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Data intelligence and analytics: A bibliometric analysis of human–Artificial intelligence in public sector decision-making effectiveness

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ABSTRACT

This study investigates the literary corpus of the role and potential of data intelligence and analytics through the lenses of artificial intelligence (AI), big data, and the human–AI interface to improve overall decision-making processes. It investigates how data intelligence and analytics improve decision-making processes in the public sector. A bibliometric analysis of a database containing 161 English-language articles published between 2017 and 2021 is performed, providing a map of the knowledge produced and disseminated in previous studies. It provides insights into key topics, citation patterns, publication activities, the status of collaborations between contributors over past studies, aggregated data intelligence, and analytics research contributions. The study provides a retrospective review of published content in the field of data intelligence and analytics. The findings indicate that field research has been concentrated mainly on emerging technologies' intelligence capabilities rather than on human–artificial intelligence in decision-making performance in the public sector. This study extends an ambidexterity theory in decision support, which enlightens how this ambidexterity can be encouraged and how it affects decision outcomes. The study emphasises the importance of the public sector adoption of data intelligence and analytics, as well as its efficiency. Furthermore, this study expands how researchers and practitioners interpret and understand data intelligence and analytics, AI, and big data for effective public sector decision-making.

1. Introduction

Technological breakthroughs have ushered in a new era for companies and governments over the last two decades (Amankwah-Amoah, 2017; You et al., 2019; Grover et al., 2020). Since 2011, the emergence of the Industry 4.0 paradigm has opened a new stage, defined as "The Fourth Industrial Revolution," which leads to the digitisation of all industrial processes and the convergence and interconnection between the different aspects of manufacturing in various departments and functions (Rieple et al., 2012; Gursoy et al., 2019). Automation and robotics replace repetitive work, as illustrated in the Industry 4.0 Global Report (WEF, 2017), while new digital technologies facilitate deeper interaction, especially across distances, between employees and companies. Cloud services, mobile applications, and real-time dashboards help to reinforce this global outlook by improving employee accountability, monitoring, networking, and business (Caputo et al., 2019b). New technologies, such as the cloud, artificial intelligence (AI), blockchain, and virtual reality, form a complex sense of the modern approach to living. The real change is continuously rapid, disruptive, and persistent (Carayannis and Meissner, 2017; Scuotto et al., 2016; Pillai et al., 2021). More precisely, big data (BD) can help organisations to recognise decision-making process opportunities and define more successful organisational processes via data collection, filtering, and coding (Caputo et al., 2019a).

Human intellect and AI are combined into one framework in Industry 4.0 and form a new intellectual capital market as one of the leading development drivers in high demand by innovation systems (Ajah and Nweke, 2019). The intellectual capital market is an arena where human intelligence and AI interact potentially as substitutes. The concept of competition between human intelligence and AI may perhaps appear questionable or rather pointless (Bogoviz, 2020). First, human intellect and AI roles are scientifically delimited owing to the standard classification of their activity (Bogoviz, 2020; Chen et al., 2012). Therefore, human intellect has the potential for development that is not unique to

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AI, which is mainly related to repetitive (mechanical) work with programmed algorithms. Artificial intelligence is directed by a human's defined guidelines during decision-making and takes decisions from identified samples. Notably, AI is useless and transfers power to humans in a situation without instructions. A significant proportion of a digital company's business processes often consider contact with individuals through human–artificial intelligence (HAI), data intelligence and analytics (DI&A), and BD concept (Bogoviz, 2020; Chen et al., 2012; Manzoor, 2016). It is prevalent to use data as a predictive tool to guide decision-making. Many studies have highlighted the use of AI for decision-making in general and the specific issues regarding the interaction and integration of AI to support or replace human decision makers in a particular situation (Duan et al., 2019). BD datasets are so complex that traditional data analysis methods cannot be employed to analyse them (Scuotto et al., 2017). Their number, speed, variety, veracity, and value differ from conventional datasets, as described by the 5Vs that characterise BD (Wamba et al., 2017). The private and public sectors that have embraced this strategy have produced tangible benefits (Bogoviz, 2020; Manzoor, 2016; Pillai et al., 2020). Manzoor (2016) states that companies with high performance and governments employ analytics five times more than lower-performing companies. These top-performing companies and governments make decisions faster than lower-performing companies based on rigorous research.

Research also reveals that organisations using a data-driven decision-making approach are 5% more effective on average and accrue 6% higher profits than their competitors (McAfee et al., 2012). In the public sector, a similar indication does not exist. Undoubtedly, the capacity to use the information for leading modifications in the public sector has not been reached by good routine (HM Government, 2013). Moreover, AI capabilities, business intelligence (BI), and data intelligence (DI) are increasing annually, and the efforts of many scholars worldwide have been based on their development (Borges et al., 2020; Shareef et al., 2021; Wamba et al., 2021). Furthermore, AI is one of emerging technology strategic breakthroughs, and thus, it is funded by the state for AI-related research and development, thereby ensuring adequate support and investment control. Digital modernisation initiatives are to be launched by 2025 in most countries worldwide (HM Government, 2013). This makes it possible to expect that the competition between HAI will become a wide-ranging activity and daily reality by 2030 (HM Government, 2013).

Notably, DI&A, which is described as the strategies, technologies, processes, procedures, methodologies, and applications that analyse critical business data to help an enterprise to acquire a better understanding of its business and market and make timely business decisions, has sparked considerable interest in different organisations due to the opportunities associated with data and analysis (Zhao et al., 2014; Dubey et al., 2021). Furthermore, DI&A includes business-centric practices and methodologies that can be applied to various high-impact applications, such as e-commerce, market intelligence, e-government, healthcare, and defence, in addition to the underlying data processing and analytical technologies (Chen et al., 2012). Nevertheless, there has been a disproportionate amount of attention on the potential and value that DI&A, AI, BD, and HAI can deliver to the public sector, with very limited empirical attention focused on the public sector (Mikalef et al., 2019; Andrews, 2019; Wirtz et al., 2020).

For both practitioners and academics, business intelligence and analytics (BI&A) has increasingly attracted a research focus, thereby reflecting the complexity and impact of data-related issues to be solved for effective decision-making processes in contemporary business organisations and the public sector (Zhao et al., 2014). Nonetheless, the introduction of emerging technologies (including AI, BD, and BI&A) has also raised essential concerns due to their accessibility, which can result in poor decision-making in government and public sector organisations (Chen et al., 2012). By using BD alone, government administrations might save over EUR 100 billion (US$ 149 billion) by enhancing operational efficiency in the modern and developed countries of Europe, rather than by utilising BD to improve tax revenue collection and reduce fraud and errors (Manyika et al., 2011). Additionally, HAI governance can help governments to optimise decision-making processes by including a data-driven model. The simulation of various scenarios that could help to enhance current goods or services by providing a detailed view of what the organisation needs to accomplish while generating awareness about the competition context has not been previously observed (Sen et al., 2016). A data-driven approach, combined with BD, DI&A, and AI techniques, combining the potential of knowledge is a fundamental approach to adopt for smart citizen-centric governance. One could envision a society where public sectors, such as national security compliance and criminal justice, share information about their decision-making processes, use data from other public e-services, and ultimately promote government openness and confidence (Janssen and van den Hoven, 2015). Furthermore, several authors have shown that human intellect and AI capabilities, as well as their outcomes depend on the interaction between DI&A and HAI (Freyn and Farley, 2020; Di Vaio et al., 2020; Dubey et al., 2020; Eriksson et al., 2020; Guan et al., 2020; Munoko et al., 2020; Mitchell et al., 2020; Al-Htaybat et al., 2019; Aja and Nweke, 2019; Otokiti, 2019; Van Rijmenam et al., 2019; Sheng et al., 2019; Wang et al., 2018; Tien, 2017; Erickson and Rothberg, 2017; Lin et al., 2017; Qasim et al., 2019; Lim et al., 2013; Chiang et al., 2012).

This study explores how DI&A improves decision-making processes by utilising BD in the public sector to consider these assumptions and draw on a systematic literature review. More precisely, the aim is to investigate whether and how AI, BD, and DI&A contribute to effective decision-making processes in the public sector. This study deals with the following study questions (RQ):

RQ1*: How does data intelligence and analytics improve decision-making processes using big data in the public sector?*
RQ2: *Is artificial intelligence a valuable tool for data intelligence and analytics in the public sector?*
RQ3: *What is the role of the human–AI interface in terms of skills and application in ethics design?*

In the present study, we attempt to respond to these questions using a bibliometric study of 161 papers published in English language between 2007 and 2021 from Web of Science (WoS), Scopus, and Google Scholar (GS) publications, using the VOSviewer software. The results provide a map of the knowledge produced and circulated by previous studies. It provides insights into key topics, citation patterns, publication activities, and the status of collaborations between contributors to past studies and aggregated DI&A research contributions. This study offers a thorough overview of DI&A, BD, AI, and HAI in the public sector utilising the AI literature. The study's main contribution should be to provide views on the state of the art in DI&A, BD, AI, and HAI, as well as future research directions.

The key motivation is to conceptualise the role of DI&A in using BD, AI, and HAI to create a better public sector framework. First, recent updates have been made in the literature discussing DI&A in public sector developments and its alliance with HAI. Second, the role of DI&A is a current major topic among government agencies, practitioners, policymakers, and academics in the improvement of public sector decision-making processes. Developing and testing the role of DI&A via HAI is worth discussing. This study adds new knowledge to the literature by presenting important insights into DI&A, BD, AI, and HAI. The findings highlight that only certain factors are involved in the latest literature cover. Specifically, DI&A by AI and BD facilitate successful public sector decision-making.

The research findings will reinforce the importance of the public sector's adoption of DI&A and its efficiency. The study highlights researchers' bias on the topic. This study is the first to undertake a bibliometric analysis and a systematic literature review on BI, AI, DI&A, and HAI in public sector decision-making processes to the best of our knowledge. This study extends an ambidexterity theory in decision support, which explains how ambidexterity can be encouraged and how it affects decision outcomes. The study is organised as follows: the theoretical background for DI&A, BD, AI, and HAI is presented in Section 2; the method used for conducting the study is elucidated in Section 3; a description of the data and results is provided in Section 4; and the discussion, realistic and theoretical perspectives, and conclusions are included in Sections 5 and 6.

2. Theoretical background

Emerging digital technologies have continued to enable new ways of collecting and analysing data. This has led investigators to contend that data analytics are skillful, and that BD can dramatically boost an organisation's performance. However, to achieve such changes, managers have to modify the overall decision-making atmosphere and increase cohesion in the decision-making process by integrating AI into organisational strategy (Frisk and Bannister, 2017; Borges et al., 2020). In a wide range of industrial, intellectual, and social applications, AI has the same transformative potential for augmenting and potentially replacing human functions and activities (Dwivedi et al., 2019). Data analytics, BI, and BD are three strongly related innovations that have evolved as a result of the development of information and communications technology (Chen et al., 2012; Shareef et al., 2021). A design strategy will help companies improve their decision-making ethos by using BD and data analytics, resulting in more intelligent and productive decisions (Frisk and Bannister, 2017). The fundamental objective of the emerging technologies embedded in the BD sector is to enhance decision-making from a process-based perspective, which decreases the time spent on decision-making (Caputo et al., 2019a; Ardito et al., 2019; Wirtz and Müller, 2019).

Business intelligence and analytics present analytics specialists with the technical abilities to provide accurate knowledge and strategic perspectives to support decision-making processes, thereby potentially increasing management decision-making efficiency. The certain nature of organisational decision-making processes creates contradictory task demands on adaptability and rigour (Kowalczyk and Buxmann, 2015; Jayakrishnan et al., 2019). Big data analytics (BDA)-powered AI and DI&A have roots in data-centric methods; for example, data warehousing includes multiple data processing, aggregation, and analytics technologies (Arnott and Pervan, 2005; Chaudhuri et al., 2011; Watson, 2011; Bag et al., 2021; Dubey et al., 2021). Furthermore, DI&A structures aim to expand data analysis to upsurge the consistency of the information accessible for decision-making (Chaudhuri et al., 2011). In this respect, DI&A includes several analytics abilities, that is, ad hoc questions, descriptive statistics, and online analytical processing, as well as prediction, advanced data mining, and optimisation analytics capabilities (Chaudhuri et al., 2011; Watson, 2011; Davenport, 2006). The use of DI&A to provide data-centred decision support is becoming a specialised activity with a growing level of analytics capabilities, thus requiring analytics specialists to help managerial decision makers, data scientists, or analysts (Viaene, 2013; Davenport, 2006). Analytical advances create a robust gap between researchers and domain-specific knowledge decision makers who specialise in analytics (Viaene, 2013). Within the context of decision processes supported by DI&A, decision makers have to rely on analysts because of their lack of analytical skills. Simultaneously, analysts depend on decision makers' domain-specific expertise for the development of applicable analytical insights and guidance. Consequently, adequate DI&A support includes alliance between decision makers and analysts (Sharma et al., 2014; Viaene, 2013). The advanced analytics techniques seem central in integrating BI and BD (Sheng et al., 2019). In this regard, the BD sector can be viewed as a decision-making environment that incorporates both technology and human capacity to make decisions compatible with its plans (Singh and Del Giudice, 2019).

2.1. Theoretical model for data intelligence and analytics through AI and BD for public sector decision-making

Data intelligence and analytics entails a resource-generating capability for public sector decision-making through AI and BD that emerges in two aspects: acquired and existing resources built and retained over time (Oliver, 1997). Therefore, as people adhere to customary practices for an extended period, they seem to take the legitimacy of these activities for granted and do not doubt their efficiency. Thus, based on three key theories and a supplementary view, this study considers the theoretical lens: *institutional theory* (DiMaggio and Powell, 1983), *resource-based point of view* (RBV) (Barney, 1991), and *ambidexterity theory* (Turner and Lee-Kelley, 2013). The institutional theory elucidates DI&A adoption by exploring the interrelations and cooperation between the focal organisation and stakeholders. The RBV stresses the internal capital role in shaping organisations' policies and results (Barney, 1991), and the ambidexterity theory is based on how to facilitate ambidexterity and how it affects decision-making outcomes (Turner and Lee-Kelley, 2013).

In the literature, several studies have tried to combine the RBV and institutional theory to describe organisational decision-making as independent organisational motivations (Oliver, 1997), as well as various external powers, internal resources, and their interactions (Tatoglu et al., 2016; Zheng et al., 2013; Bag et al., 2021). Ambidexterity research has mainly concentrated on the organisational level. In the case of more complex organisational approaches, there is nothing in the literature exploring ambidexterity. Although much has been reported about the "what" of ambidexterity, the conditions of its implementation are considered pertinent. There is a void in our understanding of the underlying processes, architectures, and dynamics through which organisations can accomplish both discovery and exploitation; however, its implementation is beneficial. Furthermore, past research has not been focused on big hypothesis about ambidexterity. Generally, this ambidexterity theory in decision support connotes that the enhancement of analysts' capacity to handle conflicts in decision-making processes would enable ambidexterity, which increases decision-making efficiency. The theory distinguishes between four types of techniques in decision-making processes to cope with conflicts and thereby attain ambidexterity. Organisational strategies (i.e., analytical team, analytical integrator, data quality assurance, and data source access standardisation) discuss the DI&A support working environment (Turner and Lee-Kelley, 2013). The DI&A context is not well established about how external pressures and organisations' culture can affect internal resource creation and adoption of DI&A to improve operational performance (Wirtz and Müller, 2019). The VRIN (value, rareness, imperfect imitability, and non-substitutability) criteria, BD, and AI-related organisational tools are used to achieve competitive gain from an RBV (Barney, 1991). However, previous research on how structural variables impact the choice of capital and creativity for organisations has been varied (Liu et al., 2010). The moderating impact of emerging technologies (BD, AI, and HAI) can also help to overcome the contradictions of previous studies (Kostova et al., 2008; Scott, 2013). However, previous research considers AI applications and challenges only in isolation and in a fragmented manner (Wirtz et al., 2019). Additionally, AI capability results in increased organisational creativity and performance (Mikalef and Gupta, 2021). Moreover, Wamba et al.'s (2021) study proposes 10 social impact domains identified from the literature, including crisis response, economic empowerment, educational challenges, environmental challenges, equality and inclusion, health and hunger, information verification and validation, infrastructure management, public and social sector management, security, and justice. Hence, this study synthesises these viewpoints to explain how, under such external constraints, public sector agencies have a particular resource portfolio for decision-making (Braganza et al., 2017; Zheng et al., 2013; Zhang and Dhaliwal, 2009).

The effects of BDA on an organisation's overall performance are

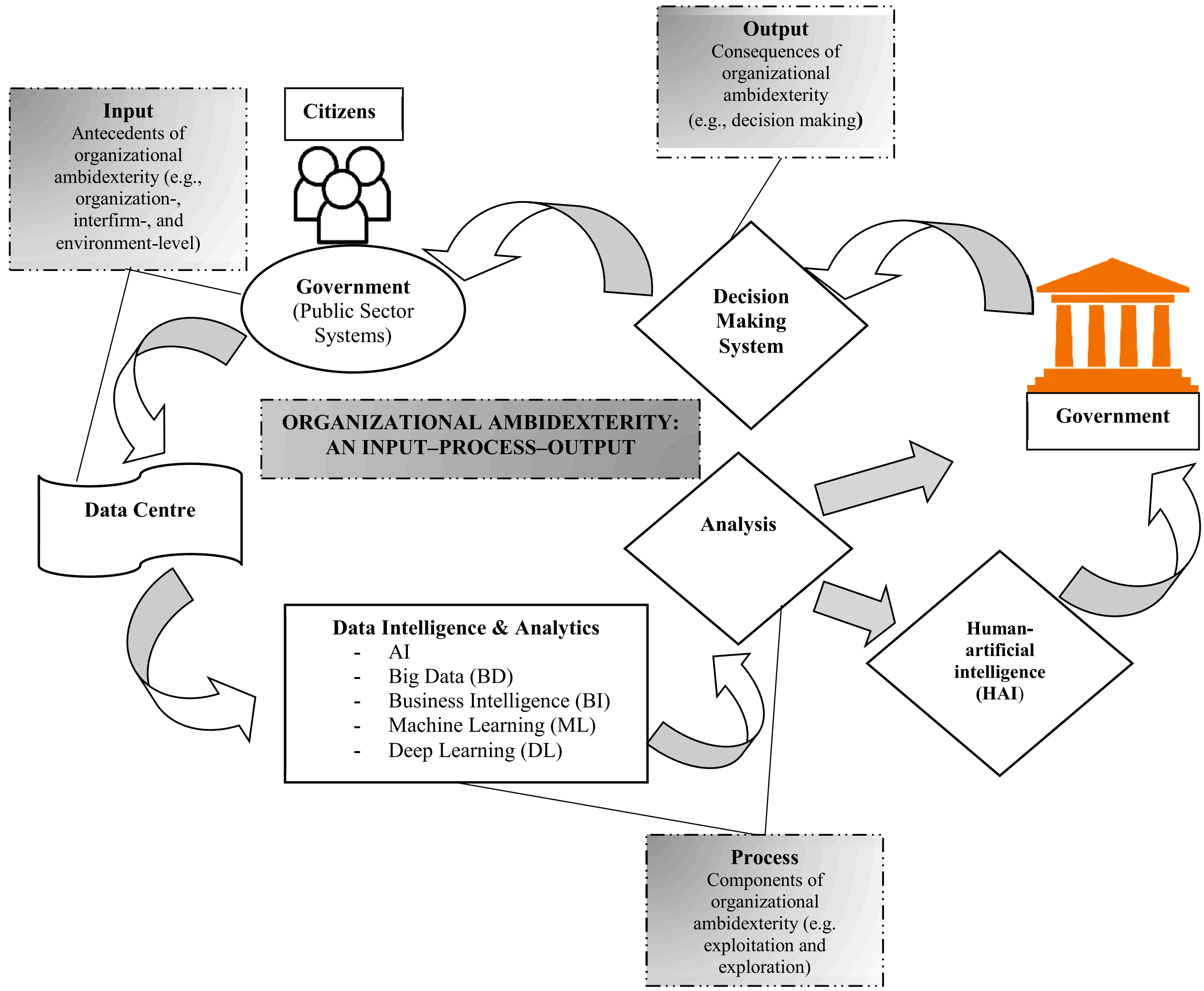

Fig. 1. Theoretical model for data intelligence and analytics through AI and BD for effective public sector decision-making.

examined (Aydiner et al., 2019; Srinivasan and Swink, 2018; Wamba et al., 2017; Akter et al., 2016; Gunasekaran et al., 2017; Gupta and George, 2016; Chen et al., 2015). Most of these studies have shown that companies who make complex decisions using BDA are competitive in this era (Wamba et al., 2017; Srinivasan and Swink, 2018; Chen et al., 2015). Aydiner et al. (2019) have concluded in a recent study that the optimal production level cannot be accomplished in organisations that neglect to react efficiently to related environmental demand or external pressures. Human skills (technical and managerial) and tangible resources (necessary resources, technology, and data) facilitate DI&A capabilities under the diminishing influence of the BD-driven culture (Gupta and George, 2016). The knock-on effect of ambidexterity theory might be relevant for organisations that aim to develop additional strategies in their decision-making because it underlines the need for skills to improve decision-making quality beyond creating a DI&A technology.

In this study, we propose a focused model driven by DI&A. It defines the DI&A-powered model as a set of digital public services that channel previously-stored data back to individuals as solutions, decisions, and accelerated national development changes. As a paradigm shift that will direct any nation that holds the model into another era of digital maturity, an intelligence and analytics-driven model can be represented. The goal of the model driven by intelligence and analytics is to aggregate all digital services and open data at each government level so that policymakers can unlock the importance of the data accessible to them and the data to guide the decision-making process. The data-driven intelligence and analytics model can measure and forecast economic effects of tax policy changes, develop national services (e.g., national health insurance and social welfare) to reduce poverty and increase the standard of education, assess potential threats (terrorist attacks resulting from access to tourist and immigration data), and analyse potential threats (terrorist attacks that arise from access to information on tourism and immigration) and data on crime to strengthen public safety. The aforementioned processes are defined by this model, as outlined in Figure 1.

3. Methodology

The current study focusses on a quantitative method of research. We analyse 161 WoS, Scopus, and GS publications gathered between 2007 and 2021 based on research tools and methodologies found in other published bibliometric studies (selecting only as document types: Article, Book Chapter, Books, and Conference Papers) (Bonilla et al., 2015). This study investigated the content of DI&A-, BD-, AI-, and HAI-related articles. Notably, WoS, Scopus, and GS databases were selected as sources based on diverse and varied references, abstracts, and research summaries according to standard procedures (Fink, 2019). Content analysis is an investigative technique that uses a software to organise comparative samples of various documents on the same subject (Krippendorff, 2004; Massaro et al., 2016). Currently, Scopus has more than 50 million documents and 37,000 titles. The database is updated continuously and is a reliable source to effectively and efficiently

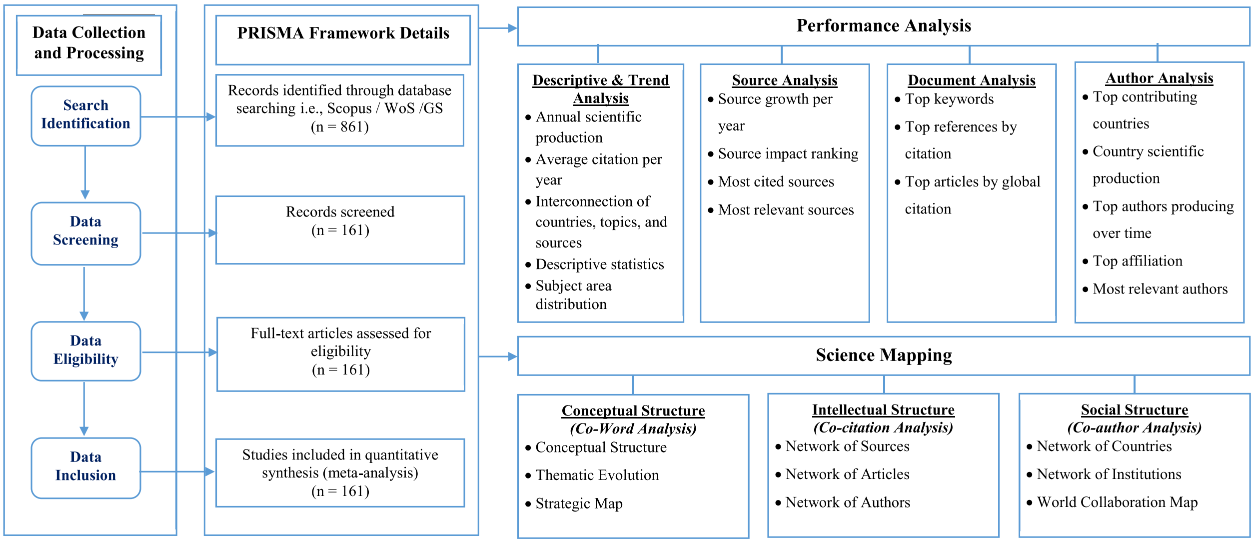

Fig. 2. Research design and methodology.

acquire worldwide academic information. The h-index utility that indicates the quality of a book, author, or journal is also impossible to ignore (Hirsch, 2005).

Some of the journals that publish theoretical or empirical research on DI&A, BD, AI, and HAI are *Technological Forecasting and Social Change, Lecture Notes in Business Information Processing, and Decision Support Systems* (Okoli et al., 2010). The VOSviewer software, version 1.6.15, was employed in this study (www.vosviewer.com; Van Eck and Waltman, 2014). To create a file with the required network analysis structure and format, the list was then processed. The VOSviewer software is an open-source tool used for bibliometric network design and development. A mapping visualisation of the bibliographic data was created to obtain better and deeper insights into the research questions' bibliometric outcomes. Additionally, a text-mining feature supported the VOSviewer. It has been used by a body of scientific literature to visualise and construct co-occurrence networks linked to subject areas. The study method was split into two phases: a) collecting and evaluating the documents concerned and b) conducting a bibliometric analysis. The first step was to study the obtained papers based on the following conditions: (i) search for databases; (ii) qualitative analysis; (iii) manual search for more consistent contributions; and (iv) development of data collection. The data collection approach is depicted in Figure 2; these measures were undertaken to ensure that the process was accurate.

Three primary databases, namely, WoS, Scopus, and GS, were used in the first phase to review academic literature publications to underline and categorise scholars' core research trends in the field. The time limits for the compilation of all submissions on the topic between 2007 and 2021 (the default years of the WoS, Scopus, and GS databases) were not externally enforced at this stage. The search was conducted using combinations of seven search string categories to obtain relevant articles:

Group 1: BI&A and BD
Group 2: AI, DI&A, decision-making processes, and public sector
Group 3: DI&A and decision-making processes
Group 4: DI&A *["Artificial Intelligence" OR "Big Data" OR "Business Intelligence") OR "Data Analytics" "Decision Making") "Big Data Analytics") "Business Analytics") OR "AI"), "Artificial Intelligence (AI)" Systematic Literature Review") "Business Intelligence and Analytics"), "Decision-making") "Digital Technologies"), "Big Data Applications"), "Business Performance"), "Digitalization")*
Group 5: DI&A and accountability
Group 6: DI and HAI interface
Group 7: Human and DI

The seven configurations were aimed to provide as many subject-related articles and validate the similarities among the papers reviewed by the various study categories. We increased the review to all studies in DI&A, BD, AI, and HAI. Indeed, this study was focused on the role and potential of DI&A through the lenses of AI, BD, and the HAI interface to improve overall decision-making processes.

The second stage involved identifying the related papers to ensure accuracy with the study objectives. By reading the abstracts and highlighting their relevance, we determined each article's content. In this study, we hypothesised in the third point that WoS and Scopus might not contain all the papers needed for the analysis; thus, we used the same parameters to conduct a manual search on GS. All the current research authors worked independently in the fourth and final phase to review each article and highlight their critical aspects. After eliminating redundant papers and duplicates, the authors compared their findings and divided themselves into separate teams to review the literature. One hundred and sixty-one papers are provided in the final list. The bibliometric review is presented in Section 4.

4. Bibliometric analysis and results

A quantitative study of the selected papers is detailed in the following sub-sections. We conducted a bibliometric analysis based on the following publication models on the DI&A, BD, AI, and HAI interface: country of publication, institution, and contributions from authors, journal, as well as the total number of publications based on year (Howard, 2017). This study utilised bibliographic data collected from the databases ISI WoS, Scopus, and GS.

4.1. Bibliometric aspects of the selected articles

4.1.1. Keyword analysis

After the presentation of methods, this study progressed to an overview of the keywords. Using the text-mining routine of VOSviewer 1.6.15 (Van Eck and Waltman, 2014), this study visualised the cascades created by numerous papers. This method has been validated in recent bibliometric studies (Marzi et al., 2017). The text-mining method creates a map that interprets the terms' distance as an implication of the relationship between different keywords. In conclusion, the more significant the gap between two or more keywords, the more significant the terms associated with each other. The publications' co-occurrences were

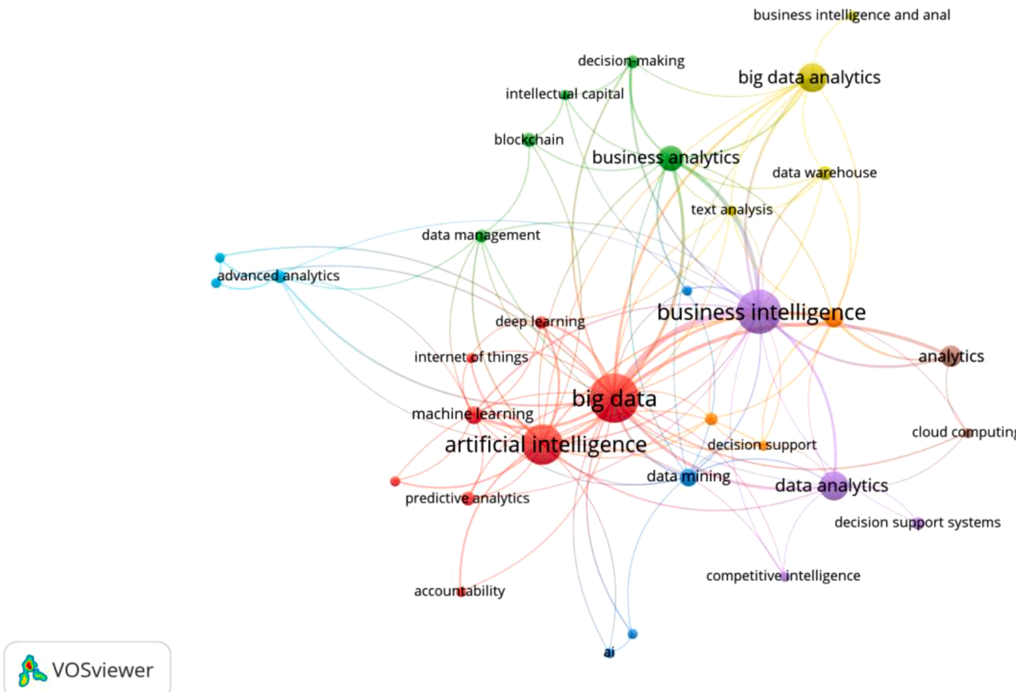

Fig. 3. Network visualization map of the author keywords.

Table 1
Top keywords.

Author Keywords	Frequency	Percent
Big Data	43	10.29
Business Intelligence	36	8.61
Artificial Intelligence	29	6.94
Big Data Analytics	16	3.83
Data Analytics	16	3.83
Business Analytics	12	2.87
Analytics	9	2.15
Data Science	7	1.67
Data Mining	6	1.44
Machine Learning	6	1.44
Decision Making	6	1.44
Blockchain	4	0.96
Data Warehouse	4	0.96
Predictive Analytics	4	0.96
Advanced Analytics	3	0.72
Data Management	3	0.72
Decision Support Systems	3	0.72
Deep Learning	3	0.72
Accountability	2	0.48
AI	2	0.48
AI Value Chain	2	0.48
Artificial Intelligence (AI)	2	0.48
Automation	2	0.48
Business Intelligence and Analytics	2	0.48
Cloud Computing	2	0.48
Competitive Intelligence	2	0.48
Decision Support	2	0.48
Decision Support System	2	0.48
Industry 4.0	2	0.48
Information Technology	2	0.48
Intellectual Capital	2	0.48
Internet of Things	2	0.48
Text Analysis	2	0.48
Text Analytics	2	0.48

Total Key words= 418.

analysed to judge the words' interconnectivity (Van Eck et al., 2014). Specifically, for this bibliometric study, the analysis of the keywords for 'Author Keywords' contains those keywords that occur in the database no less than twice. This study relied on manual selection to ensure data reliability, resulting in 34 keywords out of a total of 418, which were considered appropriate for the analysis. Then, the keywords (e.g.,' literature,' study,' content analysis', and so forth) that could not explain anything on their own were filtered out. The network visualisation map of the author's keywords for the titles is shown in Figure 3, and the most frequently used terms in the titles of the papers are highlighted. The size of the words in the picture is based solely on their inclusion in the chosen articles. As Fig. 3 shows, keywords were 'Business Intelligence', 'Big Data Analytics', and 'Artificial Intelligence', which are at the centre of the map. These keywords were used during the period of study as a constant in data collection (Di Vaio et al., 2020; Dubey et al., 2020; Eriksson et al., 2020; Freyn and Farley, 2020; Guan et al., 2020; Mitchell et al., 2020; Munoko et al., 2020; Aja and Nweke, 2019; Al-Htaybat et al., 2019; Otokiti, 2019; Qasim et al., 2019; Sheng et al., 2019; Van Rijmenam et al., 2019; Wang et al., 2018; Erickson and Rothberg, 2017; Lin et al., 2017; Tien, 2017; Lim et al., 2013; Chiang et al., 2012). In several papers reviewed, the terms DI&A, BD, AI, and HAI interface appear often (Table 1).

The conceptual map was built based on a bibliometric analysis to show the relationship between keywords in the database (Van Eck and Waltman, 2010). Fig. 3 shows the keywords and co-occurrence or

Table 2
Document type.

Document Type	Frequency	% (N=161)
Conference Paper	44	27.33
Article	93	57.76
Book Chapter	14	8.70
Review	5	3.11
Editorial	0	0.00
Article in Press	0	0.00
Conference Review	0	0.00
Note	1	0.62
Book	4	2.48
Letter	0	0.00
Short Survey	0	0.00
Erratum	0	0.00
Total	**161**	**100.00**

Table 3
Source type.

Source Type	Frequency	% (N=161)
Journals	100	62.11
Conference Proceedings	43	26.71
Book Series	14	8.70
Books	04	2.48
Trade Publications	0	0.00
Total	**161**	**100.00**

co-word estimation; it also shows some well-known topics in the literature on DI&A, BD, AI, and HAI. In colour-matching the words 'Business Intelligence', 'Big Data Analytics', and 'Artificial Intelligence have a relationship, it is important to note ex multis'. By propagating BI, as well as improving DI&A, BD, AI, and HAI comprehension, this co-occurrence index shows how strong the relationship between BI and DI&A is. The top keywords that have been used by several researchers in the past are presented in Table 1.

4.1.2. Documents and source types

There are (57.76%) articles comprised of the most numerous type of documents in the 161 selected sample. This is notably followed (27.33%) by papers from the conferences. A comprehensive overview of the various paper types is given in Table 2.

Journals (62.11 percent) are the most numerous with respect to the source of the documents. In Table 3, a detailed overview of the sources is given.

4.1.3. Year of publications—evolution of published studies

Figure 4 shows the evolution of publications on the current subject from 2007 to 2021. A gradual increase in DI&A, BD, AI, and HAI publications can be observed. The lowest number of publications was in the 2007–2010 period, induced by growth between 2012 and 2020. This demonstrates the growing interest in DI&A, BD, AI, and HAI among researchers. A complete list of the different years of publication of works is provided in Table 4, which shows that the maximum number of publications happened in 2019 and 2020.

4.1.4. Most Active Source Titles

The foremost and most active journals that published papers linked to DI&A, BD, AI, and HAI are summarised in Table 5: *Technological Forecasting and Social Change, Lecture Notes in Business Information Processing,* and *Decision Support Systems* are examples. These source titles present papers that are important to DI&A, BD, AI, and HAI. This examines the effect of DI&A and HAI dissemination on public sector decision-making efficiency (Chen et al., 2012).

Table 4
Year of publications.

Year	Frequency	% (N=161)	Cumulative Percent
2007	1	0.62	0.62
2008	2	1.24	1.86
2009	3	1.86	3.73
2010	1	0.62	4.35
2012	2	1.24	5.59
2013	5	3.11	8.70
2014	7	4.35	13.04
2015	14	8.70	21.74
2016	10	6.21	27.95
2017	25	15.53	43.48
2018	18	11.18	54.66
2019	37	22.98	77.64
2020	35	21.74	99.38
2021	1	0.62	100.00
Total	**161**	**100.00**	

Table 5
Most active source title.

Source Title	No. of Documents	%
Lecture Notes in Business Information Processing	10	6.21
Decision Support Systems	4	2.48
Industrial Management and Data Systems	3	1.86
International Journal of Recent Technology and Engineering	3	1.86
2019 IEEE Technology and Engineering Management Conference, TEMSCON 2019	2	1.24
ACM International Conference Proceeding Series	2	1.24
ACM Transactions on Management Information Systems	2	1.24
Advanced Science Letters	2	1.24
IEEE Engineering Management Review	2	1.24
International Journal of Accounting Information Systems	2	1.24
International Journal of Health Care Quality Assurance	2	1.24
Journal of Emerging Technologies in Accounting	2	1.24
Journal of Management Analytics	2	1.24
Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	2	1.24
MIS Quarterly: Management Information Systems	2	1.24
Public Policy and Administration	2	1.24
Quality - Access to Success	2	1.24
Technological Forecasting and Social Change	2	1.24
Technology Innovation Management Review	2	1.24
Towards the Digital World and Industry X.0 - Proceedings of the 29th International Conference of The International Association for Management of Technology, IAMOT 2020	2	1.24

Total source titles =125

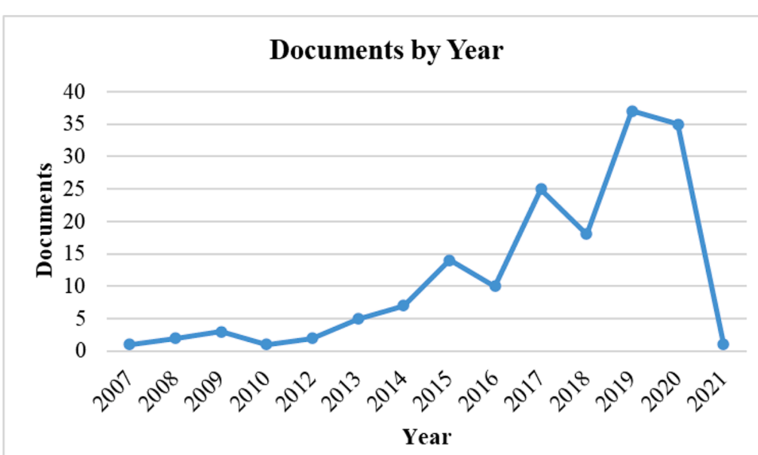

Fig. 4. Document by year.

Table 6
Top 20 Countries contributed to the publications.

Country	Frequency	% (N=161)
United States	42	26.09
United Kingdom	11	6.83
Germany	9	5.59
India	9	5.59
Australia	8	4.97
China	7	4.35
Russian Federation	5	3.11
Italy	4	2.48
Switzerland	4	2.48
France	3	1.86
Netherlands	3	1.86
South Africa	3	1.86
Taiwan	3	1.86
United Arab Emirates	3	1.86
Brazil	2	1.24
Greece	2	1.24
Hong Kong	2	1.24
Jordan	2	1.24
Malaysia	2	1.24
Singapore	2	1.24

Total countries =44

Table 7
Number of Author(s) per document.

Author Count	Frequency	% (N=161)
1	35	21.74
2	43	26.71
3	42	26.09
4	23	14.29
5	7	4.35
6	7	4.35
7	3	1.86
8	1	0.62
Total	**161**	**100.00**

Table 8
Most productive authors.

Author's Name	No. of Documents	Percentage (%)
Chen H.	3	0.75
Miller G.J.	3	0.75
Chiang R.H.L.	2	0.50
Erickson G.S.	2	0.50
Freyn S.L.	2	0.50
Rothberg H.N.	2	0.50
Van Rijmenam M.	2	0.50
Vasarhelyi M.	2	0.50
Yablonsky S.A.	2	0.50

Total Authors=402

4.1.5. *Geographical distribution of publications: the most influential countries*

Table 6 presents the percentage of contributions by the top 20 countries in publications. The United States (26.09%) leads the list in articles, followed by the United Kingdom (6.83%). This data validates that for DI&A, BD, AI, and HAI studies, the original central pillar was in the United Kingdom and the United States. Interestingly, India (5.59%) and China (4.35%) are ranked fourth and sixth in Asia. Notwithstanding the appropriate measures taken by the US government, the US records a high growth rate and encourages DI&A, BD, AI, and HAI (Chen et al., 2012). There are many studies in the context of the United States focussing on DI&A, BD, AI, and HAI to determine the causes of the country's evolving digitalisation. Jordan, Singapore, and Malaysia are at the bottom of the Table, making up 1.24 percent of the total publications. Another critical point is that there are no studies from the developed countries, such as New Zealand, Canada, South Korea, and so on, available regarding DI&A, BD, AI, and HAI. In countries with present requirements in cultural and business contexts, research focused on DI&A, BD, AI, and HAI is more often substantiated.

4.1.6. *Authorship*

The number of authors per paper is presented in Table 7. Two authors (26.71%) are followed by three (26.09%), one (21.74 %), four (14.29%), and so on. It can be confidently stated that published papers seem to be of higher quality when authorship involved more than one author.

Table 8 presents the most productive authors in DI&A, BD, AI, and HAI. Chen H. (United States), Miller G.J. (Germany) tops the Table with three documents, followed by two documents from Chiang R.H.L. (United States). All other authors had two documents. Interestingly, there are all of various genders writers, and from developed countries.

To improve any field, cooperation between different scholars is necessary; therefore, further cross-country cooperation is needed (Turner et al., 2020). The degree of cooperation between scholars with a unit of analysis as countries and authors is presented in Figures 5 and 6. The United Kingdom, the United States, India, and China are the leading nations in joint efforts. This shows a robust collaborative network that covers all continents. Deraman A., Hamdan A.R., Jusoh Y.Y., and Mansor Z., had a greater collaboration in research among researchers from various countries is the most illustrious of all. Cultural relations, geopolitical position, and language are the factors that decide and shape co-authorship preferences (Schubert and Schubert, 2020). The present study shows that geopolitical similarity and language play a key role in determining co-authorship across nations. There is, however, a greater number of US research papers and a more remarkable directness on the part of US academics to cooperate with their colleagues in other countries. Perhaps this is because the United States has a national interest in DI&A and HAI dissemination vis-à-vis decision-making efficiency.

4.1.7. *Most influential institutions*

Table 9 displays the top institutions for DI&A, BD, AI, and HAI research with a minimum of one publication and the highest citation. An equal number of papers have been contributed by the University of Cincinnati, United States, and other universities (01). However, in terms of citations, the most popular article is from the University of Cincinnati and its Carl H. Lindner College of Business. The article from Cincinnati University, United States, thus tops the most famous articles.

4.1.8. *Citation Analysis*

As per Bornmann et al. (2008), the influence of a piece of research is the degree to which other scientists have found it helpful. From 2007 to 2021, Table 10 presents the citation metrics of the 161 records. The cumulative number of citations over 14 years is 4146, resulting in 296.14 citations per year and 25.75 citations per text. Citations are meant to indicate that the quality of several other publications has been improved by a publication (in the context of the ideas of others, research findings, etc.); thus, the number of citations used in research evaluation serves as a determining factor of the impact of the research (Bornmann and Daniel, 2007).

Table 11 lists the most cited authors as Chen H., Chiang R.H.L., and Storey V.C. Their widely cited article, '*Business Intelligence and Analytics: From Big Data to Big Impact*', tops the list, and it identifies BI evolution, applications, and emerging research fields (i.e., AI and HAI), and the effect of data-related problems to be solved on modern organisations.

4.1.9. *Textual analysis*

With the VOSviewer, keywords are detected, evaluated, and then offered in a structured manner. A map was created based on bibliographic details to represent a co-word network. The association's strength was used to standardise the principles of involvement relating to the keywords (Van Eck and Waltman, 2007, p. 2). The visualisation of similarities approach was used to graphically place each word on the

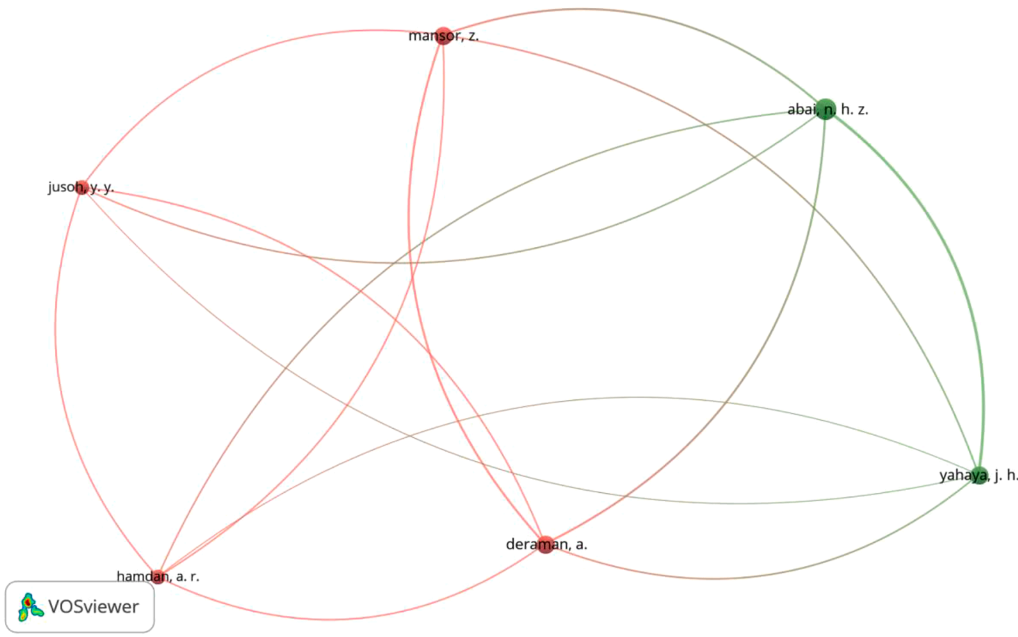

Fig. 5. Network visualization map of the co-authorship. Unit of analysis = Authors, Counting method: Fractional counting, Minimum number of documents of an author = 2, Minimum number of citations of an author = 0.

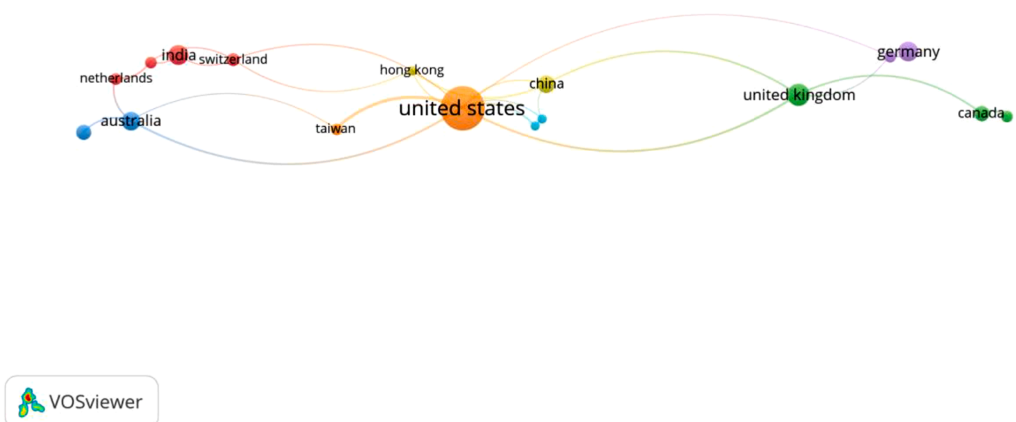

Fig. 6. Network visualization map of the co-authorship. Unit of analysis = Countries, Counting method: Fractional counting, Minimum number of documents of a country = 2, Minimum number of citations of a country = 1

map (Van Eck and Waltman, 2014). Finally, the VOSviewer algorithm offers different resolution parameters to detect the various clusters. This study zeroed in on and picked 21 keywords in this case; a measurement of the full-strength relative associations of co-occurrence with other keywords was also carried out. Colours subsequently differentiated four distinct clusters (green, blue, yellow, and red). Figure 7 (i & ii) and Figure 8 display the graphical representation of co-words or co-occurrence of keywords. Fig. 7 (i & ii) clarifies the framework relating to the concepts or knowledge of previous literature in general (Aja and Nweke, 2019). Circles of different colours and sizes show the exploration of the terms. The circle size indicates a specific term; the larger it is, the higher the frequency of abstracts and publication titles (Van Eck and Waltman, 2014). The distance between the circles observed is helpful; the greater the distance between two circles, the better the relationship. This connection is based on the number of occurrences in the articles' titles and abstracts that the words present together (Van Eck and Waltman, 2014). The occurrence of a case nine or more times was the criterion for inclusion. Twenty-one words were finally included. The VOSviewer described four different clusters and divided them into four different colours depending on the thematic community.

The co-occurrence network based on the title and abstract field is presented in Fig. 7 (i & ii) and Fig. 8; these figures reveal that the role and potential of DI&A through the lenses of AI, BD, and the HAI interface to improve overall decision-making processes (decision support system and accountability). Therefore, the government and the well-structured private sector should focus on DI&A capability with regard to digitalisation (AI and BD) for better decision-making processes.

Through the schematisation of the subtitles and the short explanation of each article's intent, the classification of the articles undertaken using 161 articles reveals that most scholars have generally analysed the consequences of the relation between DI&A, BD, AI, and HAI (Di Vaio et al., 2020; Dubey et al., 2020; Eriksson et al., 2020; Freyn and Farley, 2020; Guan et al., 2020; Munoko et al., 2020; Mitchell et al., 2020; Aja and Nweke, 2019; Otokiti, 2019; Al-Htaybat et al., 2019; Qasim et al., 2019; Van Rijmenam et al., 2019; Sheng et al., 2019; Wang et al., 2018; Tien, 2017; Erickson and Rothberg, 2017; Lin et al., 2017; Lim et al., 2013; Chiang et al., 2012).

Table 9
Most influential institutions with a minimum of one publication and forty citation.

Institution	Frequency	% (N=218)	Citations
Carl H. Lindner College of Business, University of Cincinnati, Cincinnati, Oh 45221-0211, United States	1	0.46	2577
Eller College of Management, University of Arizona, Tucson, Az 85721, United States	1	0.46	2577
J. Mack Robinson College of Business, Georgia State University, Atlanta, Ga 30302-4015, United States	1	0.46	2577
Mu Sigma, United States	1	0.46	176
Escp Europe, 79 Avenue De La République, Paris, F-75011, France	1	0.46	165
Escp Europe, Heubnerweg 8-10, Berlin, D-14059, Germany	1	0.46	165
Department of Electrical and Computer Engineering, Aristotle University of Thessaloniki, Thessaloniki, Gr-54124, Greece	1	0.46	159
Department of Electrical and Computer Engineering, Khalifa University, Abu Dhabi, 127788, United Arab Emirates	1	0.46	159
Anderson School of Management, University Of New Mexico, Albuquerque, New Mexico, United States	1	0.46	140
Center for Technology Management Research, Wesley J. Howe School of Technology Management, Stevens Institute of Technology, Hoboken, Nj 07030, United States	1	0.46	94
Department of Management Information Systems, Eller College of Management, University of Arizona, Tucson, Az 85721-0108, United States	1	0.46	94
Department of Operations, Business Analytics, And Information Systems, Carl H. Lindner College of Business, University of Cincinnati, Cincinnati, Oh 45221, United States	1	0.46	94
Eller College of Management, University of Arizona, Tucson, United States	1	0.46	69
School of Economics and Management, Tsinghua University, Beijing, China	1	0.46	69
School of Information Systems, Singapore Management University, Singapore	1	0.46	69
College of Computing Sciences, New Jersey Institute of Technology, Newark, Nj 07102, United States	1	0.46	64
Rutgers University, Newark 1 Washington Pl, Newark, Nj 07102, United States	1	0.46	58
School of Human Resources and Labor Relations, Michigan State University, 402 S. Kedzie, East Lansing, Mi 48824, United States	1	0.46	45
University at Albany, Suny, United States	1	0.46	45
Computational Sciences and Engineering Division, Oak Ridge National Laboratory, Oak Ridge, Tn, United States	1	0.46	40
Department of Decision Sciences and Management, Tennessee Technological University, Cookeville, Tn, United States	1	0.46	40
Electrical and Electronics Systems Research Division, Oak Ridge National Laboratory, Oak Ridge, Tn, United States	1	0.46	40

Table 10
Citations metrics.

Metrics	Data
Publication years	2007-2021
Citation years	14 (2007-2021)
Papers	161
Citations	4146
Citations/year	296.14
Citations/paper	25.75
Citations/author	10.31
Papers/author	0.40
Authors/paper	2.50

5. Discussion

Owing to the potential of significant benefits, public sector organisations are showing a growing interest in DI&A, AI, and BD. The findings suggest that DI&A, BD, AI, and HAI are linked to improving overall decision-making processes (decision support system and accountability) (Guan et al., 2020; Qasim et al., 2019). For public sector organisations, it will boost efficiency in the long term. New technologies (DI&A, AI, and BD) can assess their processes' efficiency and increase the sustainability of goods and services (Figures 9and 10). As for RQ1, there is an urge to change the focus of research on DI&A, AI, and BD towards new models of its representation, including HAI capacities (explicit or not), social capital, relationships with other skills, stakeholders, innovation embedded in people and the workforce within organisations that can translate information into creativity. It is also essential to analyse and consider the components mentioned above regarding the DI&A, which, in our view, influence decision-making and efficiency (Figs. 9 and 10). Among these, HAI is crucial for this goal, and ambidexterity in decision support implies that increasing analysts' capacity to handle tensions in decision-making processes would foster ambidexterity, thereby leading to greater efficiency in decision-making. Organisations have now recognised that their success is mainly due to their workers' experience and skills (human capital and knowledge). This study asserts that implementing strategies to mitigate DI&A, AI, and BD is essential for decision-making and improving the evidence base to enhance future explorations of the technology. This article intends to study the unique opportunities and challenges related to DI&A in the public sector, acknowledging that this new technology is still in its infancy and needs to be further researched, examined, and better understood.

The findings highlight that the structural constraints of organisations directly influence the distribution of internal capital and, ultimately, the adoption of DI&A. Dubey et al. (2017) argue that the scope of information technology (IT) limits the opportunity to evaluate the viewpoint of technology advancement. Diffusion is more fitting to understand the technology adoption decision-making mechanisms, such as e-government adoption (Zheng et al., 2013) or BDA adoption (Gunasekaran et al., 2017) or ERP (Liang et al., 2007). With the advancement of IT technology, maturity is no longer a major concern for improving analytics capabilities. Furthermore, AI capabilities are not independent (Zhang et al., 2021), as they interact and coevolve with human capabilities to create business value in terms of effectiveness (e.g., error reduction) and efficiency (e.g., labour productivity and space optimisation). As a substitute, public sector organisations' decisions, such as DI&A adoption decisions, are strongly affected by inter-organisational pressures. Under such conditions, this study suggests that the institutional perspective is much more crucial to public sector organisations' success in understanding the adoption of DI&A. Prior studies have employed the RBV or the dynamic view to explain BDA adoption (Wamba et al., 2017; Gupta and George, 2016; Akter et al., 2016).

Nevertheless, the RBV has been blamed for ignoring the context (Yang and Konrad, 2011). Oliver (1997) claim that the procurement of resources or resource implementation is independent of the institutional context. Therefore, this study combined the institutional viewpoint and

Table 11
Highly cited articles - most influential papers.

No.	Authors	Title	Year	Cites	Cites per year
1	Chen H., Chiang R. H.L., Storey V.C.	Business intelligence and analytics: From big data to big impact	2012	2577	286.33
2	Minelli M., Chambers M., Dhiraj A.	Big Data, Big Analytics: Emerging Business Intelligence and Analytic Trends for Today's Businesses	2013	176	19.56
3	Kaplan A., Haenlein M.	Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence	2019	165	18.33
4	Diamantoulakis P. D., Kapinas V.M., Karagiannidis G.K.	Big Data Analytics for Dynamic Energy Management in Smart Grids	2015	159	17.67
5	Bose R.	Advanced analytics: opportunities and challenges	2009	140	15.56
6	Chiang R.H.L., Goes P., Stohr E.A.	Business Intelligence and Analytics education, and program development: A unique opportunity for the Information Systems discipline	2012	94	10.44
7	Lim E.-P., Chen H., Chen G.	Business intelligence and analytics: Research directions	2013	69	7.67
8	Duan L., Xiong Y.	Big data analytics and business analytics	2015	64	7.11
9	Appelbaum D., Kogan A., Vasarhelyi M., Yan Z.	Impact of business analytics and enterprise systems on managerial accounting	2017	58	6.44
10	Dulebohn J.H., Johnson R.D.	Human resource metrics and decision support: A classification framework	2013	45	5.00
11	Sukumar S.R., Natarajan R., Ferrell R.K.	Quality of Big Data in health care	2015	40	4.44
12	Polyvyanyy A., Ouyang C., Barros A., van der Aalst W. M.P.	Process querying: Enabling business intelligence through query-based process analytics	2017	37	4.11
13	Rikhardsson P., Yigitbasioglu O.	Business intelligence & analytics in management accounting research: Status and future focus	2018	35	3.89
14	Zhao J.L., Fan S., Hu D.	Business challenges and research directions of management analytics in the big data era	2014	35	3.89
15	Lin Y.-K., Chen H., Brown R.A., Li S.-H., Yang H.-J.	Healthcare predictive analytics for risk profiling in chronic care: A Bayesian multitask learning approach	2017	35	3.89
16	Cheng S., Zhang Q., Qin Q.	Big data analytics with swarm intelligence	2016	32	3.56
17	Frisk J.E., Bannister F.	Improving the use of analytics and big data by changing the decision-making culture: A design approach	2017	28	3.11
18	Kowalczyk M., Buxmann P.	An ambidextrous perspective on business intelligence and analytics support in decision processes: Insights from a multiple case study	2015	28	3.11
19	Saecker M., Markl V.	Big data analytics on modern hardware architectures: A technology survey	2013	26	2.89
20	Chen K., Li X., Wang H.	On the model design of integrated intelligent big data analytics systems	2015	18	2.00

the RBV to clarify DI&A adoption to provide more perspectives. This study's main results are further outlined as follows:

First, this study found that DI&A, AI, and BD have significant impacts on the mechanism of decision-making. Second, this study found that DI&A, AI, and BD have an essential link with transparency and decision support. Davenport and Harris (2007) claim that managers must increase data availability as the first step in expanding predictive analytics capability and BD. Third, we found that using institutional logic, human capital can efficiently coordinate numerous technologies, and possess both domain and data science skills. Finally, the results indicate that knowledge is directly related to all forms of technology that help to strengthen decision-making.

5.1. A holistic comparison of our findings with past studies

Artificial intelligence has the potential to revolutionise every part of society, making it one of the most disruptive technologies of the twenty-first century. Preparing for 'AI in organisations' has become a hot issue, with public and scientific interest developing regarding the ideas, regulations, incentives, and ethical frameworks required for the organisation to reap the benefits of AI while limiting the conditions associated with its use. Although DI&A, BD, AI, and HAI research is a relatively new field in management studies (Wamba et al., 2021), the main findings show that numerous studies have focused on AI and organisation performance. Nonetheless, there is a lack of debate on the role and potential of DI&A, using the lenses of AI, BD, and the HAI interface to improve overall decision-making processes. For example, there have been several studies in the last few years on how AI can help understand the social changes (e.g., Wamba et al., 2021; Shareef et al., 2021; Borges et al., 2020; Bag et al., 2021; Zhang et al., 2021; Dwivedi et al., 2019). It can be argued that past studies have focused only on the impact of AI with industries, such as finance, healthcare, manufacturing, retail, supply chain, logistics, and utilities, all having the potential to be disrupted by AI technology, but DI&A, BD, AI, and HAI research is missing. Nevertheless, the public organisations are not fully implementing advanced technologies, that is, DI&A, BD, AI, and HAI, and this research area remains unexplored (Wamba et al., 2021; Nishant et al., 2020), although some concepts and new definitions of DI&A, BD, AI, and HAI are required for effective decision-making processes (Demlehner et al., 2021; Duan et al., 2019; Hu et al., 2021).

In the literature, there is even less research conducted on HAI and other advanced technologies, and the concept of DI&A, BD, and AI remains underexplored (Wamba et al., 2021; Shareef et al., 2021). After reviewing recent studies, it may also be noted that the role and potential of DI&A through the lenses of AI, BD, and the HAI interface to improve

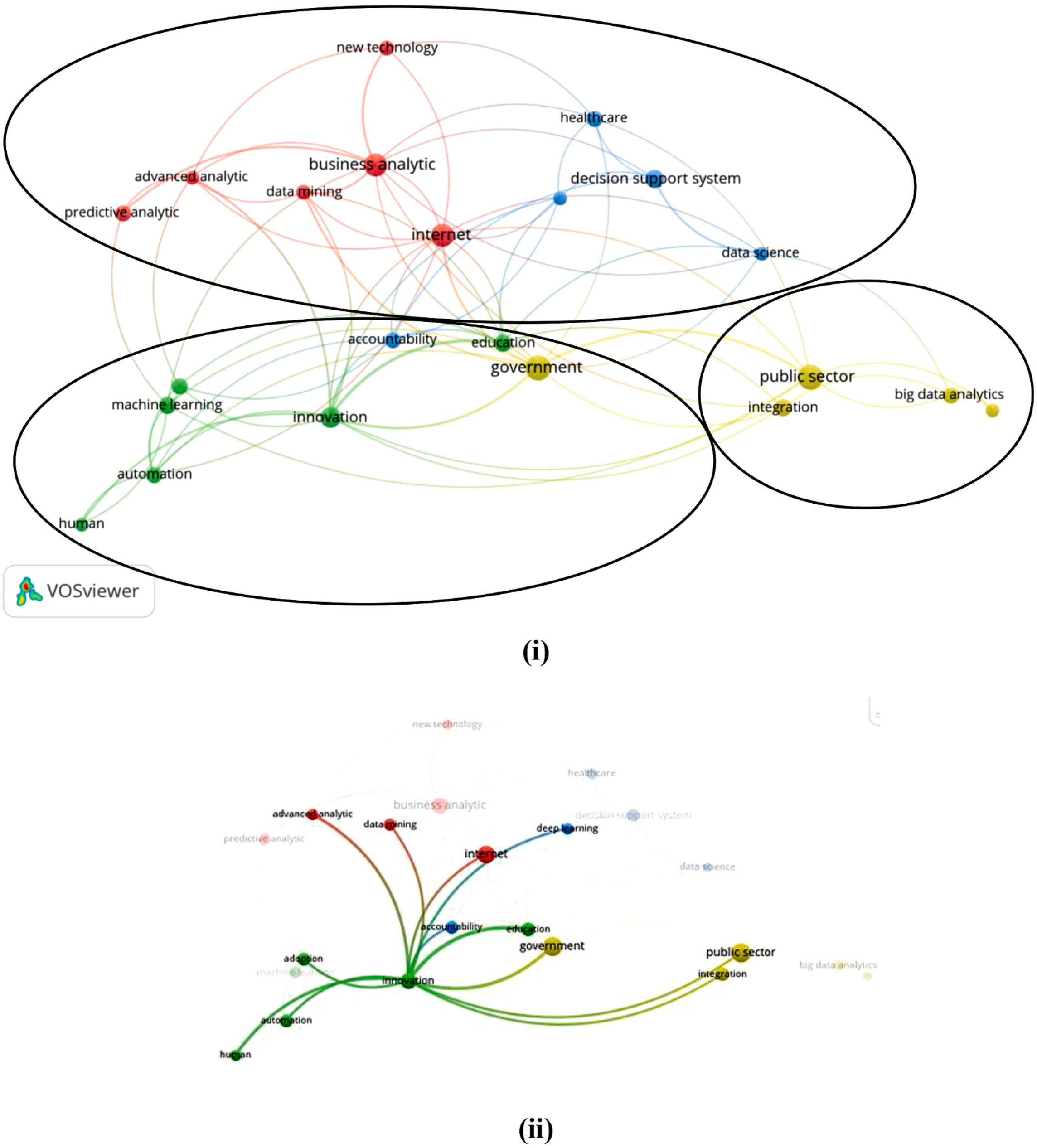

Fig. 7. (i, & ii). VOSviewer visualization of a term co-occurrence network based on title and abstract fields (Binary Counting).

overall decision-making processes remains underexplored in academic literature. Thus, these studies allow authors to recognise the importance and simultaneous exploration of DI&A, BD, AI, and HAI concerning decision-making processes. As the number of studies increases every year, scholars and companies could expect some convergences between DI&A, BD, AI, and HAI concerning decision-making processes. The spread and effectiveness of DI&A, BD, AI, and HAI domains have not been well investigated, and our findings elucidate the role of DI&A, BD, AI, and HAI from the perspective of effective decision-making processes.

5.2. Theoretical and practical implications of the study

This study has theoretical as well as practical implications. It integrates the present literature by shedding light on the key business benefits of the DI&A, AI, and BD fields that remain comparatively underexplored. It could therefore be further explored, particularly in developing countries. There is also scant research on the significance of DI&A, AI, and BD. This study makes several contributions:(1) It defines and presents previously unexplored tensions in organisational decision-making processes that challenge analysts' capacity to provide efficient DI&A support; (2) it provides understandings of the techniques used by analysts to efficiently handle these conflicts, that is, methods that foster ambidexterity; (3) it provides initial evidence on the effects of ambidexterity by analysing its influence on the quality of decisions and its impact on decision makers' reasoning and intuition by studying decision-making processes with varying levels of ambidexterity; and (4) based on these observations, the study extends ambidexterity theory in decision support, which explains how ambidexterity can be encouraged and how it affects decision outcomes. These contributions have critical functional importance, as analysts need to be informed of the stresses and methods to ensure the efficiency and use of their DI&A help.

The importance of the institutional theory and the RBV in adopting technical developments has been thoroughly studied in the literature (Zheng et al., 2013; Zhang and Dhaliwal, 2009). What is less understood

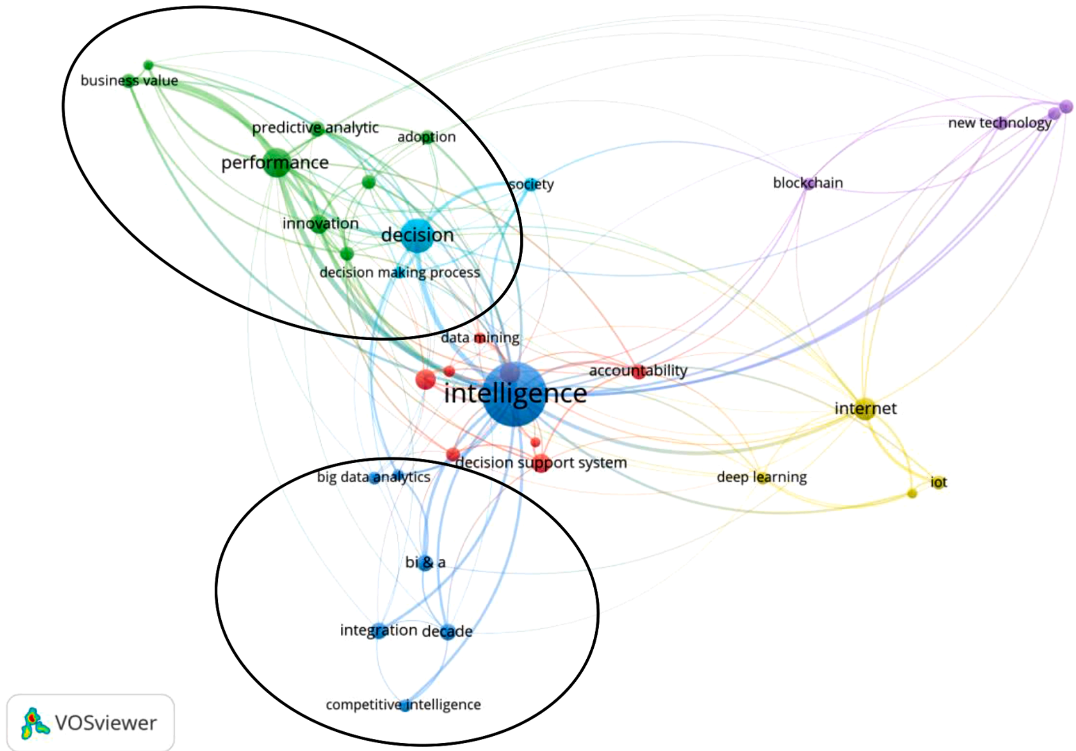

Fig. 8. VOSviewer visualization of a term co-occurrence network based on title and abstract fields (Full Counting).

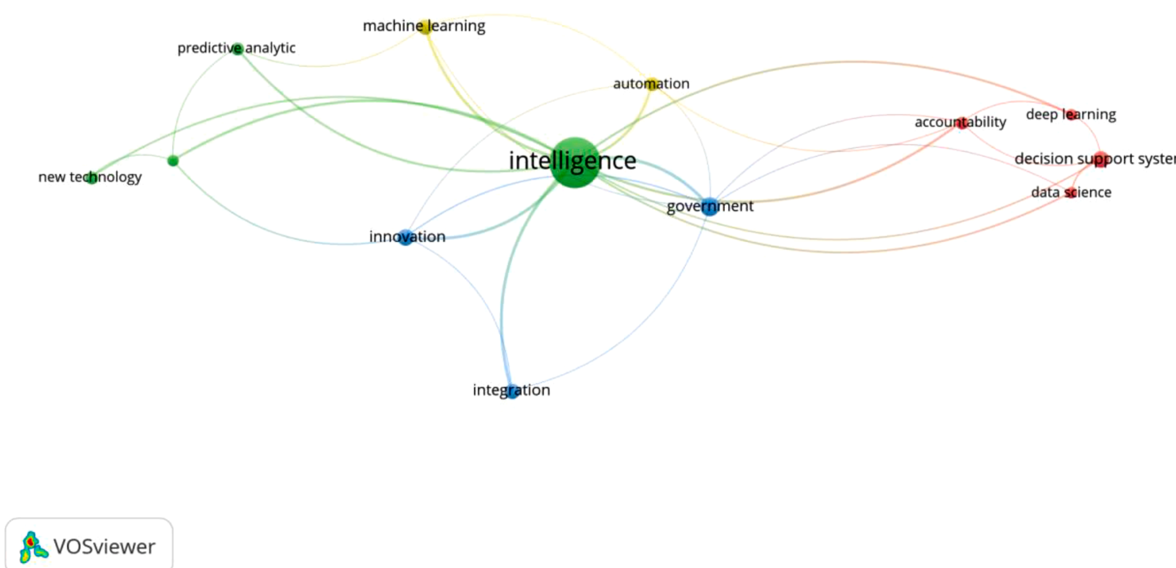

Fig. 9. VOSviewer visualization of a term co-occurrence network based on abstract fields (Binary Counting)

is how institutional forces influence the IT choices of DI&A, AI, and BD and the acceptance of BDA in particular, and how ambidexterity can be encouraged and how it influences decision-making outcomes. Two primary aspects of this study demonstrate the main contribution to the BDA literature. This study is one of the few studies to incorporate the institutional and ambidexterity theories. The institutional theory and RBV have been incorporated by previous researchers (Zhang and Dhaliwal, 2009; Zheng et al., 2013; Oliver, 1997; Tatoglu et al., 2016). Previous studies have also applied institutional theory to analyse decision-making of organisations before this research (Kostova et al., 2008; Liu et al., 2010). Our findings, therefore, offer an initial step for researchers to examine how organisational culture can further clarify the adoption of rigid and controlled organisational arrangements by DI&A.

The findings of this study may give management and IT practitioners valuable guidance. First, the position of DI&A, AI, and BD offer valuable insights into the choice of tangible resources, the development of adequate human skills, and creating the appropriate big data culture. Managers may therefore establish appropriate techniques that can help form strategies for resource selection within their organisations. This study also provides insights for BD managers by highlighting intangible resources and human skills, which can help them understand that leveraging DI&A, AI, and BD requires investment and time, and

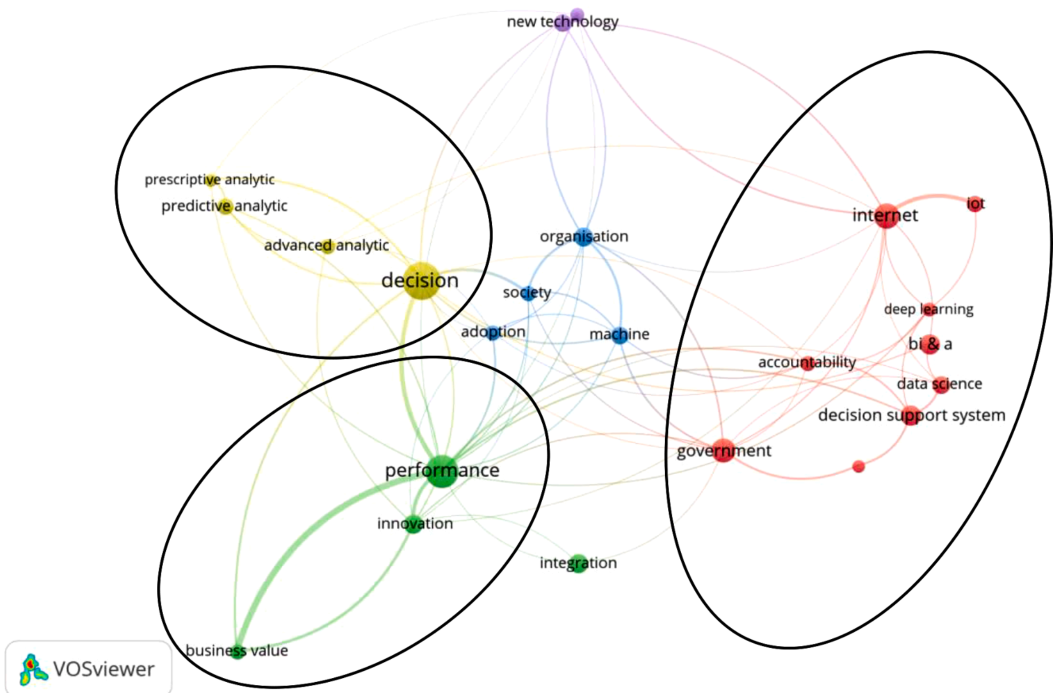

Fig. 10. VOSviewer visualization of a term co-occurrence network based on abstract fields (Full Counting)

adequate human skills to meet its diverse needs. The most important finding in this study is that AI plays a critical role in good decision-making. This research examines how researchers and practitioners perceive and interpret DI&A, AI, and BD to make better decisions in the public sector. The study provides a new awareness regarding DI&A, AI, and BD evolution, and the results go beyond previous studies that show how organisations implement strategic and tactical approaches to emerging technology.

5.3. Policy recommendation

Policymakers, regulators, practitioners, and researchers should concentrate more on DI&A, AI, and BD for public sector organisations. Policymakers can spend more on DI&A, AI, and BD to improve decision-making processes. This will help to eliminate the possibility of a knowledge discrepancy between stakeholders' perceptions, demands from regulators, and reporting in practice. By defining which levers should be pulled to achieve the optimal degree of integration, policy-makers should take measures and indicate the need for a tailor-made solution rather than a one-size-fits-all in discussing future changes.

5.4. Limitations of the study

This study has multiple limitations. It is essential to bear in mind that the information in Scopus and WoS is changed regularly, leading to a fluctuation in the number of citations and articles (Valenzuela--Fernandez et al., 2019). One of the limitations of Scopus or WoS is that when authors or journals (even those listed in Scopus/WoS) submit, they only upload articles. Therefore, the accuracy of the data collected on a specific day from the Scopus or WoS databases is doubtful. Second, scientific mapping and science profiling are quantitative approaches: it helps to analyse a broad range of reports, and it provides a comprehensive picture of the research area, enabling 'deep dive' into topics. Co-word analysis (in the present study, co-occurrence analysis of keywords) also has research limitations. Certain types of publications in bibliometric records may be understated. The quality of the co-word assessment depends on the type of indexing methods used, which the authors have little control over (Zupic, 2015). Consequently, the systematic use of an idiosyncratic approach that incorporates qualitative and quantitative processes is recommended for future investigations. This study's primary limitation is that the analysis of 14 years of research in DI&A, Bd, AI, and HAI is restricted solely to papers published in related journals. Moreover, the selection of keywords was based on literature review and the meaning of DI&A. There might be other related keywords.

5.5. Avenues for future research and recommendations

This study provides recommendations for authors, journal editors, and reviewers on how DI&A, BD, AI, and HAI add value in the public sector decision-making process, thus increasing the awareness regarding DI&A's role through new technologies to create long-term value in organisations. The literature synthesis of the current study based on a comprehensive literature review of 161 DI&A, BD, AI, and HAI articles reveals that the field is underexplored. Thus, to complement and expand our understanding, there is a need for more studies. Future research could investigate this phenomenon through empirical analysis. It must look beyond organisational borders to explore how DI&A, BD, AI, and HAI might benefit society. As a result of this study's limitations, the analyses' conclusions should be applied cautiously in various contexts. Future researchers may conduct a survey study with respondents in public sector organisations and investigate DI&A, BD, AI, and HAI applications that the public sector intends to invest in and the most important challenges they face in making this transition.

6. Concluding remarks

The exponential increase in DI&A, BD, AI, and HAI in the public sector decision-making literature prompted this study. Theory-based research on the role of DI&A, BD, AI, and HAI in government-level decision-making is still missing, despite both practitioners' and scholars' involvement. The study reveals the importance of understanding how DI&A improves the decision-making processes using BD in the public sector. There is an urge to change the focus of research on DI&A, AI, and

BD towards new models of its representation, including HAI capacities (explicit or not), social capital, relationships with other skills, stakeholders, innovation embedded in people, and the workforce within organisations that can translate information into creativity. The research highlights the potential gaps in the subject matter literature. This study is the first to perform a bibliometric overview and systematic literature review on DI&A, BD, AI, and HAI to the best of our knowledge. The article intends to be the first study on the specific opportunities and challenges posed to women, recognising that such emerging technology is in its adolescence and needs to be further studied, examined, and better understood. This study argues that it is essential that DI&A, BD, AI, and HAI consider analysing decision-making processes with varying levels of ambidexterity. By analysing DI&A, BD, AI and HAI influence on the quality of decisions and its effect on decision makers' rationality and intuition, this study provides initial evidence on the effects of ambidexterity. A theory of ambidexterity in decision support was applied to these findings, which explained how ambidexterity can be promoted and how it affects decision performance.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.techfore.2021.121201.

References

Ajah, I.A., Nweke, H.F., 2019. Big data and business analytics: trends, platforms, success factors and applications. Big Data Cognit. Comput. 3 (2), 32. https://doi.org/10.3390/bdcc3020032.

Akter, S., Wamba, S.F., Gunasekaran, A., Dubey, R., Childe, S.J., 2016. How to improve firm performance using big data analytics capability and business strategy alignment? Int. J. Prod. Econ. 182, 113–131. https://doi.org/10.1016/j.ijpe.2016.08.018.

Al Htaybat, K., Hutaibat, K., von Alberti Alhtaybat, L., 2019. Global brain-reflective accounting practices: forms of intellectual capital contributing to value creation and sustainable development. J. Intellect. Cap. 20 (6), 733–762. https://doi.org/10.1108/JIC-01-2019-0016.

Amankwah Amoah, J., 2017. Integrated vs. add-on: a multidimensional conceptualisation of technology obsolescence. Technol. Forecast. Soc. Change 116, 299–307. https://doi.org/10.1016/j.techfore.2016.10.006.

Andrews, L., 2019. Public administration, public leadership and the construction of public value in the age of the algorithm and 'big data. Pub. Adm. 97 (2), 296–310. https://doi.org/10.1111/padm.12534.

Ardito, L., Scuotto, V., Del Giudice, M., Petruzzelli, A.M., 2019. A bibliometric analysis of research on big data analytics for business and management. Manag. Decis. 57 (8), 993–2009. https://doi.org/10.1108/MD-07-2018-0754.

Arnott, D., Pervan, G., 2005. A critical analysis of decision support systems research. J. Inf. Technol. 20 (2), 67–87. https://doi.org/10.1057/palgrave.jit.2000035.

Aydiner, A.S., Tatoglu, E., Bayraktar, E., Zaim, S., Delen, D., 2019. Business analytics and firm performance: the mediating role of business process performance. J. Bus. Res. 96, 228–237. https://doi.org/10.1016/j.jbusres.2018.11.028.

Bag, S., Pretorius, J.H.C., Gupta, S., Dwivedi, Y.K., 2021. Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. Technol. Forecast. Soc. Change 163, 120420. https://doi.org/10.1016/j.techfore.2020.120420.

Barney, J., 1991. Firm resources and sustained competitive advantage. J. Manag. 17 (1), 99–120. https://doi.org/10.1177/014920639101700108.

A.V. Bogoviz (2020). Perspective directions of state regulation of competition between human and artificial intellectual capital in industry 4.0. J. Intellect. Cap.. 10.1108/JIC-11-2019-0270.

Bonilla, C.A., Merigó, J.M., Torres-Abad, C., 2015. Economics in Latin America: a bibliometric analysis. Scientometrics 105 (2), 1239–1252. https://doi.org/10.1007/s11192-015-1747-7.

Borges, A.F., Laurindo, F.J., Spínola, M.M., Gonçalves, R.F., Mattos, C.A., 2020. The strategic use of artificial intelligence in the digital era: systematic literature review and future research directions. Int. J. Inf. Manag. 102225 https://doi.org/10.1016/j.ijinfomgt.2020.102225.

Bornmann, L., Daniel, H.D., 2007. What do we know about the h index? J. Am. Soc. Inf. Sci. Technol. 58 (9), 1381–1385. https://doi.org/10.1002/asi.20609.

Bornmann, L., Mutz, R., Neuhaus, C., Daniel, H.D., 2008. Citation counts for research evaluation: standards of good practice for analyzing bibliometric data and presenting and interpreting results. Ethics Sci. Environ. Polit. 8 (1), 93–102. https://doi.org/10.3354/esep00084.

Braganza, A., Brooks, L., Nepelski, D., Ali, M., Moro, R., 2017. Resource management in big data initiatives: processes and dynamic capabilities. J. Bus. Res. 70, 328–337. https://doi.org/10.1016/j.jbusres.2016.08.006.

Caputo, F., Cillo, V., Candelo, E., Liu, Y., 2019b. Innovating through digital revolution: the role of soft skills and big data in increasing firm performance. Manag. Decis. 57 (8), 2032–2051. https://doi.org/10.1108/MD-07-2018-0833.

Caputo, F., Papa, A., Cillo, V., Del Giudice, M., 2019a. Technology readiness for education 4.0: barriers and opportunities in the digital world in ordóñez de pablos. In: Lytras, P., Zhang, M.D., Tai Chui, K., X. (Eds.), Opening Up Education for Inclusivity Across Digital Economies and Societies. IGI Global, pp. 277–296. ISBN: 9781522574743.

Carayannis, E.G., Meissner, D., 2017. Global targeted open innovation: challenges, opportunities and implications for theory, policy and practice. J. Technol. Transf. 42 (2), 236–252. https://doi.org/10.1007/s10961-016-9497-0.

Chaudhuri, S., Dayal, U., Narasayya, V., 2011. An overview of business intelligence technology. Commun. ACM 54 (8), 88–98. https://doi.org/10.1145/1978542.1978562.

Chen, H., Chiang, R.H., Storey, V.C., 2012. Business intelligence and analytics: from big data to big impact. MIS Q. 1165–1188. https://doi.org/10.2307/41703503.

Chen, D.Q., Preston, D.S., Swink, M., 2015. How the use of big data analytics affects value creation in supply chain management. J. Manag. Inf. Syst. 32 (4), 4–39. https://doi.org/10.1080/07421222.2015.1138364.

Chiang, R.H., Goes, P., Stohr, E.A., 2012. Business intelligence and analytics education, and program development: a unique opportunity for the information systems discipline. ACM Trans. Manag. Inf. Syst. 3 (3), 1–13. https://doi.org/10.1145/2361256.2361257 (TMIS).

Davenport, T.H., 2006. Competing on analytics. Harv. Bus. Rev. 84 (1), 98.

Davenport, T.H., Harris, J.G., 2007. Competing on Analytics: The New Science of Winning. Harvard Business School Press, Boston Massachusetts, Boston. A short description is retrieved at March 20, 2016.

Demlehner, Q., Schoemer, D., Laumer, S., 2021. How can artificial intelligence enhance car manufacturing? A Delphi study-based identification and assessment of general use cases. Int. J. Inf. Manag. 58, 102317 https://doi.org/10.1016/j.ijinfomgt.2021.102317.

DiMaggio, P.J., Powell, W.W., 1983. The iron cage revisited: institutional isomorphism and collective rationality in organizational fields. Am. Sociol. Rev. 147–160. https://doi.org/10.2307/2095101.

Di Vaio, A., Palladino, R., Hassan, R., Escobar, O., 2020. Artificial intelligence and business models in the sustainable development goals perspective: a systematic literature review. J. Bus. Res. 121, 283–314. https://doi.org/10.1016/j.jbusres.2020.08.019.

Dubey, R., Gunasekaran, A., Childe, S.J., Bryde, D.J., Giannakis, M., Foropon, C., Hazen, B.T., 2020. Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: a study of manufacturing organisations. Int. J. Prod. Econ. 226, 107599 https://doi.org/10.1016/j.ijpe.2019.107599.

Duan, Y., Edwards, J.S., Dwivedi, Y.K., 2019. Artificial intelligence for decision making in the era of Big data-evolution, challenges and research agenda. Int. J. Inf. Manag. 48, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021.

Dubey, R., Gunasekaran, A., Childe, S.J., Papadopoulos, T., Hazen, B., Giannakis, M., Roubaud, D., 2017. Examining the effect of external pressures and organizational culture on shaping performance measurement systems (PMS) for sustainability benchmarking: some empirical findings. Int. J. Prod. Econ. 193, 63–76. https://doi.org/10.1016/j.ijpe.2017.06.029.

Dubey, R., Bryde, D.J., Foropon, C., Tiwari, M., Dwivedi, Y., Schiffling, S., 2021. An investigation of information alignment and collaboration as complements to supply chain agility in humanitarian supply chain. Int. J. Prod. Res. 59 (5), 1586–1605. https://doi.org/10.1080/00207543.2020.1865583.

Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Williams, M. D., 2019. Artificial intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. Int. J. Inf. Manag. 101994 https://doi.org/10.1016/j.ijinfomgt.2019.08.002.

Erickson, G.S., Rothberg, H.N., 2017. Healthcare and hospitality: intangible dynamics for evaluating industry sectors. Serv. Ind. J. 37 (9-10), 589–606. https://doi.org/10.1080/02642069.2017.1346628.

Eriksson, T., Bigi, A., Bonera, M., 2020. Think with me, or think for me? On the future role of artificial intelligence in marketing strategy formulation. TQM J. https://doi.org/10.1108/TQM-12-2019-0303.

Fink, A., 2019. Conducting Research Literature Reviews: From the Internet to Paper. Sage publications.

Freyn, S.L., Farley, F., 2020. Competitive intelligence: a prescription for US health-care? Foresight 22 (5/6), 617–632. https://doi.org/10.1108/FS-02-2020-0011.

Frisk, J.E., Bannister, F., 2017. Improving the use of analytics and big data by changing the decision-making culture: a design approach. Manag. Decis. 55 (10), 2074–2088. https://doi.org/10.1108/MD-07-2016-0460.

Grover, P., Kar, A.K., Dwivedi, Y.K., 2020. Understanding artificial intelligence adoption in operations management: insights from the review of academic literature and social media discussions. Ann. Oper. Res. 1–37. https://doi.org/10.1007/s10479-020-03683-9.

Guan, C., Mou, J., Jiang, Z., 2020. Artificial intelligence innovation in education: a twenty-year data-driven historical analysis. Int. J. Innov. Stud. 4 (4), 134–147. https://doi.org/10.1016/j.ijis.2020.09.001.

Gupta, M., George, J.F., 2016. Toward the development of a big data analytics capability. Information & Management 53 (8), 1049–1064.
Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S.F., Childe, S.J., Hazen, B., Akter, S., 2017. Big data and predictive analytics for supply chain and organizational performance. J. Bus. Res. 70, 308–317. https://doi.org/10.1016/j.jbusres.2016.08.004.
Gursoy, D., Chi, O.H., Lu, L., Nunkoo, R., 2019. Consumers acceptance of artificially intelligent (AI) device use in service delivery. Int. J. Inf. Manag. 49, 157–169. https://doi.org/10.1016/j.ijinfomgt.2019.03.008.
HM Government. 2013. "Seizing the data opportunity: a strategy for uk data capability." https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/254136/bis-13-1250-strategy-for-uk-data-capability-v4.pdf.
Howard, M.C., 2017. A meta-analysis and systematic literature review of virtual reality rehabilitation programs. Comput. Hum. Behav. 70, 317–327. https://doi.org/10.1016/j.chb.2017.01.013.
Hirsch, J.E., 2005. An index to quantify an individual's scientific research output. Proc. Nat. Acad. Sci. 102 (46), 16569–16572. https://doi.org/10.1073/pnas.0507655102.
Hu, Q., Lu, Y., Pan, Z., Gong, Y., Yang, Z., 2021. Can AI artifacts influence human cognition? The effects of artificial autonomy in intelligent personal assistants. Int. J. Inf. Manag. 56, 102250 https://doi.org/10.1016/j.ijinfomgt.2020.102250.
Janssen, M., van den Hoven, J., 2015. Big and open linked data (BOLD) in government: a challenge to transparency and privacy? Gov. Inf. Q. 32 (4), 363–368. https://doi.org/10.1016/j.giq.2015.11.007.
Jayakrishnan, M., Mohamad, A.K., Yusof, M.M., 2019. Understanding big data analytics (BDA) and business intelligence (BI) towards establishing organizational performance diagnostics framework. Int. J. Recent Technol. Eng 8 (1), 128–132.
Kostova, T., Roth, K., Dacin, M.T., 2008. Institutional theory in the study of multinational corporations: a critique and new directions. Acad. Manag. Rev. 33 (4), 994–1006. https://doi.org/10.5465/amr.2008.34422026.
Kowalczyk, M., Buxmann, P., 2015. An ambidextrous perspective on business intelligence and analytics support in decision processes: insights from a multiple case study. Decis. Support Syst. 80, 1–13. https://doi.org/10.1016/j.dss.2015.08.010.
Krippendorff, K., 2004. Reliability in content analysis: some common misconceptions and recommendations. Hum. Commun. Res. 30 (3), 411–433. https://doi.org/10.1111/j.1468-2958.2004.tb00738.x.
Liang, H., Saraf, N., Hu, Q., Xue, Y., 2007. Assimilation of enterprise systems: the effect of institutional pressures and the mediating role of top management. MIS Q. 59–87. https://www.jstor.org/stable/25148781.
Lin, Y.K., Chen, H., Brown, R.A., Li, S.H., Yang, H.J., 2017. Healthcare predictive analytics for risk profiling in chronic care: a Bayesian multitask learning approach. Mis Q. 41 (2).
Lim, E.P., Chen, H., Chen, G., 2013. Business intelligence and analytics: research directions. ACM Trans. Manag. Inf. Syst. 3 (4), 1–10. https://doi.org/10.1145/2407740.2407741 (TMIS).
Liu, H., Ke, W., Wei, K.K., Gu, J., Chen, H., 2010. The role of institutional pressures and organizational culture in the firm's intention to adopt internet-enabled supply chain management systems. J. Oper. Manag. 28 (5), 372–384. https://doi.org/10.1016/j.jom.2009.11.010.
Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., Hung Byers, A., 2011. Big Data: The Next Frontier for Innovation, Competition, and Productivity. McKinsey Global Institute.
Manzoor, A., 2016. Emerging role of big data in public sector. Big Data: Concepts, Methodologies, Tools, and Applications. IGI Global, pp. 2458–2478.
Marzi, G., Dabić, M., Daim, T., Garces, E., 2017. Product and process innovation in manufacturing firms: a 30-year bibliometric analysis. Scientometrics 113 (2), 673–704. https://doi.org/10.1007/s11192-017-2500-1.
Massaro, M., Dumay, J., Guthrie, J., 2016. On the shoulders of giants: undertaking a structured literature review in accounting. Account. Audit. Account. J. 29 (5), 767–801. https://doi.org/10.1108/AAAJ-01-2015-1939.
McAfee, A., Brynjolfsson, E., Davenport, T.H., Patil, D.J., Barton, D., 2012. Big data: the management revolution. Harv. Bus. Rev. 90 (10), 60–68. https://hbr.org/2012/10/big-data-the-management-revolution.
Mikalef, P., Gupta, M., 2021. Artificial intelligence capability: conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Inf. Manag. 58 (3), 103434 https://doi.org/10.1016/j.im.2021.103434.
Mikalef, P., Fjørtoft, S.O., Torvatn, H.Y., 2019. Artificial Intelligence in the public sector: a study of challenges and opportunities for Norwegian municipalities. In: Proceeedings of the Conference on e-Business, e-Services and e-Society. Springer, Cham., pp. 267–277. https://doi.org/10.1007/978-3-030-29374-1_22
Mitchell, R.B., Woolridge, R.W., Johnson, V., 2020. The role of nontechnical skills in providing value in analytics-based decision culture. J. Educ. Bus. 1–9. https://doi.org/10.1080/08832323.2020.1719961.
Munoko, I., Brown-Liburd, H.L., Vasarhelyi, M., 2020. The ethical implications of using artificial intelligence in auditing. J. Bus. Eth. 1–26. https://doi.org/10.1007/s10551-019-04407-1.
Nishant, R., Kennedy, M., Corbett, J., 2020. Artificial intelligence for sustainability: challenges, opportunities, and a research agenda. Int. J. Inf. Manag. 53, 102104 https://doi.org/10.1016/j.ijinfomgt.2020.102104.
Okoli, C., Schabram, K., 2010. A guide to conducting a systematic literature review of information systems research. Sprouts Work. Pap. Inf. Syst. 10 (26). http://sprouts.aisnet.org/10-26.
Oliver, C., 1997. Sustainable competitive advantage: combining institutional and resource-based views. Strateg. Manag. J. 18 (9), 697–713. https://doi.org/10.1002/(SICI)1097-0266(199710)18:9<697::AID-SMJ909>3.0.CO;2-C.
Otokiti, A., 2019. Using informatics to improve healthcare quality. Int. J. Health Care Qual. Assur. 32 (2), 425–430. https://doi.org/10.1108/IJHCQA-03-2018-0062.
Qasim, A., & Kharbat, F. F. (2019). Blockchain technology, business data analytics, and artificial intelligence: Use in the accounting profession and ideas for inclusion into the accounting curriculum. Journal of Emerging Technologies in Accounting, 0000-0000. https://doi.org/10.2308/jeta-52649.
Pillai, R., Sivathanu, B., Dwivedi, Y.K., 2020. Shopping intention at AI-powered automated retail stores (AIPARS). J. Retail. Consum. Serv. 57, 102207 https://doi.org/10.1016/j.jretconser.2020.102207.
Pillai, R., Sivathanu, B., Mariani, M., Rana, N.P., Yang, B., Dwivedi, Y.K., 2021. Adoption of AI-empowered industrial robots in auto component manufacturing companies. Prod. Plan. Control 1–17. https://doi.org/10.1080/09537287.2021.1882689.
Rieple, A., Pironti, M., Pisano, P., 2012. Business network dynamics and diffusion of innovation. Symph. Emerg. Issues Manag. (2), 13–25. https://doi.org/10.4468/2012.2.02rieple.pironti.pisano.
Schubert, A., Schubert, G., 2020. Internationality at university level. Scientometrics 123 (3), 1341–1364. https://doi.org/10.1007/s11192-020-03443-3.
Scott, W.R., 2013. Institutions and organizations: Ideas, interests, and identities. Sage Publications.
Scuotto, V., Del Giudice, M., Bresciani, S., Meissner, D., 2017. Knowledge-driven preferences in informal inbound open innovation modes. an explorative view on small to medium enterprises. J. Knowl. Manag. 21 (3), 640–655. https://doi.org/10.1108/JKM-10-2016-0465.
Scuotto, V., Ferraris, A., Bresciani, S., Al-Mashari, M., Del Giudice, M., 2016. Internet of things: applications and challenges in smart cities. a case study of IBM smart city projects. Bus. Process Manag. J. 22 (2), 1–11. https://doi.org/10.1108/BPMJ-05-2015-0074.
Sen, D., Ozturk, M., Vayvay, O., 2016. An overview of big data for growth in SMEs. Proc. Soc. Behav. Sci. 235 (1), 159–167. https://doi.org/10.1016/j.sbspro.2016.11.011.
Shareef, M.A., Kumar, V., Dwivedi, Y.K., Kumar, U., Akram, M.S., Raman, R., 2021. A new health care system enabled by machine intelligence: elderly people's trust or losing self control. Technol. Forecast. Soc. Change 162, 120334. https://doi.org/10.1016/j.techfore.2020.120334.
Sharma, R., Mithas, S., Kankanhalli, A., 2014. Transforming decision-making processes: a research agenda for understanding the impact of business analytics on organisations. Eur. J. Inf. Syst. 23 (4), 433–441. https://doi.org/10.1057/ejis.2014.17.
Sheng, J., Amankwah-Amoah, J., Wang, X., 2019. Technology in the 21st century: new challenges and opportunities. Technol. Forecast. Soc. Change 143, 321–335. https://doi.org/10.1016/j.techfore.2018.06.009.
Singh, S.K., Del Giudice, M., 2019. Big data analytics, dynamic capabilities and firm performance. Manag. Decis. 57 (8), 1729–1733. https://doi.org/10.1108/MD-08-2019-020.
Srinivasan, R., Swink, M., 2018. An investigation of visibility and flexibility as complements to supply chain analytics: an organizational information processing theory perspective. Prod. Oper. Manag. 27 (10), 1849–1867. https://doi.org/10.1111/poms.12746.
Tatoglu, E., Glaister, A.J., Demirbag, M., 2016. Talent management motives and practices in an emerging market: a comparison between MNEs and local firms. J. World Bus. 51 (2), 278–293. https://doi.org/10.1016/j.jwb.2015.11.001.
Tien, J.M., 2017. Internet of things, real-time decision making, and artificial intelligence. Ann. Data Sci. 4 (2), 149–178. https://doi.org/10.1007/s40745-017-0112-5.
Turner, J.R., Baker, R., 2020. collaborative research: techniques for conducting collaborative research from the science of team science (SciTS). Adv. Dev. Hum. Res. 22 (1), 72–86. https://doi.org/10.1177/1523422319886300.
Turner, N., Lee-Kelley, L., 2013. Unpacking the theory on ambidexterity: an illustrative case on the managerial architectures, mechanisms and dynamics. Manag. Learn. 44 (2), 179–196. https://doi.org/10.1177/1350507612444074.
Valenzuela-Fernandez, L., Merigó, J.M., Lichtenthal, J.D., Nicolas, C., 2019. A bibliometric analysis of the first 25 years of the Journal of business-to-business marketing. J. Bus. Bus. Mark. 26 (1), 75–94. https://doi.org/10.1080/1051712X.2019.1565142.
Van Eck, N.J., Waltman, L., 2007. VOS: a new method for visualizing similarities between objects. Advances in Data Analysis. Springer, Berlin, Heidelberg, pp. 299–306. https://doi.org/10.1007/978-3-540-70981-7_34.
Van Eck, N.J., Waltman, L., 2010. Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics 84 (2), 523–538. https://doi.org/10.1007/s11192-009-0146-3.
Van Eck, N.J., Waltman, L., 2014. Visualizing bibliometric networks. Measuring Scholarly Impact. Springer, Cham, pp. 285–320. https://doi.org/10.1007/978-3-319-10377-8_13.
Van Rijmenam, M., Erekhinskaya, T., Schweitzer, J., Williams, M.A., 2019. Avoid being the Turkey: how big data analytics changes the game of strategy in times of ambiguity and uncertainty. Long Range Plan. 52 (5), 101841 https://doi.org/10.1016/j.lrp.2018.05.007.
Viaene, S., 2013. Data scientists aren't domain experts. IT Prof. 15 (6), 12–17. https://doi.org/10.1109/MITP.2013.93.
Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.F., Dubey, R., Childe, S.J., 2017. Big data analytics and firm performance: effects of dynamic capabilities. J. Bus. Res. 70, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009.
Wamba, S.F., Bawack, R.E., Guthrie, C., Queiroz, M.M., Carillo, K.D.A., 2021. Are we preparing for a good AI society? A bibliometric review and research agenda. Technol. Forecast. Soc. Change 164, 120482. https://doi.org/10.1016/j.techfore.2020.120482.
Wang, Y., Kung, L., Byrd, T.A., 2018. Big data analytics: understanding its capabilities and potential benefits for healthcare organizations. Technol. Forecast. Soc. Change 126, 3–13. https://doi.org/10.1016/j.techfore.2015.12.019.

Watson, H.J., 2011. Business analytics insight: hype or here to stay. Bus. Intell. J. 16 (1), 4–8.

Wirtz, B.W., Weyerer, J.C., Geyer, C., 2019. Artificial intelligence and the public sector-applications and challenges. Int. J. Public Adm. 42 (7), 596–615. https://doi.org/10.1080/01900692.2018.1498103.

Wirtz, B.W., Müller, W.M., 2019. An integrated artificial intelligence framework for public management. Pub. Manag. Rev. 21 (7), 1076–1100. https://doi.org/10.1080/14719037.2018.1549268.

Wirtz, B.W., Weyerer, J.C., Sturm, B.J., 2020. The dark sides of artificial intelligence: An integrated AI governance framework for public administration. Int. J. Pub. Adm. 43 (9), 818–829. https://doi.org/10.1080/01900692.2020.1749851.

Yang, Y., Konrad, A.M., 2011. Understanding diversity management practices: implications of institutional theory and resource-based theory. Group Organ. Manag. 36 (1), 6–38. https://doi.org/10.1177/1059601110390997.

You, K., Dal Bianco, S., Lin, Z., Amankwah-Amoah, J., 2019. Bridging technology divide to improve business environment: insights from African nations. J. Bus. Res. 97, 268–280. https://doi.org/10.1016/j.jbusres.2018.01.015.

Zhang, C., Dhaliwal, J., 2009. An investigation of resource-based and institutional theoretic factors in technology adoption for operations and supply chain management. Int. J. Prod. Econ. 120 (1), 252–269. https://doi.org/10.1016/j.ijpe.2008.07.023.

Zhang, D., Pee, L.G., Cui, L., 2021. Artificial intelligence in e-commerce fulfillment: a case study of resource orchestration at Alibaba's smart warehouse. Int. J. Inf. Manag. 57, 102304 https://doi.org/10.1016/j.ijinfomgt.2020.102304.

Zhao, J.L., Fan, S., Hu, D., 2014. Business challenges and research directions of management analytics in the big data era. J. Manag. Anal. 1 (3), 169–174. https://doi.org/10.1080/23270012.2014.968643.

Zheng, D., Chen, J., Huang, L., Zhang, C., 2013. E-government adoption in public administration organizations: integrating institutional theory perspective and resource-based view. Eur. J. Inf. Syst. 22 (2), 221–234. https://doi.org/10.1057/ejis.2012.28.

Zupic, I., Čater, T., 2015. Bibliometric methods in management and organization. Organ. Res. Methods 18 (3), 429–472. https://doi.org/10.1177/1094428114562629.

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