract, and keywords, that were published in peer-reviewed journals in business-related categories were selected. Table 1 shows the query terms per each online library.

Table 1. Queries to select Artificial Intelligence papers

WOS Query	(AB=("artificial intelligence" or "artificial-intelligence")) *AND* LANGUAGE: (English) *AND* TYPES OF DOCUMENT: (Article) WEB OF SCIENCE CATEGORIES: (OPERATIONS RESEARCH MANAGEMENT SCIENCE OR MANAGEMENT OR BUSINESS)
Scopus Query	ABS ("ARTIFICIAL INTELLIGENCE" OR "ARTIFICIAL-INTELLIGENCE") AND (LIMIT-TO (SUBJAREA, "BUSI")) AND (LIMIT-TO (DOCTYPE, "ar"))

A total of 805 articles were extracted from journals indexed in Web of Science and 900 papers were extracted from the Scopus database. A first look at the 1488 papers revealed that there is a big dispersion of the papers among many different journals and topics. Even after restricting the query to Business related articles, there were many papers in other related topics. After a manual review of the abstracts, 903 articles were excluded because they were discussing technical issues (and not business implications) around engineering issues, 29 articles were excluded because they were more focused on algorithm development, and 27 papers were excluded due to being too much focused on other related topics such as applications on pedagogical education. After this initial screening, the full text of 529 potentially relevant articles were analyzed using a systematic analysis approach. Four criteria were used for the full text screening process: validity, reliability, credibility, and integrity (Moher, Liberati, Tetzlaff, Altman, & Altman, 2009; Nill & Schibrowsky, 2007). Two researchers conducted an independent identification of the relevant articles following the quality criteria suggested by Macpherson and Holt (2007) and classified the papers according to the topic intended for the investigation: AI in Business (see Appendix A). Conflicts between researchers were discussed to reach an agreement with Cohen's Kappa coefficient >0.85. A final group of 404 articles was identified for a final analysis (see figure 1).

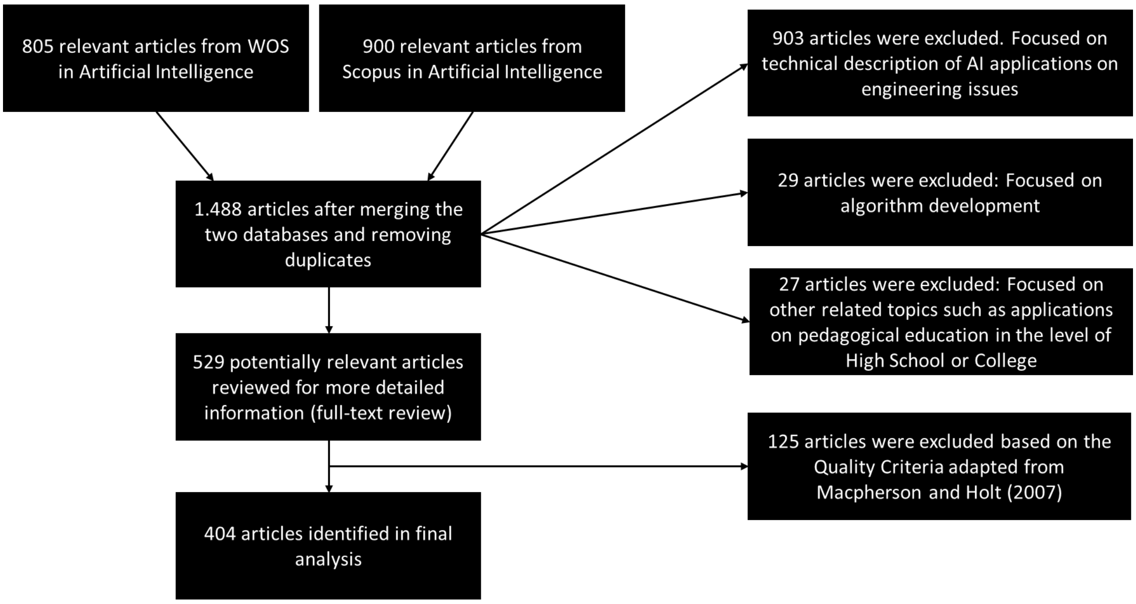

Figure 1. Process for selecting the final papers for analysis

2.1 Descriptive analysis of the literature

The literature on AI in business-related categories started in 1977 with a first paper published in *Futures* journal that addresses how AI was applied to problems in medicine (Coles, 1977). In fact, *Futures* is the journal that gathers the greatest number of papers discussing the implications of AI in business categories (20), followed by the *Journal of Operational Research Society* (19), and *Expert Systems with Applications* journal (10).

Coles's (1997) paper was the only one published between 1970 and 1979 that fulfilled the query in the current study. The next decades saw an increase in papers published around AI implications. Between 1980 and 1989, 43 papers met the criteria, and both in the 1990's and in the first decade of the 21th Century, 70 papers were published. In the last decade (2010-2019), the number of published papers around AI in business categories have increased, with a total of 220 papers included in the dataset (see figure 2).

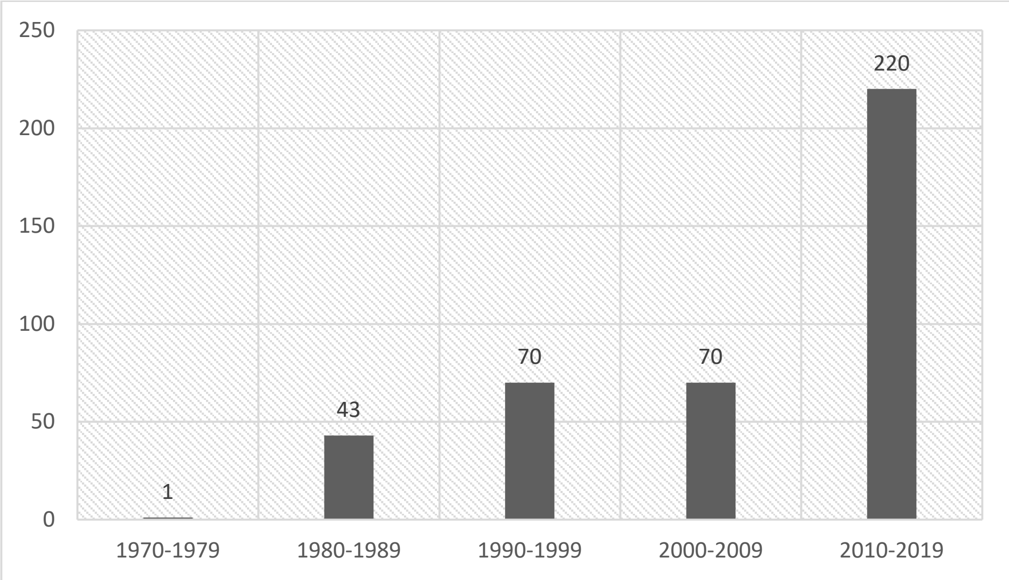

Figure 2. Distribution of published papers on AI over time

Articles were also classified according to the business applications that have received an impact from AI. Figure 3 shows the most impacted business applications. Most AI research is impacting Governance – applications for strategic decisions inside organizations or governments (48 papers), the Manufacturing (48 papers), Society as a whole (37 papers) and Finance (33 papers). Other important applications include Marketing and Retailing (43 papers) and Tourism and Hospitality with a total of 24 papers.

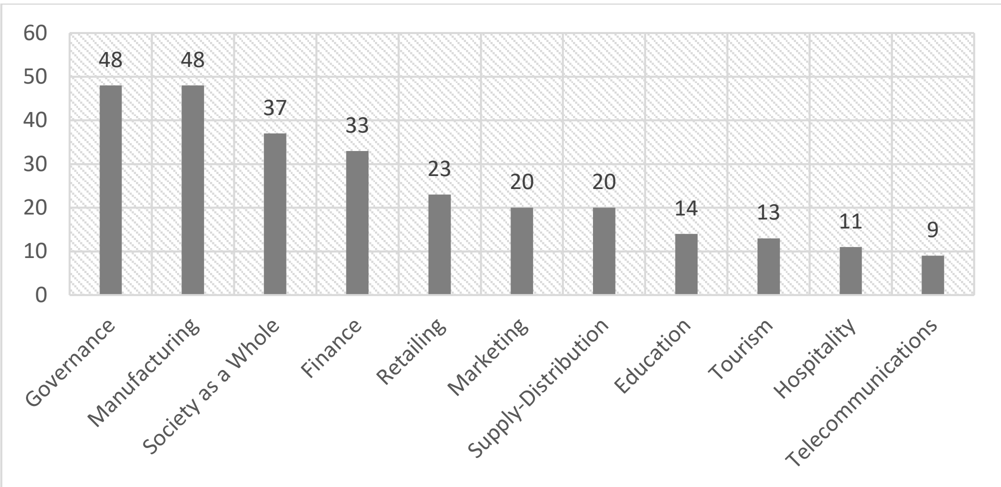

Figure 3. Distribution of Business Applications of AI articles

2.2 Reference network analysis

In order to identify seminal works on AI in business, reference network or citation analysis was conducted. First, the references cited in each paper were collected in order to create a network of citations; citations to webpages without any authors and identified title were removed. Each paper (a node) was linked to its cited references using the Gephi software (Bastian *et al.*, 2009). Such links (the edges) were then optimized. Duplicate citations were merged so that one distinct *source* paper is linked to all its *target* citations. The final directed graph had 13,241 nodes and 13,869 edges. Unconnected nodes were also filtered using the Gephi's "giant component" filter. Finally, the in-degree (the number of citations from the collected papers pointing to each referenced paper) for each node was calculated.

Results show that there is a very scattered network of paper citations. Despite a large number of citations, not many seminal references were cited in most papers. Table 2 shows the top citations sorted by in-degree scores. The reference with the highest in-degree score is a book from Russel and Norvig (1995), which was cited 17 times in the dataset collected for the purposes of this study (around 4% of the 404 initial papers). Kurzweils' (2005) book has the second highest in-degree score of 12. The first peer-reviewed paper on the top references is the study by Zadeh (1965) on fuzzy sets published in *Information and Control* journal. Table 2 also shows the number of total citations (extracted from Google Scholar) from all other academic papers (outside the scope of the current study), which highlights the relevance of the seminal references being cited.

Table 2. Top citations on Artificial Intelligence papers in Business categories

Author	Title	Source	In-Degree
Russell & Norvig (1995) and subsequent edition Russell & Norvig (2016)	Artificial Intelligence: A Modern Approach	Book	17
Kurzweil (2005)	The Singularity Is Near: When Humans Transcend Biology	Book	12

Author	Title	Source	In-Degree
Zadeh (1965)	Fuzzy sets	Information and Control	11
Brynjolfsson & McAfee (2014)	The Second Machine Age: Work, Progress, and Prosperity in A Time of Brilliant Technologies	Book	9
Turing (1950)	Computing machinery and intelligence	Mind	8
Bostrom (2014)	Superintelligence: Paths, Dangers, Strategies	Book	8
Goldberg (1989)	Genetic Algorithms in Search, Optimization and Machine Learning	Book	7
Rogers (1995)	Diffusion of Innovations	Book	7
Davis (1989)	Perceived usefulness, perceived ease of use, and user acceptance of information technology	MIS Quarterly	7

Note: In-degree refers to the number of times a paper is cited out of 404 papers analyzed.

2.3. Topic analysis

A topic analysis was conducted on the paper abstracts to uncover latent discussions in the identified literature. The R software was used to transform the text into a *corpora,* using the *tm* and *topicmodels* packages. Text was converted into lower case and whitespaces; numbers and stop-words were removed. The remaining text was tokenized into unigrams and bigrams and converted into a document-term matrix (DTM). To select the number of latent topics, measures taken from Griffiths and Steyvers (2004) and Cao et al. (2009) were used. Figure 4 shows the set of possible topics ranging from K=2 to K=60.

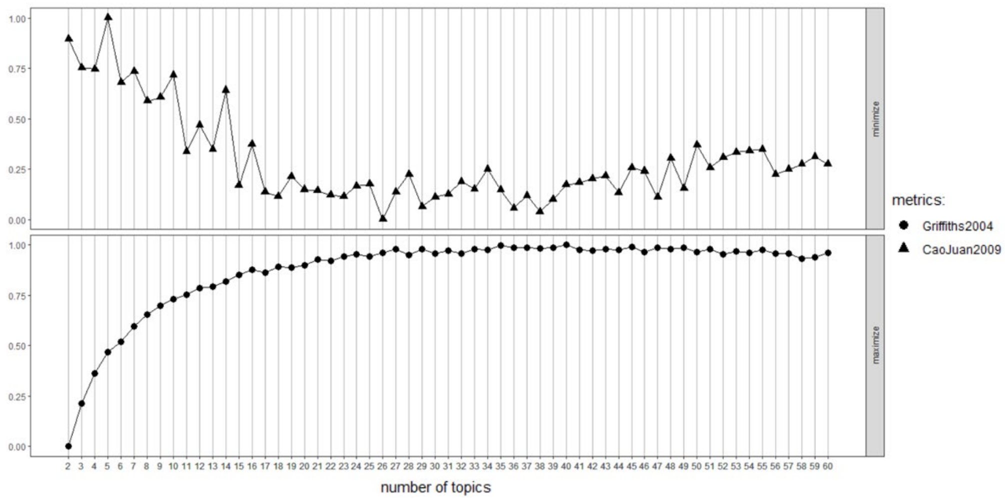

Figure 4. Log-likelihood and perplexity metrics for evaluating K

The log-likelihood and perplexity start stabilizing around K=18 reaching their optimal values around K=26 or K=27. According to Guerreiro et al. (2016, p.115), "the ideal number of clusters/topics is attained when the variability explained does not change significantly by adding more clusters." Therefore, for the sake of explainability, a K=18 was selected for the current analysis. The topic models were conducted using a Latent Dirichlet Allocation (LDA) with a Gibbs sampling technique. LDA is a mixed-membership algorithm, widely used for clustering text into latent topics (Blei et al., 2003). LDA is based on a hierarchical Bayesian analysis and calculates the posterior probability of each word found in the text and of each document (in the current case, each paper) to belong to a latent topic. Being a mixed-membership model, each paper may belong to multiple topics (several discussions being addressed in the text). In the current case, the posterior probabilities associated with each paper are not very high, which may be due to the correlations between the topics (see table 3).

Table 3. Latent Topics and Correlated Papers

Topic Name	Topic Terms	Top 3 Correlated papers with topic	Posterior Probability	Journal
T1. LEARNING	machine, learning, different, approaches, simulation	Ocampo et al. (2018)	0.28	International Journal of Integrated Supply Management
		Fang et al. (2002)	0.26	Group Decision and Negotiation
		Zhu, Marques, & Yoo (2015)	0.26	Engineering Economist
T2. DECISION SUPPORT	Decision, support, making, processes	Cabanero-Johnson & Berge (2009)	0.34	Learning Organization
		Kalantari (2010)	0.31	Journal of Management History
		Krabuanrat & Phelps (1998)	0.29	Journal of Business Research
T3. DATA ANALYSIS	Data, analysis, theory, set, rules	Reformat, Yager, & To (2018)	0.32	Intelligent Systems in Accounting, Finance and Management
		Goh & Law (2003)	0.26	Tourism Management

Topic Name	Topic Terms	Top 3 Correlated papers with topic	Posterior Probability	Journal
		Mazurek (2013)	0.25	Polish Journal of Management Studies
T4. WORK IMPACT	Work, need, context, survey, project	Lee, Shin, & Baek (2017)	0.47	Journal of Applied Business Research
		Jankovic, Cardinal, & Bocquet (2015)	0.20	International Journal of Product Development
		Kolbjørnsrud, Amico, & Thomas (2017)	0.20	Strategy and Leadership
T5. FORECASTING	Model, models, time, approach, forecasting	Chen, Su, Cheng, & Chiang (2011)	0.44	African Journal of Business Management
		Raghunathan (1994)	0.30	Journal of Management Information Systems
		Yu & Schwartz (2006)	0.27	Journal of Travel Research
T6. NEURAL NETWORKS	Neural, network, networks, market, financial	Claveria, Monte, & Torra (2015)	0.26	International Journal of Contemporary Hospitality Management
		Er & Hushmat (2017)	0.26	Eurasian Business Review
		Cui & Wong (2004)	0.24	International Journal of Market Research
T7. SYSTEMS DESIGN	System, process, design, intelligent, methodology	Chan, Jiang & Tang (2000)	0.21	International Journal of Production Economics
		Aiken, Sheng, & Orl (1991)	0.21	Information & Management
		Robinson, Alifantis, Edwards, Ladbrook, & Waller (2005)	0.20	Journal of the Operational Research Society
T8. PROBLEM SOLVING	Problem, problems, search, reasoning, developed	Bekkouche et al. (2017)	0.35	Service Oriented Computing and Applications
		Lee (2001)	0.31	Computers & Operations Research
		Schmidt (1998)	0.28	International Journal of Production Economics

Topic Name	Topic Terms	Top 3 Correlated papers with topic	Posterior Probability	Journal
T9. ROBOTS	Human, service, robots, future, robotics	Wirtz et al. (2018)	0.32	Journal of Service Management
		Gonzalez-Jimenez (2018)	0.26	Futures
		Cockshott & Renaud (2016)	0.25	Technology in Society
T10. KNOWLEDGE MANAGEMENT	Knowledge, management, business, supply, including	Liu et al. (2013)	0.31	International Journal of Production Research
		Paradice & Courtney (1989)	0.23	Information Resources Management Journal
		Cheung, Lee & Wang (2005)	0.20	Journal of Knowledge Management
T11. INFORMATION INFRASTRUCTURE	Information, technology, issues, tools, processing	Tseng & Ting (2013)	0.24	Innovation-Management Policy & Practice
		De Moor (1998)	0.18	Failure and Lessons Learned in Information Technology Management
		Dickson & Nusair (2010)	0.17	Worldwide Hospitality and Tourism Themes
T12. LAW AND REGULATIONS	Development, framework, legal, application, whether	Greenleaf, Mowbray, & Chung (2018)	0.25	Computer Law and Security Review
		Sehrawat (2017)	0.24	Computer Law and Security Review
		Hede, Nunes, Ferreira, & Rocha (2013)	0.19	Technology in Society
T13. METHODS	Techniques, based, results, methods, performance	Abidoye & Chan (2017)	0.26	Pacific RIM Property Research Journal
		Stansfield (1995)	0.22	Property Management
		Zurada, Levitan, & Guan (20069	0.22	Journal of Applied Business Research
T14. MARKETING	Marketing, new, customer, services, internet	Baesens et al. (2004)	0.28	European Journal of Operational Research
		Kim et al. (2001)	0.22	International Journal of

Topic Name	Topic Terms	Top 3 Correlated papers with topic	Posterior Probability	Journal
				Electronic Commerce
		Gustavsson (2005)	0.20	Gender Work and Organization
T15. CONTROL AND RISK MANAGEMENT	Quality, proposed, fuzzy, risk, applied	Tsang et al. (2018)	0.43	Industrial Management and Data Systems
		Geramian et al., (2017)	0.31	International Journal of Quality & Reliability Management
		Choy et al. (2018)	0.22	VINE Journal of Information and Knowledge Management Systems
T16. MANUFACTURING	New, industry, manufacturing, production, concept	Vasin et al. (2018)	0.32	European Research Studies Journal
		Olsson & Funk (2009)	0.26	Journal of Quality in Maintenance Engineering
		Wu et al. (2018)	0.17	Journal of Manufacturing Systems
T17. EXPERT SYSTEMS	Systems, expert, applications, computer, years	Collins (1984)	0.27	Journal of Personal Selling and Sales Management
		Baldwin-Morgan (1995)	0.25	Accounting Education
		Gupta (1990)	0.22	Technovation
T18. SOCIAL AND DIGITAL IMPACTS	Technologies, social, digital, impact, key	Kane, 2017	0.32	Information and Organization
		Payne, Peltier, & Barger (2018)	0.32	Journal of Research in Interactive Marketing
		Kostin (2018)	0.29	Strategic Management

3. Topic description

The profiling of each topic was drawn up by analyzing the papers with the highest posterior probability of belonging to each topic and performing a discussion on the findings of those papers. After analyzing the 18 topics, some groups of discussions emerged as related to how AI may influence the overall society in a broader sense, how it impacts the organizations, what types of systems have been used and what methodologies are employed. Therefore, in order to classify the representative research domains within the field of AI in business, the identified topics are organized into four main clusters*: societal impact of AI, organizational impact of AI, AI systems,* and *AI methodologies*. The content in each cluster (and topic) is described and analyzed in the next sub-sections.

3.1 Societal impact of AI

The first cluster, societal impact of AI, comprises topics which handle issues regarding how AI if influencing society, such as: robots in society, law and regulations, marketing, and social and digital impacts.

Robots. A number of articles discuss the topic associated with the use of AI robot, especially in the service context, and its implications for society. Robots are machines capable of handling complex series of actions (Singer, 2009). Service robot systems are autonomous and adaptable interfaces that interact, communicate, and deliver services to an organization or customers (Ashrafian 2014; Wirtz, Patterson, Kunz, Gruber, Lu, Paluch, & Martins, 2018). These systems can learn from past experiences (Pagallo, 2013; Wright & Schultz, 2018) and become connected and embedded into a bigger system via knowledge bases and cloud-based systems (e.g., Wirtz et al., 2018). Service robots can integrate local input (e.g., through cameras, microphones, and sensors), data from a wide range of other sources, such as the internet and organizational knowledge system, as well as biometrics information of customers (e.g., through facial and voice recognition systems) to identify a customer and provide him/her with highly customized and personalized services (e.g., Keisner, Raffo, & Wunsch-Vincent, 2016; Cockshott & Renaud, 2016; Gonzalez-Jimenez, 2018). In this cluster, articles on integrated robot and artificial intelligence (AI robots) (Kamishima, Gremmen, & Akizawa, 2018) compare person-to-person service encounters with those involving the use of AI robots, highlighting which tasks are most appropriate for humans and which can be delivered by machines (e.g., Glushko & Nomorosa, 2013; Huang & Rust, 2018). There are emerging studies discussing the hypotheses that, in the near future, the use of AI robots may become dysfunctional and may cause mental disorders and other psychiatric issues in humans (e.g., Ashrafian, 2017; Wright & Schultz, 2018). In sum, as a warning, researchers and thinkers argue that the use of AI robots can have a huge impact in society, not only because they will be more embedded in service encounters, but they can also put themselves and human beings at risk, become capable of performing creative tasks (thus leave nothing for human beings), and achieve the same level of intelligence of human beings (e.g., Brundage, 2015; Ashrafian, 2017; Wright & Schultz, 2018).

Law and regulations. From the 1980's, continuous work has been done to develop legal expert systems, raising the number of researches on legislation and regulations of AI (e.g., Sehrawat, 2017; Greenleaf, Mowbray, & Chung, 2018). Other studies examine the right to be forgotten in AI memory (i.e., whether or not individuals can request that information made public about themselves be deleted), attempting to discuss and analyze whether and how the law should address such issue, the technical problems behind it, and the dearth of interdisciplinary scholarship supporting privacy law and regulation (e.g., Hede, Nunes, Ferreira, & Rocha, 2013; Villaronga & Kieseberg, 2018; Dalenberg, 2018; Čerka, Grigienė, & Sirbikytė, 2017). Cath, Wachter, Mittelstadt, Taddeo, and Floridi (2018) highlight and compare the three reports that the White House, the European Parliament, and the United Kingdom House of Commons, each delivered in 2016, regarding their visions on how to prepare society for the widespread use of AI. In common, the three reports claim for transparency, accountability, and a positive impact of AI on the economy and society. In an overview, the US report is the only one to have an elaborate research and development (R&D) strategy to support its recommendations. The EU report recommends the creation of a "European Agency for Robotics and AI" and makes several recommendations for legislation, reflecting a "less light touch" approach to governance of AI and robotics. The UK report claims for the development of novel regulatory frameworks. Cath et al. (2018, p.22) concludes by stating that: "Exposed to such extraordinary technologies, human life may easily be distorted, with humans adapting to inflexible technologies, following their predictive suggestions in self-generated bubbles, or being profiled into inescapable and generic categories, for example. We need to ensure that our new smart technologies will be at the service of the human project, not vice versa."

Marketing. The field of marketing is one of the most developed regarding AI issues. Discussions around AI in marketing include how AI techniques can contribute to predicting whether a new customer will decrease or increase his/her future spending from initial purchase information (Baesens, Verstraeten, Van den Poel, Egmont-Petersen, Van Kenhove, & Vanthienen, 2004), how AI can personalize recommendations on Internet storefronts (Kim, Lee, Shaw, Chang, & Nelson, 2001), how gender of virtual employees matters (Gustavsson, 2005), how AI can be associated with public relations, as well as how human-like technologies can operate without human intervention, making their own decisions and acting proactively (Galloway & Swiatek, 2018), thus changing the relationship between firms (machines substituting frontline employees) and customers.

Social and digital impacts. The papers in this topic discuss how AI can evolve in social media applications and contribute to sales in retailing or banking contexts (Moncrief, 2017; Payne, Peltier, & Barger, 2018; Kostin, 2018).

The papers also discuss the negative impacts of AI due to the distortion that can happen when online platforms and systems manipulate the content of traditional documents, such as books, newspapers, and legal documents, change the past, and eventually disseminate bad practices and criminal thoughts (e.g., Rumpala, 2012; Singh, Gaur, & Agarwal, 2017; Kane, 2017; Pueyo, 2018).

3.2 Organizational impact of AI

The organizational impact of AI cluster aggregates topics on AI impact on work, manufacturing, knowledge management, decision supports, fuzzy logic approach, and risk management.

Work impact. This topic is associated with studies that suggest how work will be transformed using AI and other technologies and how such technological innovation generates impact to the organization. As suggested by Lee, Shin, and Baek (2017), organizations should fully utilize and support employees to become fully engaged in their work by establishing general roles and specific tasks. Other studies claim the importance of incorporating AI in organizational decision, project, and enterprise contexts (e.g., Danila, 1989; Jankovi, Cardinal, & Bocquet, 2015), and how AI transforms the nature of work and the employee-machine relationships (e.g., Li, Tang, Man, & Love, 2002; Kolbjørnsrud, Amico, & Thomas, 2017). Sousa and Wilks (2018) point out the importance of retaining critical skills for employees in organizations that use AI. These include complex problem-solving, critical thinking, creativity, people management, coordinating with others, emotional intelligence, judgement, and decision making, service orientation, negotiation, and cognitive flexibility. In sum, the papers suggest that AI will develop a sense of initiative and entrepreneurial capabilities inside the organizations. AI systems can develop persuasive communication with employees, capture the essentials of communication concisely to assist in promoting goods and services, formulate questions that contribute to solving problems, and stimulate curiosity to create new knowledge (e.g., Aicardi, Fothergill, Rainey, Stahl & Harris, 2018; Sousa & Wilks, 2018).

Manufacturing. With the fourth industrial revolution, marked by the use of AI and other technologies, production (industrial) may become the main source of prosperity and creation of new jobs in developed countries (Vasin, Gamidullaeva, Shkarupeta, Palatkin, & Vasina, 2018), such as the case of the Russian Federation. AI contributes to optimizing the quality of production system and consequently the quality of products (Olsson & Funk, 2009; Wu, Ren, Zhang, Fan, Liu, Fu, & Terpenny, 2012; Dassisti & Giovannini 2012); AI also allows for production of highly customizable products (Wu, Ren, Zhang, Fan, Liu, Fu, & Terpenny, 2018; Tao, Qi, Liu, & Kusiak, 2018). From this topic emerge the concept of case-based experience reuse, which refers to systems that facilitate experience reuse for different individuals working with standardized production models, or to an efficient experience transfer system, which contributes to more time savings, higher predictability, and less risk (e.g., Dietrich, Kozlenkov, Schroeder, & Wagner, 2003; Olsson & Funk, 2009). As an example, when employees retire or companies need to downsize, organizational knowledge is often lost. New employees require training and they can repeat past mistakes. Using an AI agent enterprises can avoid such situation (e.g., Dietrich, Kozlenkov, Schroeder, &Wagner, 2003; Olsson & Funk, 2009). Russel and Norvig (1995) claim that an agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through effectors. Thus, an agent can be a computer system that interacts with employees, having properties, such as autonomy, social abilities, reactivity, and proactiveness.

Knowledge management. This group of articles deals with systematic management systems of organization's knowledge to create value through initiatives, processes, strategies, and systems that sustain and enhance the storing, sharing, refining, and creating of knowledge (Davis, 1989; Paradice & Courtney, 1989; Smith, Dykman, & Davis, 1989; Shadbolt & Milton, 1998; Siurdyban, Møller, Cheung, Lee, & Wang, 2015). Within an organization, AI is intervening in such systems as lean supply chain (e.g., Choy & Lee, 2003; Liu, Leat, Moizer, Megicks, & Kasturiratne, 2013), quality management systems (Srdoc, Sluga, & Bratko, 2005), and crowdsourcing systems (Bradeško, Witbrock, Starc, Herga, Grobelnik, & Mladenić, 2017).

Decision support. Decision support and the importance of a good decision making that integrates technical, human, and organizational systems to achieve the strategic success of an enterprise is the core issue developed in this topic (e.g., Krabuanrat & Phelps, 1998, Cabanero-Johnson & Berge, 2009; Cesta, Cortellessa, & De Benedictis, 2014; Kosala, 2017). A paper by Kalantari (2010) highlights the excellent value and contribution of Herbert Simon in decision making process within economic organizations, claiming that Simon "was a true interdisciplinary scholar and has contributed to many disciplines […] he worked with Newell to create a new science of AI which set the ground for studying human thought patterns using computational models" (p. 511).

Fuzzy logic approach and risk management. The last topic in the organizational impact cluster aggregates papers focusing on fuzzy logic approach under AI technology to improve the quality of industrial products and reduce failures (e.g., Geramian, Mehregan, Mokhtarzadeh, & Hemmati, 2017; Tsang, Choy, Wu, Ho, Lam, & Koo, 2018). Fuzzy logic is an approach to computing based on degrees of truth rather than the usual true or false (1 or 0) Boolean logic. That is, using the Fuzzy logic, the truth value of a variable may be any real number between 0 and 1 (e.g., Novák, Perfilieva, & Močkoř, 1999). The applications of fuzzy logic are found in automobile industry (Geramian, Mehregan, Mokhtarzadeh, & Hemmati, 2017) and health care sector (Choy, Siu, Ho, Wu, Lam, Tang, & Tsang, 2018). The papers suggest that the fuzzy logic approach contributes to the overall process of quality improvement through risk analysis, risk evaluation, and risk control (e.g., Taylan & Darrab, 2012; Tsang, Choy, Wu, Ho, Lam, & Koo, 2018).

3.3 AI Systems

This topic cluster includes topics that aggregate AI systems deployed on the organizations such as expert system, systems design, and information infrastructure.

Expert system. This topic focuses on expert system, which is the knowledge base consisting of facts and heuristics. Facts are information that are publicly available and widely shared and discussed. The performance level of an expert system is a function of the quality and size of its knowledge base. The basic knowledge rule employs if-then statements. The "if" is the premise and represents a group of conditions; when the conditions are satisfied, the "then" (i.e., the conclusion) is inferred (Gupta, 1990). Thus, these articles deal with the development and improvement of algorithms of AI.

Systems design. This topic deals with the design of flexible manufacturing systems where AI is integrated (e.g., Aiken, Sheng, & Orl, 1991; Chan, Jiang, & Tang, 2000). Intelligent tools, such as expert systems, fuzzy systems, and neural networks, are developed for supporting the flexible manufacturing systems (FMS) or for group decision support systems (GDSS) (Aiken & Orl, 1991). For example, in the automotive industry, nuclear power plants, or other industries, the use of visual interactive simulations and AI simulated representations allow companies to predict the performance of operational systems under different decision-making strategies and to search for improved strategies (Yang, Jeong, & Park, 1994; Chan, Jiang, & Tang, 2000; Robinson, Alifantis, Edwards, Ladbrook, & Waller, 2005; Chakraborty & Boral, 2017).

Information infrastructure. The articles within this topic discuss the creation of expert systems for the interface between industry (a firm) and the public (external to the firm), such as consumers and a wider society. To this end, AI is categorized into four sub-technological fields: problem reasoning and solving (comprising a specific circuit arrangement for performing approximate reasoning where truth values and quantifiers are represented by possibility distributions), machine learning (a system having the capability to automatically add to its current integrated collection of facts and relationships), network structures (the system contains construction details of processors or their interconnections), and knowledge processing systems (a system comprising specific domain data that is integrated as a collection of facts and relationships [knowledge representation] and applies a reasoning technique) (Tseng & Ting, 2013, p.464-465). As AI contributes to the knowledge economy in a network of several countries, the roles of each country in the network can be determined by their performance in the four sub-technological fields of AI, such as disseminators and catch-up players (e.g., Peña, 1998; Antonescu, 2018). AI systems may also assist in meeting the needs of the present without compromising the ability of future generations (i.e., supporting sustainable development) by creating expert systems that facilitate numerous stakeholders to communicate globally for sustainable causes (De Moor, 1998). These systems can also be applied in the recruitment process of employees on a global scale (Dickson & Nusair, 2010).

3.4 AI Methodologies

The AI Methodologies cluster comprises six topics that are connected to the methodological techniques used in the companies: methods, forecasting, data analysis, neural networks, learning, and problem solving.

Methods. This topic discusses the possibilities of using AI in complex methodological techniques to predict market evolution and analyze customer churn, contributing to the marketing field. Examples of these methods include neural network-based methods, fuzzy logic, memory-based reasoning, text mining, aspect sentiment analysis, data mining, and machine learning (e.g., Stansfield, 1995; Zurada, Levitan, & Guan, 2006; Burez, & Van den Poel, 2009; Marques, Garcia, & Sanchez, 2013; Kovacs, Bogdanov, Yussupova, & Boyko, 2015; Abidoye & Chan, 2017; Tatiya, Zhao, Syal, Berghorn, & LaMore, 2018).

Forecasting. This topic is attributed to studies that use AI algorithms to analyze statistical time series models and grey theory in predicting tourist arrival, consumer behavior, and air quality, contributing for market planning (e.g., Raghunathan, 1994; Cho, 2003; Yu & Schwartz, 2006; Chen, Su, Cheng, & Chiang, 2011; Goh & Law, 2011; Dohnal & Doubraysky, 2016; Zhou, Chang , Chang, Kao, & Wang, 2019).

Data analysis. Studies within this topic contemplate how data could be better analyzed, such as how to extract essential facts that are embedded in the data, how to manage large amounts of business data, and how to use of rough set theory to deal with uncertainty (e.g., Goh & Law, 2003; Mazurek, 2013; Shishehgar, Mirmohammadi, & Ghapanchi, 2015; Park & Han, 2016; Ostad, Mahmoee, & Nezhad, 2017; Wong, Ho, & Tsui, 2017; Reformat, Yager, & To, 2018).

Neural networks. As the name suggest, articles within this topic use the predictive performance of neural networks to predict consumer' responses to direct marketing and the use of a semantic network that describes the model for developing communication message design pattern (Cui & Wong, 2004; Fish & Ruby, 2009; Chang & Wang, 2013; Claveria, Monte, & Torra, 2015; Er & Hushmat, 2017; Yekhlakov & Malakhovskaya, 2018; Soltani-Fesaghandis & Pooya, 2018).

Learning. This topic includes a set of articles dedicated to the methods to be used in multimedia learning, online education (including faculty preparation and course connections), and learning approaches for solving game theoretic models (e.g., Fang, Kimbrough, Valluri, Zheng, & Pace, 2002; Collins, & Thomas, 2012; Zhu, Marques & Yoo, 2015; Lyons, 2017; Lin, Wooders, Wang, & Yuan, 2018).

Problem solving. This group presents methods for search approaches and formulation of problems, and propose alternative solutions using AI algorithms for operations management (e.g., Schmidt, 1998; Lee, 2001; Liang, 2012; Tsafarakis, Saridakis, Baltas, and Matsatsinis, 2013; Bekkouche, Benslimane, Huchard, Tibermacine, Hadjila, & Merzoug, 2017; McCarthy, 2017; Georgiev & Georgiev, 2018; Khosravi, Nunes, Assad, & Machado, 2018).

4. Future Trends in AI: Stakeholder Implications

In recent years, with the expanding availability of consumer information and information coming from multiple devices connected to the internet (IoT), companies have started to improve their maturity in terms of data science skills and business analytics. According to Gartner, business analytics maturity can be measured in 4 stages, from a (1) more descriptive use of information, to (2) a diagnostic analysis stage that implies an understanding of the root causes that led to a specific outcome, (3) a predictive analytics stage, in which companies use data mining algorithms to predict what will happen and (4) prescriptive analytics that uses advanced optimization and artificial intelligence algorithms to guide the company on how to make changes in the foreseeable future. However, despite the big data being collected and stored, in the end of 2018, 87% of organizations worldwide were still considered as having low analytics maturity (Gartner, 2018). Skilled resources, such as Data Scientists -the professionals that know how to analyze the big data and use it to improve the business- are still scarce (Statista, 2019). In contrast, data mining algorithms have become more accurate and faster in processing data. Although traditional analytical algorithms -such as artificial neural networks (ANN)- are still being successfully implemented in businesses to address problems such as fraud detection (Zakaryazad & Duman, 2016), the recent advent of new algorithms based on deep learning networks and convolution neural networks (Krizhevsky, Sutskever, & Hinton, 2012), have allowed companies to handle complex predictive problems (e.g., image and video processing) (Pouyanfar *et al.,* 2018). Some examples include driver behavior intention to improve how self-driving cars adapt to the consumers' individual characteristics (Shahverdy, *et al.*, 2020), or learning algorithms to predict project profitability (Bilial & Oyedele, 2020). Given the recent rise in computer power and algorithm complexity, new applications are expected to impact how companies work and prepare for improving their competitive advantages. For example, the Gartner hype cycle for emerging technologies classified generative adversarial networks (GAN) (Goodfellow *et al.*, 2014) and eXplainable AI (XAI) (Arrieta *et al.*, 2020*)* as innovative AI technologies that may drive future applications (Gartner, 2019).

Although much have been written about AI in the literature, there are still many challenges and management implications that are far from being fully addressed in previous studies. A search on SCOPUS and WoS for papers on future trends in AI ranging from 2018 to 2020 in the Business subject area, revealed eight fundamental articles. Such trends are used here to highlight how AI may affect company stakeholders (see table 4)

Table 4. Papers on Future AI Trends in Business

Author	Title	Journal
Capatina et al., 2020	Matching the future capabilities of an artificial intelligence-based software for social media marketing with potential users' expectations	Technological Forecasting and Social Change
Davenport, Guha, Grewal and Bressgott, 2020	How artificial intelligence will change the future of marketing	Journal of the Academy of Marketing Science
Haenlein and Kaplan, 2019	A brief history of artificial intelligence: On the past, present, and future of artificial intelligence	California Management Review
Clarke, 2019	Why the world wants controls over Artificial Intelligence	Computer Lay and Security Review
Yampolski, 2019	Predicting future AI failures from historic examples	Foresight
Upadhyay and Khandelwal, 2019	Artificial intelligence-based training learning from application	Development and Learning in Organizations
Kaplan and Haenlein, 2019	Rulers of the world, unite! The challenges and opportunities of artificial intelligence	Business Horizons

Following the stakeholder theory (Freeman, 2004), we discuss how AI may affect (1) the internal stakeholders, in which we discuss implications for businesses driven by the use of AI for the workforce and management (employees and managers/owners), and (2) the external stakeholders, where implications of AI future trends for the companies may come from the customers, the suppliers, the society, the government and other interest groups.

4.1 Internal Stakeholders

4.1.1 EMPLOYEES

AI is often referred to when discussing the future of the working environment. AI agents will someday take over repetitive tasks and maximize efficiency (Huang, Rust & Maksimovic, 2019). As a result, millions of jobs will be lost while new types of jobs will be created due to automation (Ford, 2013; Pueyo, 2018). In the first round of AI impact on work, creative jobs are projected to be safe from AI replacement. In fact, some researchers argue that AI will always fail to recognize and use human creativity (e.g., Holford, 2019) and that a new type of Feeling Economy (based on emotions, empathy and interpersonal relations) will drive job creation (Huang, Rust & Maksimovic, 2019). Yet, recent examples also show AI systems that perform “creative” tasks by producing their own art (Christies, 2018) and music (Guardian, 2018). Just as human beings AI agents are influenced by their experience when developing their creative ideas. AI agents will have more power to learn from their human ancestors to develop new creative and innovative concepts that may be applied in the workplace. This can also contribute to the creation of smart workplaces as AI systems could assist in providing safer working conditions and convenience due to a better understanding of patterns of task fulfillment and creative processes. For example, Hyundai and Mercedes-Benz are already using AI embedded in exoskeletons to help human workers to perform better most repetitive tasks (Wilson & Daugherty, 2018).

Smart systems are also revolutionizing manufacturing. In fact, Industry 4.0 is already a reality in many medium-to-large companies (Diez-Olivan et al., 2019; Ghobakhloo, 2018). Smart manufacturing, with its roots dating back to the works of Kusiak (1990; 2018), represents integrated systems that respond in real-time to the demand of the factory, the supply network, and the customer. The Internet of Things (IoT) will assist companies in measuring their operational performance by implementing connected sensors to track most of their activity (Turner *et al.*, 2019). A company that is already using the benefits of embedding IoT with AI is Nature Fresh Farms, which has reduced packaging times from more than 35 seconds to just 8 seconds by improving the way it screens its fresh products (Forbes, 2018). Furthermore, AI systems will be able to learn from past successes and failures in all the decision layers and come up with better solutions such as lighter and more creative ways to produce airline components or completely new conceptual designs (as the ones developed by PTC-Frustum's AI systems) (PTC, 2018).

4.1.2 ROBOTIC EMPLOYEES

Today, robots can sense their surrounding environment to learn how to interact in the real-world. AI agents embedded in robotic systems are thus evolving as they are learning to walk, to avoid obstacles, and to master complex human skills (Fevre, Goodwine & Schmiedeler, 2019; Singh & Bera, 2020). There has also been an increasing development in human-AI interactions to help AI agents learn faster by asking for (human) help when confronted with a limitation, just like a human does in its evolution (Silva, Faria, Melo,

& Veloso, 2017). The proliferation of automated systems that are using AI to execute complex tasks, such as self-driving cars and customer service bots, will eventually lower the cost of producing such systems, making them more readily available (Ivanov and Webster, 2019). In addition, as AI agents are integrated into daily experiences (e.g., as customer assistants or factory workers), and particularly in tasks where they take the master role in the human-object relationship, as put forward by Schweitzer et al. (2019), they will also become a new type of buyer. An example would be an AI system embedded in a smart device or an AI-embedded robot that would search, filter, select and buy a set of goods on behalf of their owners without explicit consent other than following its owner patterns of behavior.

4.1.3 MANAGEMENT AND OWNERS

The implications of a hybrid working environment are humans and AI systems working together and changing how managers and owners need to act to ensure a healthy working balance between multiple different needs (Kaplan & Haenlein, 2018). Today, companies are already using AI systems to help managers decide who to hire. Unilever, for example, has been using HireVue to successfully analyze and survey thousands of potential candidates for internships, while L'Oreal has been using a similar approach to recruit international candidates and the time needed to screen a candidate has decreased by 90% (Black & van Esch, 2020). Such automated systems based on AI, although still in its infancy, are known to be much less biased and much more objective than traditional Human based recruiting (Van Esch, Black, & Ferolie, 2019). A more distant future trend may rise from the use of brain-computer interfaces to enhance cognitive skills for both managers and employees.

Today, brain-computer interfaces (BCI) are widely developed to allow people to interact with a computer (smartphone or AI) using only their brain waves (Martinez-Cagigal et al., 2019; Cheng, 2017). However, the future will also rely on bi-directional systems that not only capture brain waves, but also interact with the human brain though deep brain stimulation (DBS).

Although DBS is not a new field in cognitive neuroscience and has been used to treat neurological conditions and in neuroprosthetics (Rouse et al., 2011; Horch & Dhillon, 2004), its maturation has allowed its use to extend to other fields, such as immersive realities or memory enhancement (Cangelosi & Invitto, 2017). Yet, despite the evident benefits of using BCI for commercial applications, the future and potential applications will face numerous ethical challenges (Glannon, 2016), especially because of the possibility of such systems creating a new type of hybrid humans (Humans 2.0) with levels of intelligence much higher than their older, "natural" generation. Such cognitive difference will have significant business implications as more intelligent workforce may dominate society.

The integration of neurostimulators and nanochips into the brain enhances the human organism toward transhumanism (Bostrom, 2005a; Bostrom, 2014), and eventual creation of the hybrid humans (e.g., Kumar, Dixit, Javalgi, & Das, 2016; Rust & Kannan, 2002; Ng & Wakenshaw, 2017). Transhumanism is a movement that "understands and evaluates the opportunities for enhancing the human condition and the human organism opened up by the advancement of technology" (Bostrom, 2005b, p. 3). Transhumanists believes that the actual biological condition of humans limits them to a range of feelings, thoughts and experiences, which may be leveraged by incorporating technology. The goal of such improvement of human capabilities is their subjective well-being and for organizations to enhance employees' job performance. The meaning behind subjective well-being comprises personal traits of individuals, their positive and negative affect, and life events (e.g., Headey & Wearing, 1989; Myers & Sweeney, 2004; Dodge et al., 2012).

Enhancing the cognitive, emotional, and physical characteristics of humans can leave them with positive feelings and moods, improve their cognitive capabilities and physical dexterity to overcome their life's challenges and negative events, and achieve their life goals. An engagement process will be needed for individuals to accept transhumanistic technologies. Indeed, these technologies may be so intrusive and transformative that people will show a tendency to be afraid, feel insecure, and thus avoid them.

For organizations working on transhumanistic technologies, involving people in the cause by inviting them to actively participate during the whole process of new product development and openly explaining the potentialities, benefits, and eventual failures of these technologies will be a challenge. Notwithstanding, only through internal and external engagement process with all stakeholders (including consumers), organizations will be able to contribute to enhance human well-being and at the same time improve job performance (e.g., Greenwood, 2007; Rodriguez-Melo & Mansouri, 2011). As suggested in the literature, employees who are engaged with the organization, internalizing its mission and goals, will perform their job better (Kumar & Pansari, 2016).

Following such predicted advancements in the literature, we frame the first AI trend under the realms of **Robots and Automated Systems** and the second AI trend under **Brain-Computer Interfaces (BCI) and Deep Brain Stimulation (DBS)**.

4.2 External Stakeholders

4.2.1 CUSTOMERS

The previous section explored how companies are preparing for an AI society. Such changes in the business landscape are already affecting the way companies interact with consumers. For example, advanced AI assistants capable of proactively taking actions for their users, as demonstrated by Google Assistant calling a restaurant to schedule a reservation (BBC, 2018), will become the norm in the near future, presenting new ways of delivering and consuming services. Following the self-expansion model (Aron & Aron, 1986) and the extended-self proposed by Belk (2013) we suggest that consumers will increasingly adopt AI technologies (even BCI to enhance their cognitive skills) to reduce repetitive tasks while enhancing hedonic/aesthetic experiences. Some examples include Replika, an empathetic AI chatbot that learns from its owners' behavior and acts as an emotional partner (Replika, 2020) and Conversica, that augments customer support during the decision-making process (Conversica, 2020).

4.2.2 SUPPLIERS AND SOCIETY

The evolution of the Internet of Things (IoT) coupled with AI to form intelligent cyberphysical systems will also bring new implications for how we live our lives. In the near future, it is expected that everything we use in our daily lives will be connected (Leminen et al., 2018). Such networked devices will generate significant amount of real-time behavioral data, which may only be analyzed using AI algorithms to uncover latent knowledge that can be used to help cities becoming better managed and more sustainable (O'Dwyer, 2019). As AI becomes more intelligent, it is expected that smart systems will find ways to optimize the daily lives of city dwellers in ways we have never thought about before. The relationship between companies and suppliers will also need to address the ever increasing need to integrate Big Data information to better serve the consumer and improve production efficiency. Following such predicted advancements in the literature, we frame the third AI trend under the reals of **Internet-of-Things and AI integration.**

4.2.3 GOVERNMENT: Law and ethics

Deep learning was developed to accurately predict a given outcome by learning from the environment. However, with hidden layers embedded in the networks, they are largely black-boxes (Pouyanfar, *et al.*, 2018). However, recent AI techniques framed under the eXplainable AI (XAI) algorithms are paving the way for future transparent applications based on AI (Arrieta, 2020). However, despite studies conducted to bring transparency to the complex learning procedures that are inherent to AI (Miller, 2019), more research is needed to translate AI language to human language. Yet, not only the communication process between AI systems and humans needs to be settled, a whole AI systems and robots rights charter with duties and obligations should emerge and be approved by an international governing body, such as the United Nations. Current laws governing citizens on tort and liability should be reviewed and potentially extended to include AI systems to regulate who will be liable, for instance, if AI systems and robots caused bodily harm to others (e.g., humans, AI agents, and hybrid beings). In the same line of thoughts, when AI systems produce products/experiences or when they receive and use them, they should be entitled to intellectual property and have the duty to pay taxes. Despite some initiatives are already in place to develop some of these best practices, such as AI for Humanity or the Institute for Ethics in Artificial Intelligence (Nebeker et al., 2019), there is a growing concern that, as AI becomes more intelligent, humans would be unable to control its evolution. A super intelligent society based on AI agents and hybrid humans may bring both enormous benefits and challenges in terms of environmental and societal changes (Pueyo, 2018). Singularity, commonly referred as a state of super intelligence where AI overcomes HI, may occur in the next decades (Turchin, 2018). However, risks and contingencies should be discussed today to prepare for the future. Such risks include lack of safety of future AI systems, lack of transparency, a potential biased and unfair treatment from self-learning systems which may deepen socio-economic inequalities and the degree of dependency of HI from such intelligent systems (Green, 2018). So far, recommendations of how machine Ethics should be imposed on future systems have been focused mainly on a two-way approach that should drive the discussions in the next decade. The first posits that such Ethics should be derived from learning systems that use past moral behaviors and rules from the current society (Bello & Bringsjord, 2012), while the second proposes the definition of a new set of agreed-upon moral rules that should be embedded in every AI system from its inception (Arkoudas et al., 2005). Recent trends suggest a mix of both approaches under a set of *hard and soft* ethics standards (Floridi et al., 2018). Following such predicted advancements in the literature, we frame the fourth AI trend under **AI integration, and Law and Ethics** (see table 5).

Table 5. Future Trends in AI

Trend Type	Summary of Trend	Example	Implications
Robots and Automated Systems	The development of advanced automated systems to handle daily tasks	Customer service bots; self-driving cars	Job Loss (repetitive jobs); Job Satisfaction (creative jobs); Customer Engagement and Satisfaction
BCI and DBS	Integration of neurostimulators and nanochips into the brain to allow bi-directional communication	Social communication; cognitive enhancement	Transhumanism; Job performance; stakeholder engagement; human well-being
Integrated IoT and AI	Smart devices connected to AI systems to maximize efficiency and relationships	Smart cities; Operational efficiency	More sustainable cities; Increased profits
Law and Ethics	Definition of ethical codes and rules of law to regulate AI	Regulations for liabilities; Regulation of work	AI agents, hybrid (half human, half robot) and humans will exist together in society and at work, thus, without regulation the society may become chaotic.
	AI becoming more intelligent than humans	AI systems may demand to manage important infrastructures for human life support and society	Human beings lose control over infrastructures for human life support and society

Table 5. Papers on Future AI Trends in Business

Author	Title	Journal

Capatina et al., 2020	Matching the future capabilities of an artificial intelligence-based software for social media marketing with potential users' expectations	Technological Forecasting and Social Change
Davenport, Guha, Grewal and Bressgott, 2020	How artificial intelligence will change the future of marketing	Journal of the Academy of Marketing Science
Haenlein and Kaplan, 2019	A brief history of artificial intelligence: On the past, present, and future of artificial intelligence	California Management Review
Clarke, 2019	Why the world wants controls over Artificial Intelligence	Computer Lay and Security Review
Yampolski, 2019	Predicting future AI failures from historic examples	Foresight
Upadhyay and Khandelwal, 2019	Artificial intelligence-based training learning from application	Development and Learning in Organizations
Kaplan and Haenlein, 2019	Rulers of the world, unite! The challenges and opportunities of artificial intelligence	Business Horizons
Geisel, 2018	The current and future impact of artificial intelligence on business	International Journal of Scientific and Technology Research

5. Concluding Remarks

Recently AI has become a topic of interest for many researchers and practitioners in the Business field due to its diverse applications in several industrial domains. Past research has pointed out the need for more research that contributes to knowledge and strategies in the four identified topic clusters. The major concerns claimed in past research include (i) how organizations should re-envision organizational structure, job function, and skills, and educate future workforce (students), (ii) ethical and legal issues regarding data protection of citizens and the new role of robots in society, and (iii) how new methods may emerge that could perform more reliable future predictions. Table 6 provides several potential questions to guide the directions of future research addressing these concerns.

Table 6. Questions for future research

Future Trends	**Business Domains**	**Research Questions**
Robot and automated systems	Strategy	• How to design human–machine integrated service strategies? • How to create original, unique goods with AI applications?

Future Trends	Business Domains	Research Questions
		• How to identify consumer preferences for human or machine services? • How to streamline processes for human and machine service providers? • How hard is to duplicate competitive advantages based on robots and automated systems? • How robots and automated systems depreciate over time and what kind of investment is required to keep the pace of innovation under an AI-led business environment?
	Relationship Marketing	• How will cognitive and emotional-social complexity dimensions influence robot design? • Which relationship marketing capabilities should be programmed in service robot? • How will the engagement process evolve between humans and AI-enabled machines? and what about enabled-AI Robot-to-Robot engagement? • How can robots and automated systems based on AI empower consumers with disabilities to go beyond their cognitive and physical limitations?
	Servicescape	• How can service robots be effectively integrated into the servicescape? • How will the new servicescape look like in a robot dominated service environment? • What will be the core dimensions of servicescape in the service robots?
	Customer acceptance	• Beyond the physical and virtual nature of service objects, what drives customer preference for physical or virtual robots? • How can the more cost-effective virtual robots (e.g. holograms rather than physical robots at information counters) be designed to achieve greater consumer acceptance? • Which consumer and context factors determine the optimal level of humanoid appearance and social skills for service robots? • How robot gender and personality will impact consumer responses to service robots? • Which service and industry characteristics will potentially moderate the impacts of determinants of customer acceptance of service robots?
	Social acceptance	• How can employees deal with working alongside humanoid robots that can operate for extended periods without human intervention (making their own decisions and acting independently)? • How can humans deal with autonomous systems in social environments?

Future Trends	Business Domains	Research Questions
		• Can humanoid robots be accepted to be part of social events (professional or not) as any human?
	Management	• How should organizations manage and implement AI systems in their organizations? • How should organizations stimulate employees to use such systems? • How can we re-train workers for intuitive and empathetic skills to remain employable? • How can we educate students for intuitive and empathetic skills to remain employable in an AI-led business environment? • How can organizations improve knowledge creation with automation using generative models of deep learning?
BCI and DBS	Workforce	• How can we engage stakeholders to develop new product/experiences embracing BCI and DBS technologies? • How can we engage employees in the application of transhumanistic technologies to improve job performance? • What is the impact for the company of recruiting employees with BCI and DBS technologies?
	Transhumanism	• How to connect humans and/or AI-enabled machines for collective intelligence? • How may transhumanistic technologies enhance human well-being? • How citizens/consumers/employees who decide not to use BCI and DBS technologies will interact with those who do?
Integrated IoT and AI		• How will AI systems evolve to aggregate all important infrastructures in a city? • Can these networks allow a global management of the physical infrastructures, social and political governance? • Will AI systems support the development of a sustainable planet?
Legal and ethical issues		• How to balance the competing interests of innovative data use and personal data privacy rights? • How should regulators attempt to enforce laws that are not practicable with new technology, for instance, the *Right to Be Forgotten*? • Could AI-powered machines develop a conscience of self? • Could machines using AI become depressed and have other human-like psychological problems? If so, how to create new laws that could deal with this reality?

Future Trends	Business Domains	Research Questions
		• Will AI agents, hybrids and humans exist together at the same time? How may the relationship among them be stablished and maintained? • When AI systems become smarter than humans, will humans lose control over infrastructures for human life support and society? If so, will humanity (as we know it) cease to exist?

The contribution of the current paper is twofold. First a structured analysis shows how AI implications for Business has evolved over the last decades. Such contribution may help future researchers to guide their own literature review depending on their topics of interest in AI. Second, future trends are debated following the recent findings in the literature. We also propose a set of research questions stemming from the recent trends that are still in need for further development. Despite using prior research as a basis for proposing future directions, the suggested questions may still be far from being fully answered as no one knows the pace of AI evolution.

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Appendix A

Element	0: Absence	1: Low level	2: Medium level	3: High level	Not Applicable
1. Directly related to the objective of the research	There is not enough information to evaluate this criterion	Not related	Somehow related	Totally related	Not Applicable
2. Theory robustness	There is not enough information to evaluate this criterion	Weak development of literature	Superficial development of theories and constructs within existing literature	Robust use of theory	Not Applicable
3. Congruence of theory, methodology and findings	There is not enough information to evaluate this criterion	Incomplete data and not related to theory	Data somehow related to the arguments	Strong link between the arguments presented and data	Not Applicable
4. Contributions to theory and/or practice	There is not enough information to evaluate this criterion	Makes a low contribution	Makes a medium contribution	Makes a high contribution	Not Applicable

Source: Adapted from Macpherson & Holt (2007).

Methodological Appendix

Table 3 presents the topics extracted by using LDA (Latent Dirichlet Allocation). LDA is a mixed-membership clustering algorithm that creates latent topics using a hierarchical Bayesian approach (Blei et al., 2003). The first step towards analyzing the latent topics was to collect the full text of each paper and transform them into a text mining *corpus*. The text was then transformed into lower case and stop-words, numbers and whitespaces were removed. The text was then tokenized into unigrams and bigrams. The corpus was then used to test the log-likelihood and perplexity (Griffiths and Steyvers, 2004; Cao et al., 2009) of a set of possible topics ranging from 2 latent topics up until 60 latent topics. An optimal K was reached at 18 latent topics. The first column of table 3 represents the profiling of such topics after carefully reading all the papers correlated with each topic and assigning names that matched the discussions in those papers.

In LDA, each topic is characterized by a distribution over terms. Therefore, it is possible to compute the most correlated terms with each of the 18 topics (column 2 of table 3). For each paper, the posterior probability of belonging to the latent topics was also computed and used to present the three papers more correlated with each topic (column 3 of table 3 shows the authors and year of publication and column 4 of table 3 shows the posterior probability). The last column has the Journals that published such papers.

Table 4 contains papers that were identified after a search on SCOPUS and WoS using the query: TITLE-ABS-KEY ("Future of AI" OR "Future of Artificial Intelligence" OR "Future AI" OR "Future Artificial Intelligence" OR "AI Research Directions" OR "Artificial Intelligence Research Directions") AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018)) AND (LIMIT-TO (SUBJAREA , "BUSI")). A total of 8 papers were identified in both SCOPUS and WoS that met the criteria. The papers on the table reflect the articles on future trends in AI ranging from 2018 to 2020 in the Business subject area. The first column represents the names of the authors and year of publication. The second column is the name of the paper and the final (third) column represents the Journal that has published the paper.