Leveraging Artificial Intelligence in Business: Implications, Applications and Methods

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2 authors:

Andrea Sestino
Università Cattolica del Sacro Cuore

Andrea De Mauro
University of Rome Tor Vergata

Leveraging Artificial Intelligence in Business: Implications, Applications and Methods

Andrea Sestino[*], Andrea De Mauro[†]

[*] Ionian Department of Law, Economics and Environment,
University of Bari Aldo Moro Taranto, Italy
[†] Department of Enterprise Engineering,
University of Rome Tor Vergata, Rome, Italy

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Abstract: The concept of Artificial Intelligence (AI) as a business-disruptive technology has developed in academic and professional literature in a chaotic and unstructured manner. This study aims to provide clarity over the phenomenon of business activation of AI by means of a comprehensive and systematic literature review, aimed at suggesting a clear description of what Artificial Intelligence is today. The study analyses a corpus of 3780 contributions through an original combination of two established machine learning algorithms (LDA and hierarchical clustering). The review produced a structured classification of the various streams of current research and a list of promising emerging trends. Results have shed light on six topics attributable to three different themes, namely Implications, Applications and Methods (IAM model). Our analysis could provide researchers and practitioners with a meaningful overview of the body of knowledge and research agenda, to exploit AI as an effective enabler to drive business value.

Keywords: Artificial intelligence; Business innovation; Business management; Big data; Marketing; Technology management.

1. Introduction

Today Artificial Intelligence (AI) is a buzzword. The steady growth of its applications has radically penetrated human lives and business organizations. Companies have recognized relevant business opportunities deriving from AI adoption aimed at driving competitiveness, reengineering products or services, or rethinking business strategies (Campbell *et al.*, 2020). Although AI appeared as a discipline in the 1950s, its first business application emerged only in the 1980s, spurred by the success of the expert system paradigm. Since then, its success has progressively accelerated thanks to the exponential growth of available computing power as described by Moore's law (1965). Organizations are now increasingly relying on AI and related Machine Learning (ML) models to improve human understanding of complex systems and to automate decision making, also requiring constant expert contributions (Galanos, 2019). The availability of large, varied and fast–moving information assets, also known as Big Data, ensures large attention to AI applications with substantial advances in calculation, computation, study and design of methodologies based on intelligent algorithms, impacting business and societies. The present study aims to provide a conceptual model of Business Activation of AI by means of a systematic literature review, obtained through the adoption of text mining and ML techniques. The two research questions we aim to answer by means of the systematic review are:

> ***RQ1:*** *what are the fundamental topics dealt with in current literature in relation to the Business Activation of AI?*
> ***RQ2:*** *what are the most promising strands of research, which require further investigation?*

To address our research questions, we implemented a literature review leveraging on an original combination of established machine learning algorithms (LDA and hierarchical clustering), to design human-meaningful topic structures on a list of 3,780 discovered research papers. The paper is organized as follows: the second section introduces concepts related to AI and a brief overview about this phenomenon. The third section describes the methodology we adopted in this study, including text mining procedures and topic modelling. In the fourth section we present the obtained and the identified main themes, namely: *Implications*, *Applications* and *Methods*. Subsequently, in the fifth section, each topic is discussed in depth, shedding light on practices, challenges and opportunities for each. Finally, the last section offers some conclusions and discusses the limitations of this review.

2. Toward Artificial Intelligence: concepts and definitions

Terms such as AI, Big Data, Machine Learning, and Data Analytics are ubiquitous in current academic and business articles dealing with data. To prevent any confusion to the reader, the current section introduces each of these concepts and offers a structured explanation of how they relate to each other.

AI aims at reproducing some aspects of human intelligence through technology. The discipline could be defined as a set of studies and techniques, dealing with computer science and mathematical aspects of statistical modelling, carrying significant economic and social implications, aimed to create technological systems capable of solving problems and carrying out tasks and duties, normally attributable to the human mind (Konar, 2018).

One of the current most recognized definitions describes AI as the process of making a machine display behaviors that would be called intelligent if a human were so behaving. According to Russel and Noving (2010), current literature identifies four conceptual clusters of AI acceptations: AI as Systems that think like humans (Hugeland, 1989); AI as Systems that think rationally (Winston, 1992); AI as Systems that act like human beings (Rich and Knight, 1991); and AI as Systems that act rationally (Nillson and Nillson, 1998).

The growing attention on AI in the business field is due to the technological maturity achieved both in a computational calculation and in the ability to analyse in real–time and in a short time huge quantities of data in any form: this is Big Data Analytics. From a business perspective, the AI and data analysis systems allow individuals to systematize information, usually already available on the markets in a disaggregated way, transforming data into business decisions, thus only considering those tools useful to facilitate the decision–making processes within a company.

Davenport and Harris (2007) define Business Analytics (BA) as the "extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact–based management" which ultimately drives decisions and actions. Vidgen *et al.* (2007) notice how Business analytics can be considered a mediator between the data at disposal by the organization and the actual economic value that such data can leverage through actions and improved decisions. We argue that the most advanced display of this transformation is obtained by the application of AI techniques.

Data Analytics techniques are normally classified as descriptive, predictive and prescriptive, offering a growing level of business potential (Deka, 2014). Descriptive analytics is the most traditional application of data analytics and it is historically linked with the concept of *Business Intelligence* (BI), as introduced by Luhn (1958). The more advanced applications of Data Analytics make use of AI in the attempt to anticipate scenarios by promptly implementing useful business strategies (Waller and Fawcett, 2013). Exploring and analysing data, might support the construction of AI, facilitating predictive analysis and automation tools (De Mauro *et al.*, 2019). The term *Big Data* usually refers to the technological storage capacities, the huge amount of structured and unstructured data deriving from online transactions (Erevelles *et al.*, 2016;) characterized by *volume*, *variety*, *speed* (McAfee *et al.*, 2012) and further characteristics such as *variability*, *veracity*, *value* (Ebner *et al.*, 2014). Business recognition of *Big Data* as a strategic resource, radically transformed managerial practices (Dogan and Gurcan, 2019; Holler *et al.*, 2016; Lycett, 2013; Wamba *et al.*, 2017). Some studies provided a stronger background toward *Big Data* opportunities and applications (Hilbert *et al.*, 2016; Mikalef *et al.*, 2018), also providing classifications, considering their effects on Information, Technologies, Methods and Impacts (De Mauro *et al.*, 2018).

Business processes can benefit by the introduction of AI in various ways. Predictive analysis solutions are largely powered by ML and AI tools (Hazen *et al.*, 2014), and are profitably leveraged for managerial or marketing purposes aimed such as designing new business strategies or investigating consumer behaviour (Malthouse *et al.*, 2013). The biggest challenge is about study techniques and algorithms based on typical approaches, aimed to activate AI in business in order to reduce the gap between human intelligence and AI (Kumar and Thakur, 2012). Merging mathematical, statistical and optimization techniques with AI practices can create intelligent environments able to transform organizational structures, processes and services. AI can

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also refer to the attempt to provide machines (such as information systems and physical devices) with the ability to complete tasks typically related to human intelligence (Yang and Siau, 2018).
Over the last decade (2010 – 2019) web users have increasingly searched for webpages dealing with "*Artificial Intelligence"* and its related terms "*Big Data*", "*Business Intelligence*" and "*Machine Learning*".

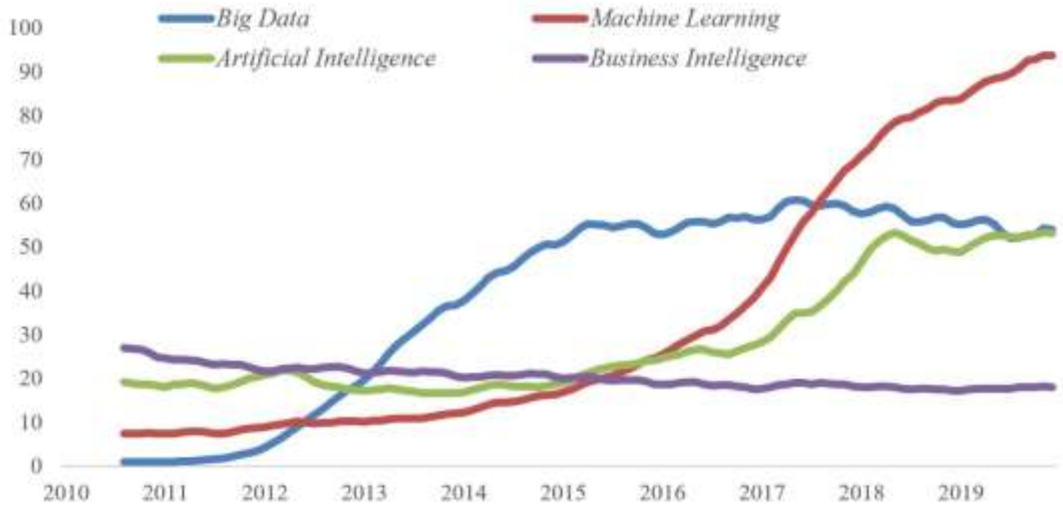

Figure 1 – Popularity of Artificial Intelligence, Big Data, Business Intelligence and Machine Learning as a term among web users between 2010 and 2019. The vertical axis shows the relative search frequency of each term included the group of selected terms, normalized within the [0, 100] range.

As suggested by Figure 1, *Business Intelligence* used to be the most popular keyword and has constantly decreased its popularity, as reporting has become increasingly commoditized in companies. Big Data has surged in popularity as of 2011 and, after reaching its peak, is now starting to decline. Artificial intelligence, which was a concept already well established at the beginning of the decade, has benefited from the vast availability of data and cheaper technologies enabling computing power, hence increasing its popularity. Within the realm of AI, Machine Learning has lately become the most popular topic as it relates to skills which encounter an increasing demand from companies. Therefore, our prior trend analysis highlighted the chaotic development of these concepts and reaffirmed the need for a robust literature review. Such a review can systematize the domain and provide a useful classification of concepts for both researchers and managers to enable a more effective knowledge development.

3. Methodology

3.1 Text mining for Literature Reviews

Preparing a literature review enables the identification of the fundamental contributions to the scientific progress by identifying which ones inspired subsequent research and what are the current gaps on which researchers and experts might focus further in the future. Considering that our literature review encompasses a full decade, a structured analytical approach aimed at detecting meaningful trends is necessary. The spreading of the Internet and the electronic nature of numerous journals and scientific documents allows an in-depth analysis of all the existing material on a topic, with a lower probability of neglecting relevant documents. Our systematic literature review has been carried out by applying text mining techniques on the strings of text extracted by papers which served as documents. Research techniques sometimes used traditional clustering techniques to return a set of *N* clusters of documents, in which each cluster identifies a topic covered in literature consistent with the research objective (Milligan and Cooper, 1985; Sunikka and Bragge, 2012; van Altena *et al.*, 2016).
Considering the complexity of the domain and the inherent multidisciplinary character of the papers in the corpus, we decided to adopt mixed membership models which allow individual units to belong at the same time to multiple categories, at a different extent. Therefore, in each considered element, the grade of belonging to a group is identified by a vector of a positive variable obtained summing up to one, also known as membership proportion (Airoldi *et al.*, 2014). By using mixed membership techniques instead of traditional clustering, the assumption according to whom each unit belongs to a single cluster is violated (Airoldi *et al.*, 2008; Grün, 2018). One of the most popular mixed membership models is Latent Dirichlet Allocation (LDA)

which has been previously used to analyse the contents of documents and the meaning of words related to a research topic (Blei, 2012; Steyvers and Griffiths, 2007).

3.2 Latent Dirichlet Allocation (LDA)

LDA is a generative probabilistic model commonly used to identify the thematic structure of a corpus of documents. The input text is treated as a collection of observations, arising from a generative random process, that include hidden variables. Such variables reflect the topic structure of the documents and can define how the relative presence of words is linked with the topic that is dealt with in the text. More specifically, each topic is a probability distribution over terms within the vocabulary made of all the words present in the corpus. Therefore, every document in the corpus, each composed of multiple terms, will be associated with a mixture of K topics. The relative prevalence of K topics in a document can be described as a tuple $\{x_i\}_{i=1}^{i=K}$ of K numbers for which the following condition holds:

$$\sum_{i=1}^{K} x_i = 1 \text{ and } x_i \geq 0 \ \forall i \in [1, K]$$

which describes the support of a Dirichlet distribution. The application of LDA will have a threefold output. First, the topic proportion for each single document, resulting in a $N \times K$ matrix, where N is the number of documents included in the corpus while K is the number of topics. Second, the per–word topic assignment, which is the probability of presence of each word within each specific topic. Noticeably, an easy surrogate of such output is the list of the top keywords, i.e. the ones that display the highest level of probability for each topic and are providing hints to a human reader about the essential components of the topic definition. Third, we are also able to obtain the per–corpus topic distribution, which tells us the overall popularity of each topic within the total set of documents being analysed. By reading both the list of topic keywords and considering the documents in the corpus displaying a high level of presence of each topic, a human evaluator is able to deduce the conceptual content of the topic and assign a name to it, as done by multiple previous works (Delen and Crossland, 2008).

3.3 Implementation of the methodology

3.3.1 Phase 1, Data collection and preparation

According to the proposed methodology, a list of input documents was extracted from Elsevier Scopus. We queried Scopus to intercept documents dealing with both Artificial Intelligence and Business activations, by forcing the co–presence of AI (i.e. "Machine Learning", "Artificial Intelligence") and Business studies (i.e. "Business", Marketing") into the Title, Abstract or paper's keywords[1]. On March 28th, 2020 we exported a list of 6,031 published journal and conference papers. As a first insight, researchers toward Big Data and AI, increased in the recent years, particularly around 2013–2014, as confirmed in the §2 below and in Fig. 3. Secondarily, we analysed documents containing the full term "Big Data" or "Artificial Intelligence" in the titles, focusing on the 3,780 remaining articles, then applying the LDA after a previous data preparation. In particular, we removed white spaces and punctuation, obtaining tokens as a single word except for compound words (i.e. with intra–word dashes). Then, we converted all caps to lowercase, thus stemming the corpus by using Porter's algorithm (1980) which returned the stem of each word with its suffix removed. Furthermore, we removed common English stop words (i.e. articles, conjunctions) and other non-relevant words (i.e., copyright information and years).

3.3.2 Phase 2, Latent Dirichlet Allocation (LDA)

As done by Delen and Crossland (2008), the number of topics *k* was chosen by selecting the model capable of providing the most readable output in the authors' minds. We have run LDA for all integer values of *k* included [6, 10] and concluded by human judgement that the most readable model was obtained with k=6. Later, in order to confirm the robustness of the result, we have analysed the words which were most relevant for the definition of each topic and concluded that they were mostly relevant to the conceptual domain under consideration in the study.

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[1] The full Scopus query was: "TITLE-ABS(("Artificial Intelligence" or "machine learning")and("business" OR"marketing")) AND PUBYEAR > 2009 AND (LIMIT-TO (DOCTYPE,"ar") OR LIMIT-TO (DOCTYPE,"cp")) AND (LIMIT-TO (LANGUAGE,"English"))".

4. Results of the Topic Modelling

We named each of the six topics after their essential conceptual content, resulting in the following list: T01) *Business Implications;* T02) *Human Implications;* T03) *Industrial Applications;* T04) *Social Applications;* T05) *Predictive Methods;* T06) *Recognition Methods*. To achieve our goal, the contents related to the topics were further analysed considering a total of 3,780 contributions in the considered period (2010-2020) as shown in Table 1.

Table 1 – Considered contributions grouped by the six topics discovered

Year	*Business Implications*	*Human Implications*	*Industrial Applications*	*Social Applications*	*Prediction Methods*	*Recognition Methods*	*Grand Total*
2010	28	7	11	14	15	12	87
2011	40	12	19	22	19	8	120
2012	42	10	8	17	21	18	116
2013	42	5	23	22	27	13	132
2014	58	8	15	33	26	17	157
2015	49	20	24	42	47	31	213
2016	66	23	34	38	54	34	249
2017	83	49	77	64	61	53	387
2018	149	113	164	113	109	106	754
2019	200	191	356	226	176	148	1297
2020	35	38	76	41	38	40	268
Grand Total	**792**	**476**	**807**	**593**	**593**	**480**	**3780**

With the aim of analysing the topical structure of the analysed corpus, we have built a network model using the outputs of the LDA. Each topic has been associated to a node of the network while edges represented the inter-topic distance across topics. The inter-topic distance is obtained by analysing the level of correlation of topic presence across the documents in the corpus. We calculated a correlation matrix R by measuring the pair-wise Pearson correlation across topics (Table 2). Since a smaller level of correlation can be associated with a larger distance across two topics, we calculated a distance matrix D using the formula $D = 1 - R$ as proposed by Glynn (2019).

We have used the matrix D as a distance matrix for the topic network and forced the width of the edges to be proportional to the pair-wise distance stored in D, obtaining the graphical output reported in Figure 2, where the size of the nodes is proportional to the relative presence of topics in the corpus of documents. Edge-width is proportional to the inter-topic distance obtained from the pair-wise correlation across topics in the corpus.

Table 2 – Inter-topic correlation matrix, R.

	Business implications	*Human implications*	*Industrial applications*	*Social applications*	*Predictive methods*	*Recognition methods*
Business implication	1.00	-0.24	-0.17	-0.22	-0.24	-0.20
Human implications	-0.24	1.00	-0.14	-0.25	-0.25	-0.27
Industrial applications	-0.17	-0.14	1.00	-0.25	0.17	-0.15
Social applications	-0.22	-0.25	-0.25	1.00	-0.18	-0.09
Predictive methods	-0.24	-0.25	-0.17	-0.18	1.00	-0.16
Recognition methods	-0.20	-0.27	-0.15	-0.09	-0.16	1.00

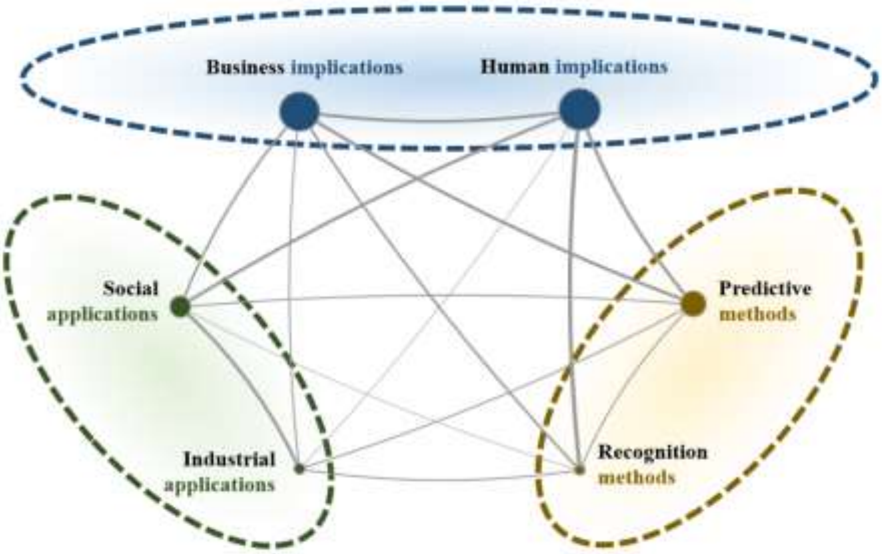

Figure 2 – Network visualization of the topic model, grouped by Implications, Applications and Methods

The identified topics constitute the essential components of scholars' exploration of the domain lying at the interface between Artificial Intelligence and Business Management disciplines. By analysing their conceptual content, we found that the six topics identified by LDA can be organized into three homogenous groups or themes, namely *Application*, *Implications* and *Methods*. The Application theme focuses on the research that describes the business outcome of artificial intelligence, i.e. the transformation of data and algorithms into actual economic value. Within this group we have identified two fundamental areas of application that clarify the ultimate receiver of the AI-enabled service, i.e. humans (*Social Applications)* and machines or objects (*Industrial Applications)*. The Implications theme aims at illustrating the human-centred (*Human Implications*) and business process-centred (*Business Implications*) transformations which are a consequence of the AI integration into twenty-first-century companies. Lastly, the Methods theme refers to the main value-driving uses of artificial intelligence algorithms which can be loosely encompassed into recognizing some business-relevant aspects in data (*Recognition Methods*) or anticipating the future (*Predictive Methods*), as summarized in Table 3. In the next section we will discuss the composition of each topic.

Table 3 – Implications, Applications, and Methods: topics and key focus areas

Theme	Topic	Key focus areas
Implications	Business Implications	*Digital Management*
		Process Automation
		Process Mining
	Human Implications	*Organizational needs*
		Ethical implications
		Talent management
Applications	Industrial Applications	*IoT*
		Resources management (energy, utilities)
		Smart cities
	Social Applications	*Social media analysis*
		Sentiment analysis
		Consumers understanding
Methods	Prediction Methods	*Forecasting*
		Classification
		Supervised learning
	Recognition Methods	*Anomaly recognition*
		Patterns identification
		Unsupervised learning

5. Topic Discussion

5.1 Business Implications

This topic showed the impact of AI on the processes and management of the organization, thus revealing interesting *Business Implications*. Papers dealing with this topic explain practices of data-driven decision making, process mining and automation. AI has been leveraged in the implementation of Decision Support Systems (DSS) for some decades already (Turban, 1988) and proven valuable in creating knowledge by transforming raw data into usable information. As noticed by Davenport (2018), AI can positively impact organizations in three main ways: firstly, by automating administrative, financial and bureaucratic activities through Robotic Process Automation; secondly, by identifying hidden models in the data and supporting managers in the interpretation of the meaning; lastly, by increasing employee or customer emotional involvement, using chat-boxes and other human-like connections. According to this perspective, AI becomes a promoter of the man-machine symbiosis, allowing researchers to instruct advanced machines by asking AI to express judgments that require high cognitive skills, previously considered as impossible (Mahroof, 2019). Nonetheless, it is not uncommon to observe cases in which decision making is entrusted to powerful intelligent machines, specially trained without the need for final human approval (Zlotowski *et al.*, 2017). Another business implication of the leverage of AI is the ability to instantiate Expert Systems (ES), which are able to both simulate human reasoning and to explain the criteria used to reach certain conclusions (Metaxiotis and Psarras, 2003). Moreover, an additional business implication dealt with in literature within this topic is the growing role of process mining, i.e. the ability of using AI to infer useful trends, patterns and opportunities for improving the effectiveness of business processes through the analysis of log data (Zhang *et al.*, 2020)

5.2 Human Implications

AI can support the digitalisation of *Human Resource Management* (HRM) in the workplace, influencing methods and environments, ensuring greater activity effectiveness and efficiency both in terms of time and costs, and in the quality of the activity carried out offering itself as a valid ally to human work (Zehir *et al.*, 2020). Further opportunities might be identified in applying AI to Big Data analysis to automate service-desk business process (Lo *et al.*, 2019). The continuous evolution of technology and business environments impose continuous challenges for managers who must face the challenge to create knowledge and develop internal skills (De Mauro *et al.*, 2018; Gatouillat *et al.*, 2018). AI has been widely recognized as a business enabling factor, by ensuring a growth of individuals' productivity and a decrease in the cost of executing a project (Shankar, 2012). Additionally, as highlighted above in §5.1, AI become an "ally" in management decision, supporting human judgement and decision-making processes in strategy, planning, implementation and actions. The establishment of data science and AI as a mission-critical activity (Davenport, 2020) forced companies to rethink their organization by acquiring novel professional data-focusing roles like Data Scientists, Data Analysts, Analytics developers and big data Systems Engineers (De Mauro *et al.*, 2018). Multiple ethical challenges have arisen, mainly focusing on the evolving definition of Privacy and the decisions that companies may make on the extent they should push the data boundaries and dig into lives of individual (Corea, 2016).

5.3 Industrial Applications

The role of AI in *Industrial Applications* is yet to be fully comprehended and broadly adapted in companies as managers still struggle with identifying and providing the organizational, cultural and technology enablers (Chen, 2017; Johnson, 2019). Within this topic, we have found that papers report opportunities of AI Industrial Applications in several sectors: medical sciences (Jiang *et al.*, 2017; Szolovits, 2019) and specifically either in diseases cure such as in cardiology (Johnson *et al.*, 2018) and radiology (Hosny *et al.*, 2018), in neuroscience (Hassabis *et al.*, 2017), in preventing epidemic diffusion such as the recent COVID-19 as a tool to protect healthcare workers and curb dissemination (McCall, 2020); in the chemical industry (Venkatasubramanian, 2019) of pharmacy (Hessler and Baringhaus, 2018); in social sciences such as in politics (Hudson, 2019), in marketing (Kumar et. al., 2019), and in finance (Faccia *et al.*, 2019).

Furthermore, AI enables opportunities in the organizational purchasing processes and supply models in the supply chain (Laínez *et al.*, 2010), in the definition of price strategies (Chou *et al.*, 2015), in product development and scheduling (Metaxiotis and Psarras, 2003), in the management of services in markets and simulations (Li and Li, 2010) and finally web intelligence and e – B2B commerce (Li, 2007; Zhong *et al.*, 2007). Interesting opportunities might be activated by AI in integrating the financial accounting cycle (Faccia *et al.*, 2019) and industrial marketing (Martínez-López and Casillas, 2013).

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Furthermore, our literature review made apparent that AI applications can highly benefit from modern IoT devices, in data collection, in the transmission of results deriving from AI algorithms, in supporting industrial applications by bringing AI into physical objects (Arsénio *et al.*, 2014). The maximum contribution is thus shown by Industrial Internet of Things IIoT, when IoT is integrated into the production process with the result of precise data analysis and from connected equipment, operating technology, places, and people or providing smart devices in manufacturing (Vermesan *et al.*, 2017). Data collection derived from IIoT is useful for AI-based analysis which can serve in turn the same devices from which it was collected. Therefore, when combined with operational technology monitoring devices, IIoT helps regulate and monitor industrial systems in an integrated manner, monitor events or changes in structural conditions, ensure cost savings, reduced time, better quality, and increased productivity. Moreover, when combined with AI, IIoT proves effective at enabling real-time plan analysis and corrections (Jeschke *et al.*, 2017).

5.4 Social Applications

In papers dealing with *Social Applications,* AI shows its role in supporting marketing studies to understand consumer social behaviour. On the other hand, fuzzy logic techniques, Artificial Neural Network (ANN) and AI-based methods support the management of the uncertain events that accompany the development of marketing strategies (Li, 2000). The major contributions are aimed at completing traditional activities, making knowledge and information of common interest available in order to ultimately provide the end customer with products with increasing value (Prior *et al.*, 2019; Ramaswamy and Ozcan, 2018). AI can also support the understanding of consumer choices, by obtaining descriptive models to be used in optimisation schemes (Laínez *et al.*, 2010). The greater proximity to consumers enabled by new technologies makes the relationship between a business and its consumers deeper and more robust (Zeithaml *et al.*, 2001). Moreover, data plays a key role in enabling personalised offers by means of AI-based inference of their levels of propensity in making a purchase (Moro *et al.*, 2016) and in supporting strategies that entail extra-sensory experiences and automation (Buhalis *et al.*, 2019).

5.5 Prediction Methods

This topic deals with those specific data methodologies aiming at anticipating the future based on the analysis of the past. More precisely, as clarified by Hair, predictive analytics leverages "*confirmed relationships between explanatory and criterion variables from past occurrences to predict future outcomes*" (2007, p. 304). Algorithms enabling fast and cheap predictions of the future have been identified as a competitive advantage for companies, as they support an increase of productivity and an improvement of speed and quality of decision making (Agrawal *et al.*, 2018). We found that papers dealing with this topic were disproportionally describing the usage of supervised machine learning techniques, both regression and classification techniques, for supporting business processes through a deeper understanding of market, consumer and competitors, or a forecast of forthcoming changes. As we focused on papers dealing with both AI and Business, this topic focuses on how to implement general-use algorithms for business implementation. The most prominent usage scenarios we found in our corpus included: sales forecasting to ensure the sufficiency of companies' plans (Castillo *et al.*, 2014), Sentiment analysis and opinion mining to extract subjective information out of consumer-generated comments (Giatsoglou *et al.*, 2017, Rambocas and Pacheco, 2018), and Anticipating financial distress of companies and end-users to improve risk evaluation (Tsai *et al.*, 2014; Zhang *et al.*, 2010). Moreover, Prediction Models could be exploited in several industries as well, as recent studies suggest in the medical field for instance to prevent and forecast epidemics.

5.6 Recognition Methods

The topic deals with the analytical methodologies, often based on machine learning algorithms, which are aimed at recognizing noteworthy patterns in data. One noteworthy example of application is the generation of consumers segments for marketing campaigns (Campbell *et al.*, 2020). Algorithms able to identify meaningful segments are exploited within Customer Relationship Management (CRM) systems for tailoring promotional activities to provide significant positive impacts on both profitability and sales for segment-specific direct marketing campaigns (Reutterer *et al.*, 2006). Another possible use of recognition methods is to automatically detect anomalies. Business applications of anomaly detection include: the identification of frauds to systematically reduce the risks related to credit issuance (Ryman-Tub *et al.*, 2018) and the automated detection of potential business process anomalies (Rogge-Solti and Kasneci, 2014).

6. Conclusions

The quick development of AI business applications has caused the creation of a disorganised knowledge on the matter. In this paper we presented the results of a systematic review of the literature investigating AI business activation throughout an entire decade (2009-2019). We obtained a double-level hierarchical structure which describes the central topics of current research and possible future developments. We leveraged an original combination of two established machine learning algorithms (LDA and hierarchical clustering), in order to design human-meaningful topic structures. As a response to RQ1, we have identified three different themes (Implications, Applications, Models), namely IAM, each one comprising two topics, namely: *Business* and *Human Implications*, *Industrial* and *Social Applications*, and *Prediction* and *Recognition Models.* In response to RQ2, our findings supported the identification of the most promising further research directions as confirmed quantitatively by the evolution of topic presence reported in Table 4. According to our results we anticipate that the following topics require further expansion in future research:

1. *Human implications,* especially in developing skills able to integrate people and IA in a synergetic ecosystem in which their interaction activates their greatest potential.
2. *Industrial applications,* strengthening the research towards technological devices and tools (such as IoT) able to support AI practices, algorithms and methods in communicating results of AI strategies, supporting data collection and becoming the peripheral object that "hosts" AI applications.
3. *Recognition methods,* spurred by the latest development of deep learning techniques requires further investigation for effective business activation.

Table 4 – Relative presence of the identified topics in existing literature. The last column shows the shift of topic presence in recent years.

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Total abs	Total %	2018/20 vs. previous years
Business implications	32%	33%	36%	32%	37%	23%	27%	21%	20%	15%	13%	792	21%	-14%
Human implications	13%	16%	7%	17%	10%	11%	14%	20%	22%	27%	28%	807	21%	+12%
Industrial applications	8%	10%	9%	4%	5%	9%	9%	13%	15%	15%	14%	476	13%	+6%
Social applications	17%	16%	18%	20%	17%	22%	22%	16%	14%	14%	14%	593	16%	-4%
Predictive Methods	16%	18%	15%	17%	21%	20%	15%	17%	15%	17%	15%	632	17%	-1%
Recognition methods	14%	7%	16%	10%	11%	15%	14%	14%	14%	11%	15%	480	13%	+1%
Grand Total	***87***	***120***	***116***	***132***	***157***	***213***	***249***	***387***	***754***	***1,297***	***268***	***3,780***	***100%***	-

The IAM model presented in this study could support future research and business management in multiple ways. Firstly, AI researchers can position their future contributions in a precise theoretical background within the IAM framework, acknowledging the intrinsic multidisciplinary nature of the domain. Secondly, our classification allows researchers and practitioners to make sense of the development of the domain and to identify the most promising topics to invest on. Lastly, business managers could use the model as a conceptual structure to understand which aspects require more attention and display an opportunity for improving the maturity of their firms.

We recognize multiple limitations in the current study that offer the opportunity for future research. Firstly, the corpus of documents we used in our analysis was exclusively sourced from Scopus: despite its extent and authoritativeness this choice could have led to a partial view of the literature. Furthermore, we considered only contributions written in English and relevant documents written in different languages could have been overlooked. Lastly, despite the usage of a replicable combination of methodologies like LDA and hierarchical clustering, the assessment of the model accuracy has been left to human judgement, making it prone to subjective biases.

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