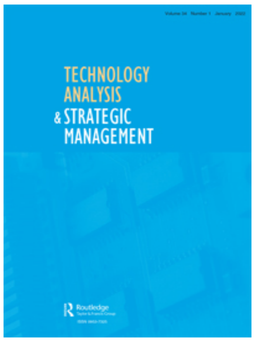

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Leveraging Artificial Intelligence in Business: Implications, Applications and Methods

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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.

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Artificial intelligence; business innovation; business management; big data; marketing; technology management

1. Introduction

Artificial Intelligence (AI) is a buzzword today. The steady growth of its applications has radically penetrated human lives and business organisations. Companies have recognised 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 (McCarthy, Minsky, and Rochester 1959), its first business application emerged only in the 1980s, spurred by the success of the expert system paradigm (i.e. in Schoech et al. 1985). Since then, its success has progressively accelerated thanks to the exponential growth of available computing power as described by Moore's law (1965). Organisations 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 (Duan, Edwards, and Dwivedi 2019; Dwivedi et al. 2019). The present study aims to provide a conceptual model of Business Application of AI, i.e. of its utilisation in firms, by means of a literature review obtained through the adoption of text mining and ML techniques. The two research questions we aim to answer by means of the review are:

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RQ1: What are the fundamental topics dealt with in current literature in relation to the utilization of AI in the business domain?

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 3780 discovered research papers. The paper is organised 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 main themes we identified, namely: *Implications*, *Applications* and *Methods*. Subsequently, each topic is discussed by 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 *Artificial Intelligence*, *Big Data*, *Machine Learning*, and *Data Analytics* are ubiquitous in current academic and business articles dealing with data. To prevent any confusion, the current section introduces each of these concepts and offers a structured explanation of how they mutually relate.

AI aims at reproducing some aspects of human intelligence through technology (Yang and Siau 2018). 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).

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. From a business perspective, AI and data analysis systems allow individuals to systematise 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, 102) 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, Shaw, and Grant (2017) notice how BA can be considered a mediator between the data at disposal by the organisation 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, i.e. the usage of data warehouses and analytical processing techniques for supporting decision making with historical data. Predictive and prescriptive analytics 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, going beyond the analysis of historical data (Malthouse et al. 2013) and effectively improving human activities (Kumar and Thakur 2012).

The value of AI in companies has been amplified by the availability of large quantities of business-relevant information, i.e. Big Data. This term refers to those extensive collections of structured and unstructured data points characterised by volume, variety, velocity (McAfee et al. 2012) and further characteristics such as variability, veracity, value (Ebner, Bühnen, and Urbach 2014). Business recognition of Big Data as a strategic resource, radically transformed managerial practices (Lycett 2013;

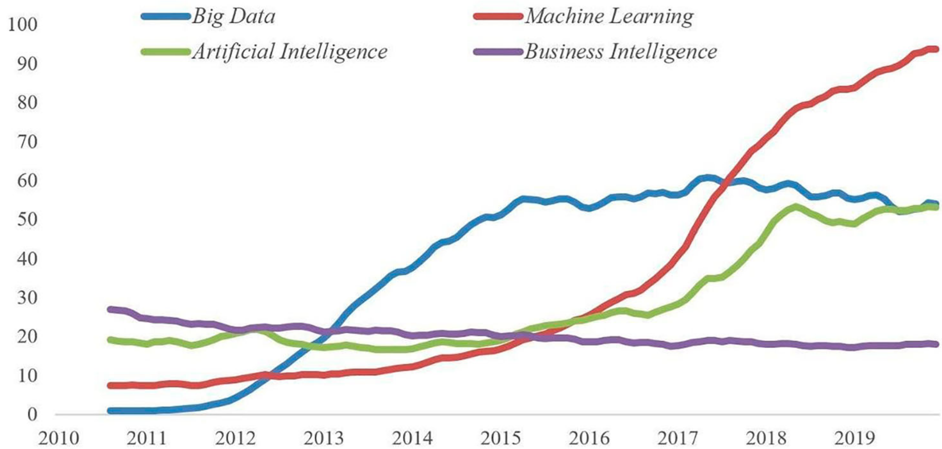

Figure 1. Popularity of Artificial Intelligence, Big Data, Business Intelligence and Machine Learning as a term among web users between 2010 and 2019. The vertical axis shows the relative search frequency of each term on a normalised scale. Source: Google Trends.

Wamba et al. 2017). Some studies provided conceptual frameworks of Big Data opportunities and applications in business (Mikalef et al. 2018), considering their effects on Information, Technologies, Methods and Impacts (De Mauro et al. 2018).

Over the last decade (2010–2019), web users have increasingly searched for pages dealing with '*Artificial Intelligence'* and its related terms '*Big Data*', '*Business Intelligence*' and '*Machine Learning*'.

As suggested by Figure 1, *Business Intelligence* used to be the most popular keyword and has constantly decreased its popularity, as reporting and other descriptive analytics applications have become increasingly commoditised in companies. *Big Data* has surged in popularity as of 2011 and, after reaching its peak, has shown to attract a stable level of interest. *AI*, 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.

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 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:

$$\sum_{i=1}^{K} x_i = 1$$

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. Third, 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 in 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 its utilisation in firms, 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 28 March, 2020, we exported a list of 6031 published journal and conference papers. As a first insight, we found that research on *Big Data* and AI increased in the recent years, particularly around 2013–2014, as confirmed in the Section 3.3.2 below and in Figure 1. Secondarily, we analysed documents containing the full term 'Big Data' or 'Artificial Intelligence' in the titles, focusing on the 3780 remaining articles, then applied LDA, after the required pre-processing. 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 and stepped 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 (e.g. articles, conjunctions) and other non-relevant words (e.g. 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.

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 3780 contributions in the considered period (2010–2020) as shown in Table 1.

With the aim of analysing the topical structure of the analysed corpus and the mutual inter-relation across topics, 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 et al. (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.

The identified topics constitute the essential components of scholars' exploration of the domain lying at the interface between AI and Business Management disciplines. By analysing their conceptual content, we found that the six topics identified by LDA can be organised into three homogenous groups or themes, namely Application, Implications and Methods. The Application theme focuses on

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

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

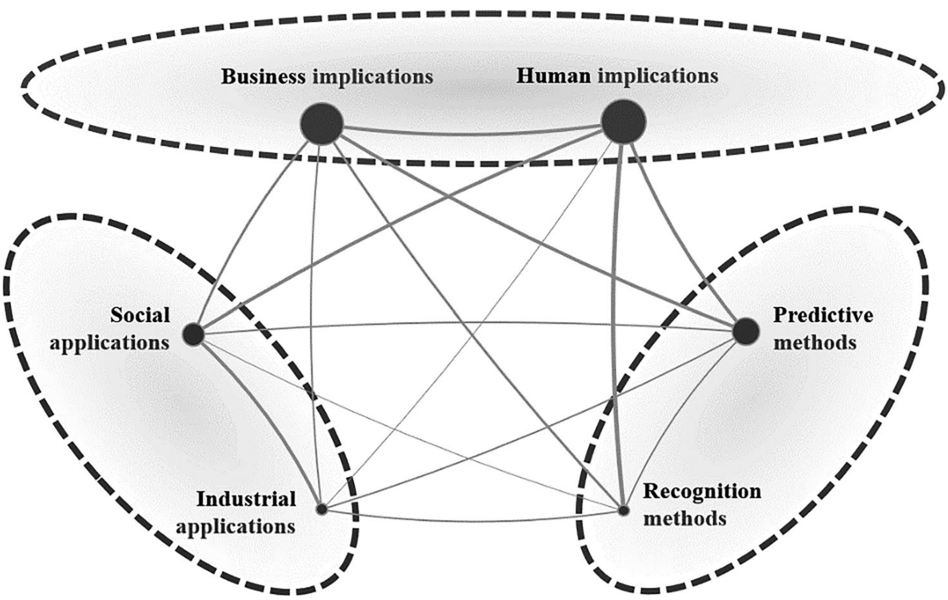

Figure 2. Network visualisation of the topic model, grouped by Implications, Applications and Methods. Nodes' size is proportional to the relative presence of the topic in the corpus while the width of each edge shows the level of inter-topic distance in our model.

the research that describes the business outcome of AI, 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 AI algorithms which can be loosely encompassed into recognising some business-relevant aspects in data (Recognition Methods) or anticipating the future (Predictive Methods), as summarised in Table 3. In the next section, we will discuss the composition of each topic by reporting a mix of noteworthy references included in the corpus and other studies which, although not included in the selection criteria for the review, can effectively support the description of the concept.

Table 3. Implications, Applications, and Methods: Topics and key focus area.

Theme	Topic	Key focus areas
Implications	Business implications	Digital Management Process Automation Process Mining
	Human implications	Organisational 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 organisation, 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 organisations in: automating administrative, financial and bureaucratic activities through Robotic Process Automation, supporting managers in decision making and, lastly, increasing employee or customer emotional involvement through the usage of human-like agents, such chatbots. Another business implication of the leverage of AI is the ability to instantiate Expert Systems (ES), which can both simulate human reasoning and to explain the criteria used to reach certain conclusions (Metaxiotis and Psarras 2003). Within this topic, our review unveiled also 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, Karaboğa, and Başar 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 recognised 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 Section 5.1, AI becomes 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 et al. 2020) forced companies to rethink their organisation 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 organisational, cultural and technology enablers (Chen 2017; Johnson, Pasquale, and Chapman 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), in finance (Faccia, Al Naqbi, and Lootah 2019).

Furthermore, AI enables opportunities in the organisational purchasing processes and supply models in the supply chain (Laínez, Reklaitis, and Puigjaner 2010), in the definition of price strategies (Chou et al. 2015), in product development and scheduling (Metaxiotis and Psarras 2003), and B2B commerce (Li 2007; Zhong, Liu, and Yao 2007).

Furthermore, 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). Indeed, the maximum contribution is thus shown by Industrial Internet of Things, IIoT, where IoT is embedded in production processes, resulting in cost and time savings, 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 amplifying the value of marketing activities thanks to the deep understanding of end-consumers resulting from the analysis of their social interactions (Prior, Keränen, and Koskela 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, Reklaitis, and Puigjaner 2010). The greater proximity to consumers enabled by new technologies makes the relationship between a business and its consumers deeper and more robust (Zeithaml, Rust, and Lemon 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, Cortez, and Rita 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, 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, Gans, and Goldfarb 2018). We found that papers dealing with this topic were disproportionately 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 that enable the assessment of sufficiency of companies' plans (Castillo et al. 2017), sentiment analysis and opinion mining to extract subjective information out of consumer-generated comments (Giatsoglou et al. 2017; Rambocas and Pacheco 2018), and risk evaluation (Tsai 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 recognising 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-Tubb, Krause, and Garn 2018) and the automated detection of potential business process anomalies (Rogge-Solti and Kasneci 2014).

6. Conclusions

6.1 Artificial Intelligence Implications, Applications, Methods: the IAM framework

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 review of the literature investigating AI business applications throughout an entire decade (2009–2020). 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 framework, each one comprising two topics, namely: *Business* and *Human Implications*, *Industrial* and *Social Applications*, and *Prediction* and *Recognition Models*.

6.2 An agenda for future research

In response to RQ2, our findings identified 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 should be prominent in the future research agenda:

1. *Human implications*. Additional investigation is needed to clarify: the level of analytical fluency required by employees to leverage AI effectively, the design of organisational models that can support AI programs in marketing and the definition of robust methods for integrating quantitative and qualitative consumer research. Additionally, we suggest that future research should focus

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	1297	268	3780	100%	–

on the so-called ‘humanisation’ of AI (Kaplan 2020), aimed at enriching numerical techniques with creativity and common sense.
2. *Industrial applications*. Our research unveiled a gap in the understanding of how IoT devices can systematically integrate AI algorithms and methods so to build competitive advantage for firms. In particular, we expect further development of strategy frameworks to support IoT-AI joint business models.
3. *Recognition methods.* Although deep learning techniques are meeting an increasing research interest within Computer Science outlets, further investigation is required to shed light on business-relevant uses cases and on the organisational implications of adopting black-box models, such as neural networks, for decision making.

6.3 Implications, limitations and future works

The IAM model presented in this study could support 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. Thirdly, 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. Lastly, by considering the recent advances in those technologies able to drive digitalisation (Sestino et al. 2020), managers and marketers can leverage the IAM framework to recognise and facilitate the role of AI in supporting their business strategy.

We acknowledge some limitations in our study that could offer opportunities 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.

Note

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 ”))”.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

Agrawal, A., J. Gans, and A. Goldfarb. 2018. *Prediction Machines: The Simple Economics of Artificial Intelligence*. Brighton, MA: Harvard Business Press.

Airoldi, E. M., D. M. Blei, E. A. Erosheva, and S. E. Fienberg. 2014. "Introduction to Mixed Membership Models and Methods." *Handbook of Mixed Membership Models and Their Applications* 100: 3–14.

Airoldi, E. M., D. M. Blei, S. E. Fienberg, and E. P. Xing. 2008. "Mixed Membership Stochastic Blockmodels." *Journal of Machine Learning Research* 9: 1981–2014.

Arsénio, A., H. Serra, R. Francisco, F. Nabais, J. Andrade, and E. Serrano. 2014. "Internet of Intelligent Things: Bringing Artificial Intelligence Into Things and Communication Networks." In *Inter-cooperative Collective Intelligence: Techniques and Applications*, edited by F. Xhafa and N. Bessis, 1–37. Berlin: Springer.

Blei, D. M. 2012. "Probabilistic Topic Models." *Communications of the ACM* 55 (4): 77–84.

Buhalis, D., T. Harwood, V. Bogicevic, G. Viglia, S. Beldona, and C. Hofacker. 2019. "Technological Disruptions in Services: Lessons from Tourism and Hospitality." *Journal of Service Management* 30 (4): 484–506.

Campbell, C., S. Sands, C. Ferraro, H. Y. J. Tsao, and A. Mavrommatis. 2020. "From Data to Action: How Marketers Can Leverage AI." *Business Horizons* 63 (2): 227–243.

Castillo, P. A., A. M. Mora, H. Faris, J. J. Merelo, P. García-Sánchez, A. J. Fernández-Ares, and M. I. García-Arenas. 2017. "Applying Computational Intelligence Methods for Predicting the Sales of Newly Published Books in a Real Editorial Business Management Environment." *Knowledge-Based Systems* 115: 133–151.

Chen, Y. 2017. "Integrated and Intelligent Manufacturing: Perspectives and Enablers." *Engineering* 3 (5): 588–595.

Chou, J. S., C. W. Lin, A. D. Pham, and J. Y. Shao. 2015. "Optimized Artificial Intelligence Models for Predicting Project Award Price." *Automation in Construction* 54: 106–115.

Corea, F. 2016. "Key Data Challenges to Strategic Business Decisions." In *Big Data Analytics: A Management Perspective*, edited by F. Corea, 19–24. Cham: Springer.

Davenport, T. H. 2018. "From Analytics to Artificial Intelligence." *Journal of Business Analytics* 1 (2): 73–80.

Davenport, T., A. Guha, D. Grewal, and T. Bressgott. 2020. "How Artificial Intelligence Will Change the Future of Marketing." *Journal of the Academy of Marketing Science* 48 (1): 24–42.

Davenport, T. H., and J. G. Harris. 2007. *Competing on Analytics: The New Science of Winning*. Boston, MA: Harvard Business School Press.

Deka, G. C. 2014. "Big Data Predictive and Prescriptive Analytics." In *Handbook of Research on Cloud Infrastructures for Big Data Analytics*, edited by P. Raji and G. C. Deka, 370–391. IGI Global.

Delen, D., and M. D. Crossland. 2008. "Seeding the Survey and Analysis of Research Literature with Text Mining." *Expert Systems with Applications* 34 (3): 1707–1720.

De Mauro, A., M. Greco, M. Grimaldi, and P. Ritala. 2018. "Human Resources for Big Data Professions: A Systematic Classification of Job Roles and Required Skill Sets." *Information Processing & Management* 54 (5): 807–817.

Duan, Y., J. S. Edwards, and Y. K. Dwivedi. 2019. "Artificial Intelligence for Decision Making in the Era of Big Data–Evolution, Challenges and Research Agenda." *International Journal of Information Management* 48: 63–71.

Dwivedi, Y. K., L. Hughes, E. Ismagilova, G. Aarts, C. Coombs, T. Crick, and V. Galanos. 2019. "Artificial Intelligence (AI): Multidisciplinary Perspectives on Emerging Challenges, Opportunities, and Agenda for Research, Practice and Policy." *International Journal of Information Management*, 101994.

Ebner, K., T. Bühnen, and N. Urbach. 2014. Think Big With Big Data: Identifying Suitable Big Data Strategies in Corporate Environments. In 2014 *47th Hawaii International Conference on System Sciences* (pp. 3748–3757). IEEE.

Faccia, A., M. Y. K. Al Naqbi, and S. A. Lootah. 2019, August. Integrated Cloud Financial Accounting Cycle: How Artificial Intelligence, Blockchain, and XBRL Will Change the Accounting, Fiscal and Auditing Practices. In *Proceedings of the 2019 3rd International Conference on Cloud and Big Data Computing* (pp. 31–37).

Galanos, V. 2019. "Exploring Expanding Expertise: Artificial Intelligence as an Existential Threat and the Role of Prestigious Commentators, 2014–2018." *Technology Analysis & Strategic Management* 31 (4): 421–432.

Gatouillat, A., Y. Badr, B. Massot, and E. Sejdic. 2018. "Internet of Medical Things: A Review of Recent Contributions Dealing with Cyber–Physical Systems in Medicine." *IEEE Internet of Things Journal* 5 (5): 3810–3822.

Giatsoglou, M., M. G. Vozalis, K. Diamantaras, A. Vakali, G. Sarigiannidis, and K. C. Chatzisavvas. 2017. "Sentiment Analysis Leveraging Emotions and Word Embeddings." *Expert Systems with Applications* 69: 214–224.

Glynn, C., S. T. Tokdar, B. Howard, and D. L. Banks. 2019. "Bayesian Analysis of Dynamic Linear Topic Models." *Bayesian Analysis* 14 (1): 53–80.

Grün, B. 2018. "Model-based Clustering." *Handbook of Mixture Analysis* 2:163–198.

Hair, J. F. 2007. "Knowledge Creation in Marketing: The Role of Predictive Analytics." *European Business Review* 19 (4): 303–315.

Hassabis, D., D. Kumaran, C. Summerfield, and M. Botvinick. 2017. "Neuroscience-inspired Artificial Intelligence." *Neuron* 95 (2): 245–258.

Hazen, B. T., C. A. Boone, J. D. Ezell, and L. A. Jones-Farmer. 2014. "Data Quality for Data Science, Predictive Analytics, and Big Data in Supply Chain Management: An Introduction to the Problem and Suggestions for Research and Applications." *International Journal of Production Economics* 154: 72–80.

Hessler, G., and K. H. Baringhaus. 2018. "Artificial Intelligence in Drug Design." *Molecules* 23 (10): 2520.

Hosny, A., C. Parmar, J. Quackenbush, L. H. Schwartz, and H. J. Aerts. 2018. "Artificial Intelligence in Radiology." *Nature Reviews Cancer* 18 (8): 500–510.

Hudson, V. M. 2019. *Artificial Intelligence and International Politics*. New York: Routledge.

Jeschke, S., C. Brecher, T. Meisen, D. Özdemir, and T. Eschert. 2017. "Industrial Internet of Things and Cyber Manufacturing Systems." In *Industrial Internet of Things*, edited by S. Jeschke, C. Brecher, H. Song, and D. Rawat, 3–19. Cham: Springer.

Jiang, F., Y. Jiang, H. Zhi, Y. Dong, H. Li, S. Ma, and Y. Wang. 2017. "Artificial Intelligence in Healthcare: Past, Present and Future." *Stroke and Vascular Neurology* 2 (4): 230–243.

Johnson, K., F. Pasquale, and J. Chapman. 2019. "Artificial Intelligence, Machine Learning, and Bias in Finance: Toward Responsible Innovation." *Fordham Law Review* 88: 499.

Johnson, K. W., J. T. Soto, B. S. Glicksberg, K. Shameer, R. Miotto, M. Ali, and J. T. Dudley. 2018. "Artificial Intelligence in Cardiology." *Journal of the American College of Cardiology* 71 (23): 2668–2679.

Kaplan, A. 2020. "Retailing and the Ethical Challenges and Dilemmas Behind Artificial Intelligence." In *Retail Futures*, edited by E. Pantano, 181–191. New York: Emerald Publishing Limited.

Konar, A. 2018. *Artificial Intelligence and Soft Computing: Behavioral and Cognitive Modeling of the Human Brain*. CRC Press.

Kumar, V., B. Rajan, R. Venkatesan, and J. Lecinski. 2019. "Understanding the Role of Artificial Intelligence in Personalized Engagement Marketing." *California Management Review* 61 (4): 135–155.

Kumar, K., and G. S. M. Thakur. 2012. "Advanced Applications of Neural Networks and Artificial Intelligence: A Review." *International Journal of Information Technology and Computer Science* 4 (6): 57.

Laínez, J. M., G. V. Reklaitis, and L. Puigjaner. 2010. "Linking Marketing and Supply Chain Models for Improved Business Strategic Decision Support." *Computers & Chemical Engineering* 34 (12): 2107–2117.

Li, S. 2000. "The Development of a Hybrid Intelligent System for Developing Marketing Strategy." *Decision Support Systems* 27 (4): 395–409.

Li, S. 2007. "AgentStra: An Internet-Based Multi-Agent Intelligent System for Strategic Decision-Making." *Expert Systems with Applications* 33 (3): 565–571.

Lo, D., K. K. Tiba, S. Buciumas, and F. Ziller. 2019, July. An Emperical Study on Application of Big Data Analytics to Automate Service Desk Business Process. In 2019 *IEEE 43rd Annual Computer Software and Applications Conference (COMPSAC)* (Vol. 2, pp. 670–675). IEEE.

Lycett, M. 2013. "'Datafication': Making Sense of (big) Data in a Complex World." *European Journal of Information Systems* 22 (4): 381–386.

Malthouse, E. C., M. Haenlein, B. Skiera, E. Wege, and M. Zhang. 2013. "Managing Customer Relationships in the Social Media Era: Introducing the Social CRM House." *Journal of Interactive Marketing* 27 (4): 270–280.

McAfee, A., E. Brynjolfsson, T. H. Davenport, D. J. Patil, and D. Barton. 2012. "Big Data: The Management Revolution." *Harvard Business Review* 90 (10): 60–68.

McCall, B. 2020. "COVID-19 and Artificial Intelligence: Protecting Health-Care Workers and Curbing the Spread." *The Lancet Digital Health* 2 (4): e166–e167.

McCarthy, J. J., M. L. Minsky, and N. Rochester. 1959. *Artificial Intelligence*. Cambridge, MA: Research Laboratory of Electronics (RLE), Massachusetts Institute of Technology (MIT).

Metaxiotis, K., and J. Psarras. 2003. "Expert Systems in Business: Applications and Future Directions for the Operations Researcher." *Industrial Management & Data Systems* 103 (5): 361–368.

Mikalef, P., I. O. Pappas, J. Krogstie, and M. Giannakos. 2018. "Big Data Analytics Capabilities: A Systematic Literature Review and Research Agenda." *Information Systems and e-Business Management* 16 (3): 547–578.

Milligan, G. W., and M. C. Cooper. 1985. "An Examination of Procedures for Determining the Number of Clusters in a Data set." *Psychometrika* 50 (2): 159–179.

Moore, G. 1965. "Moore's Law." *Electronics Magazine* 38 (8): 114.

Moro, S., P. Cortez, and P. Rita. 2016. "An Automated Literature Analysis on Data Mining Applications to Credit Risk Assessment." In *Artificial Intelligence in Financial Markets*, edited by C. Dunis, P. Middleton, A. Karathanasopolous, and K. Theofilatos, 161–177. London: Palgrave Macmillan.

Porter, M. F. 1980. "An Algorithm for Suffix Stripping." *Program* 14 (3): 130–137.

Prior, D. D., J. Keränen, and S. Koskela. 2019. "Customer Participation Antecedents, Profiles and Value-in-use Goals in Complex B2B Service Exchange." *Industrial Marketing Management* 82: 131–147.

Ramaswamy, V., and K. Ozcan. 2018. "What is Co-Creation? An Interactional Creation Framework and its Implications for Value Creation." *Journal of Business Research* 84: 196–205.

Rambocas, M., and B. G. Pacheco. 2018. "Online Sentiment Analysis in Marketing Research: A Review." *Journal of Research in Interactive Marketing* 12 (2): 146–163.

Reutterer, T., A. Mild, M. Natter, and A. Taudes. 2006. "A Dynamic Segmentation Approach for Targeting and Customizing Direct Marketing Campaigns." *Journal of Interactive Marketing* 20 (3–4): 43–57.

Rogge-Solti, A., and G. Kasneci. 2014, September. Temporal Anomaly Detection in Business Processes. In *International Conference on Business Process Management* (pp. 234–249). Springer, Cham.

Ryman-Tubb, N. F., P. Krause, and W. Garn. 2018. "How Artificial Intelligence and Machine Learning Research Impacts Payment Card Fraud Detection: A Survey and Industry Benchmark." *Engineering Applications of Artificial Intelligence* 76: 130–157.

Schoech, D., H. Jennings, L. L. Schkade, and C. Hooper-Russell. 1985. "Expert Systems: Artificial Intelligence for Professional Decisions." *Computers in Human Services* 1 (1): 81–115.

Sestino, A., M. I. Prete, L. Piper, and G. Guido. 2020. "Internet of Things and Big Data as Enablers for Business Digitalization Strategies." *Technovation*, 102173.

Shankar, P. R. 2012, July. The Cybernetics of Enabling Competence in People Competence Building to Ensure Quality and Productivity in People in Software Industries. In 2012 *IEEE International Conference on Computational Intelligence and Cybernetics (CyberneticsCom)* (pp. 83–87). IEEE.

Steyvers, M., and T. Griffiths. 2007. "Probabilistic Topic Models." *Handbook of Latent Semantic Analysis* 427 (7): 424–440.

Sunikka, A., and J. Bragge. 2012. "Applying Text-Mining to Personalization and Customization Research Literature–Who, What and Where?" *Expert Systems with Applications* 39 (11): 10049–10058.

Szolovits, P. 2019. *Artificial Intelligence in Medicine*. London: Routledge.

Tsai, C. F. 2014. "Combining Cluster Analysis with Classifier Ensembles to Predict Financial Distress." *Information Fusion* 16: 46–58.

Turban, E. 1988. *Decision Support and Expert Systems: Managerial Perspectives*. New York: Macmillan.

van Altena, A. J., P. D. Moerland, A. H. Zwinderman, and S. D. Olabarriaga. 2016. "Understanding Big Data Themes from Scientific Biomedical Literature Through Topic Modeling." *Journal of Big Data* 3 (1): 23.

Venkatasubramanian, V. 2019. "The Promise of Artificial Intelligence in Chemical Engineering: Is it Here, Finally?" *AIChE Journal* 65 (2): 466–478.

Vidgen, R., S. Shaw, and D. B. Grant. 2017. "Management Challenges in Creating Value from Business Analytics." *European Journal of Operational Research* 261 (2): 626–639.

Wamba, S. F., A. Gunasekaran, S. Akter, S. J. F. Ren, R. Dubey, and S. J. Childe. 2017. "Big Data Analytics and Firm Performance: Effects of Dynamic Capabilities." *Journal of Business Research* 70: 356–365.

Yang, Y., and K. Siau. 2018. A Qualitative Research on Marketing and Sales in the Artificial Intelligence Age. *Midwest United States Association for Information Systems (MWAIS) 2018 Proceedings*.

Zehir, C., T. Karaboğa, and D. Başar. 2020. "The Transformation of Human Resource Management and Its Impact on Overall Business Performance: Big Data Analytics and AI Technologies in Strategic HRM." In *Digital Business Strategies in Blockchain Ecosystems*, edited by U. Hacioglu, 265–279. Cham: Springer.

Zeithaml, V. A., R. T. Rust, and K. N. Lemon. 2001. "The Customer Pyramid: Creating and Serving Profitable Customers." *California Management Review* 43 (4): 118–142.

Zhang, H., H. Nguyen, X. N. Bui, T. Nguyen-Thoi, T. T. Bui, N. Nguyen, and H. Moayedi. 2020. "Developing a Novel Artificial Intelligence Model to Estimate the Capital Cost of Mining Projects Using Deep Neural Network-Based Ant Colony Optimization Algorithm." *Resources Policy* 66: 101604.

Zhang, D., X. Zhou, S. C. Leung, and J. Zheng. 2010. "Vertical Bagging Decision Trees Model for Credit Scoring." *Expert Systems with Applications* 37 (12): 7838–7843.

Zhong, N., J. Liu, and Y. Yao. 2007. "Web Intelligence (WI)." In *Wiley Encyclopedia of Computer Science and Engineering*, edited by N. Zhong, 1–11.