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Exploring the social and technical factors in organisational AI adoption: A systematic literature review

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Abstract

Embedding artificial intelligence as part of an organisation's analytics portfolio can lead to better data-driven business insight, optimised IT systems for greater reliability, and new AI-enabled innovations. However, organisations are struggling to achieve these potential benefits. This paper reviews 45 publications across the Basket of Eight and MIS Quarterly Executive. The study aims to highlight the state-of-the-art information systems research on organisational AI adoption and how to embed AI in organisations. A combination of manual analysis and augmented AI through topic modelling was utilised to conduct the systematic literature review. The literature review confirms that an AI-supported method to conduct a literature review is efficient, but human insight is still required. From the topic modelling analysis, four underlying research themes emerged: AI to support decision-making and its effect on the social side, design of AI solutions, bringing value to business and humans, and lastly, the challenges of embedding AI in organisations. Furthermore, state-of-the-art research is discussed, and the requirement for a holistic sociotechnical view on how organisations can increase the adoption of AI as part of their quest to become more data-driven is highlighted.

1 Introduction

Embedding artificial intelligence (AI) as part of an organisation's analytics portfolio can lead to better data-driven business insight [58], optimised IT systems for greater reliability, and new AI-enabled innovations [17]. Using AI in an organisational context can also augment auditing processes [34] and support the organisation's sustainability goals [69]. Gartner highlights AI as one of the primary technologies in its report on the top strategic technologies trends 2023 [36]. Therefore, it is clear that the adoption of AI in organisations is the next evolutionary step in using IT and digital systems [21]. However, the potential benefits of implementing AI in organisations are often not known by organisations [48]. Moreover, even if they acknowledge the benefits and aspire to become AI-powered, there are many complex sociotechnical components related to the successful adoption of AI [59]. Therefore, it is not surprising that organisations struggle to adopt AI [48].

Given the struggle of organisations to adopt AI successfully and embed it in their analytics portfolio, the requirement exists to gain a deeper understanding of how the adoption can be enabled on an organisational level. A systematic literature review is proposed to comprehensively understand the current state of research in the field and identify the gaps in existing knowledge. This paper reviews 45 publications across the Basket of Eight and MIS Quarterly Executive. The study aims to highlight the state-of-the-art information systems research on organisational AI adoption and how to embed AI in organisations. Additionally, using topic modelling [20], a text mining tool, themes and patterns in the literature are identified and summarised as focus areas in the field. The goal is that the results can inform the design and implementation of future research studies.

For the structure of the systematic literature review, the framework of vom Broke et al. (2009) [77], together with the method proposed by Dresch et al. (2015) [31] is used as the basis. A systematic literature review approach is followed as it provides a rigorous and comprehensive way to synthesising existing knowledge and inform future research opportunities. As a result, the rest of the paper is structured as follows: firstly, the research background is explained, and after that, the methodology and the results are covered. A discussion and the conclusion follow this.

2 Research background: Definition of AI

One of the significant challenges in reviewing literature lies in defining an appropriate scope of the research [77]. Therefore, this section will provide a research background to support the scope definition. The research is interested in answering how organisations can increase the adoption of AI as part of their quest to become more data-driven. Three main elements of the research question are unpacked to gain a deeper understanding of the topic. They are data-drivenness, AI and organisational AI adoption.

From an epistemological point of view, in a data-driven context, the source of knowledge is made of observed data and experimental observations, not theory [32]. Data-drivenness is about building tools, abilities, and a culture that acts on data [10]. Furthermore, Wixom and Someh (2018) describe a data-driven organisation as one that creates, integrates and sets free analytical expertise [82]. Additionally, data-driven organisations use some form of data-driven business model, which can lead to financial or non-financial benefits [89]. Given the vast amount of digital data available [62], one may intuit that organisations should automate this knowledge-building process. AI can self-learn and act autonomously [73], AI is critical to enabling true data-drivenness. AI cannot be referred to in a monolithic sense. AI is both an old technology, which dates back to the 1950s [16] and an emerging technology that is currently disrupting industries [28]. Moreover, AI can be classified into different types, for example, based on technology (for example, machine learning and deep learning), based on function (for example, conversational and algorithmic), and based on intelligence (such as narrow intelligence, general intelligence and super intelligence) [16]. AI is increasingly used to augment intelligence [88]. Looking at AI, the view is that mental processes can be simulated in computers [1], and as a result, AI is often anthropomorphism [67]. Looking at AI through a business lens shifts the focus to business capabilities rather than technology. AI supports automated structured and repetitive work processes, gaining insight through extensive analysis of structured data and engaging with customers through chatbots [27]. Furthermore, AI can also optimise IT systems for reliability or enable new business models [36]. AI can impact the people within the organisation or its environment [25]. Therefore, organisations need to make crucial decisions not only on the adoption but also on considering interdependent facets of AI, like autonomy, learning, and inscrutability [18].

Given this background, the context of this study is the adoption of AI in large organisations. An AI implementation within an organisation can be seen as a sociotechnical system, with the interaction between social and technical components of the systems within a complex environment [81]. For this reason, this study considers AI part of an organisation's sociotechnical system.

3 Methodology

A systematic literature review was conducted to help understand the current research landscape of how an organisation can increase the adoption of AI. The scope of the review was to analyse research outcomes of the AIS College of Senior Scholars "basket of eight" journals [9][1]. By focussing on the basket of eight, we access to most influential journals in information systems. This allows for a review of state-of-the-art research. The goal was to identify the themes related to AI's organisational adoption. To focus the study on recent issues, the articles considered were restricted to articles published between 2012 and 2022. Even though not part of the basket of eight, MIS Quarterly Executive was included. This was done as this study is specifically focussed on organisational adoption and MIS Quarterly Executive presents results in a relevant manner to practitioners.

As mentioned in the introduction, the approach followed in this study was adopted from the method proposed by Dresch et al. (2015), which is tailored toward design science research [31]. This method includes defining a review question, search terms, search sources, inclusion and exclusion criteria and resources. The review question is defined as: *how can an organisation increase the adoption of AI as part of its quest to become more data-driven?* To search for literature related to AI adoption, the search terms artificial intelligence and *adoption* were combined with the "and" operator. Additionally, in order to limit the search to organisational adoption, search terms *organisation*, *organisation company*, *enterprise* were added and used the "or" operator to combine them[2]. The PRISMA search strategy was followed [55][3] and is summarised in Figure 1. Google Scholar was used as the search engine and using the specified search terms resulted in a list of 718 records. In Google Scholar was used as it allowed for easy access to all the relevant articles. No additional articles were included through other sources. Duplicate items, articles in languages other than English and false positives (articles are not published in the basket of eight or MIS Quarterly Executive, which were removed from the list. As a result, 640 records remained, of which all 640 were screened. The articles' titles were screened to identify whether they relate to AI adoption. Based on the screening, records were removed that did not have at least one of the following terms in the title: "artificial", "AI', "deep learning", "machine learning", "data", "analytics", "algorithm" and"cognitive". After the screening, the full text of the remaining 84 articles was assessed for eligibility. The number of articles in the qualitative synthesis was 48. Of the 48, 3 were excluded as they do not cover organisational AI adoption. Finally, 45 studies were included in the meta-analysis.

To analyse the literature, an augmented approach was followed, where both manual and AI-supported techniques were used [56]. First, the 48 articles were manually analysed and coded in Atlas.ti. Atlas.ti is a tool used in academic research, especially in qualitative analysis in social science disciplines [43]. Sociotechnical theory was used as a theoretical lens to group and

[1]The journals identified to include in this study are: European Journal of Information Systems, Information Systems Journal, Information Systems Research, Journal of the AIS, Journal of Information Technology, Journal of Management Information Systems, Journal of Strategic Information Systems and Management Information Systems Quarterly (see https://aisnet.org/page/SeniorScholarBasket).

[2]Search string example: *organisation OR organisation OR company OR enterprise AND intext:"artificial intelligence" AND intext:"adoption" AND source:"European Journal of Information Systems"*.

[3]The Jupyter Notebook used to analyse the data together with the list of articles screened is available on GitHub: http:www .removedforblindreviewpurposes.com.

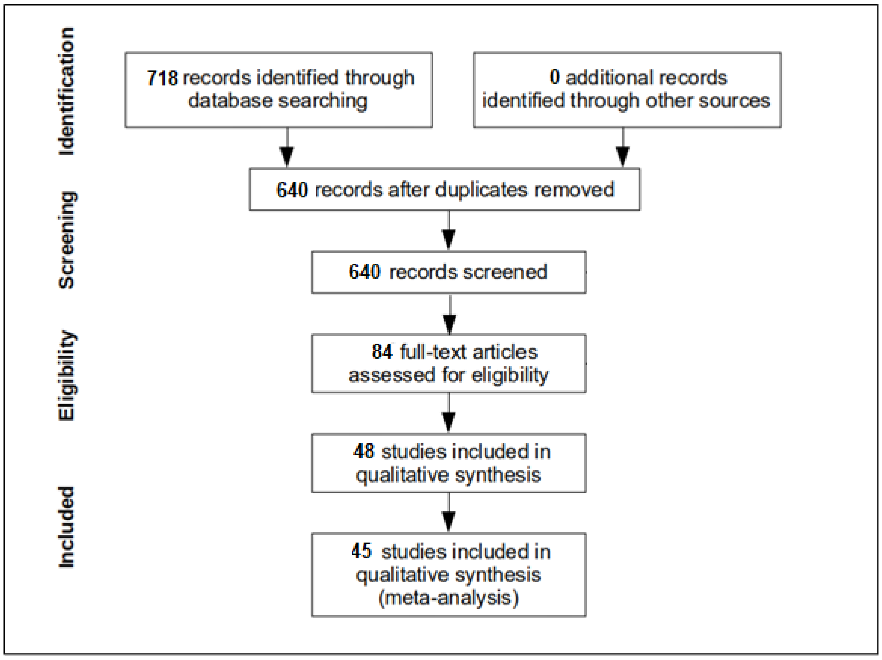

Figure 1: Search strategy, adapted from [55]

order the codes. From this analytics-related research focus areas were identified. Second, topic modelling, a natural language processing AI technique, was used to expedite the systematic literature review [78]. Latent Dirichlet Allocation (LDA) [20], the most common topic model algorithm, in combination with the Gensim, a Python library [64], processed and analysed the text. The text used for the topic modelling input was extracted from the abstracts of the articles. This technique was used to cluster text into themes and allowed an augmented AI approach to gain insights from the published literature. The results of this augmented AI approach are described in the following section.

4 Results

As seen from the metadata analysis of the 48 articles and Figure 2, there has been a considerable increase in articles published on this topic since 2020. Articles about the topic were found in all the journals that were searched, with the most articles being published in the European Journal of Information Systems (see Figure 3).

4.1 Manual coding

To build a holistic view of the literature, sociotechnical theory is used to analyse the literature [81]. The articles are linked to social elements, which comprises of actors (people) and organisational structure. And then the technical, which includes physical and task [59]. For example, people within certain structures in the organisation complete tasks by using the available technologies. Additionally, the interaction between the social elements, the technical and the

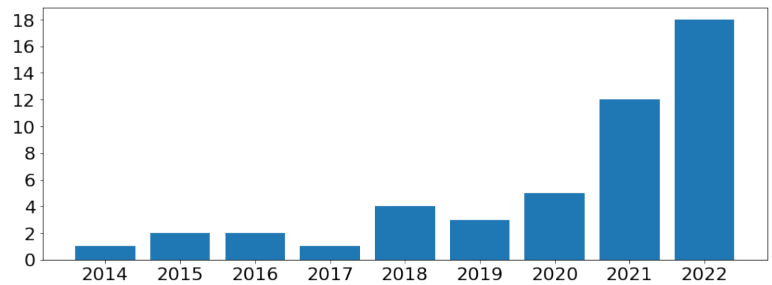

Figure 2: Articles per year included in the systematic review

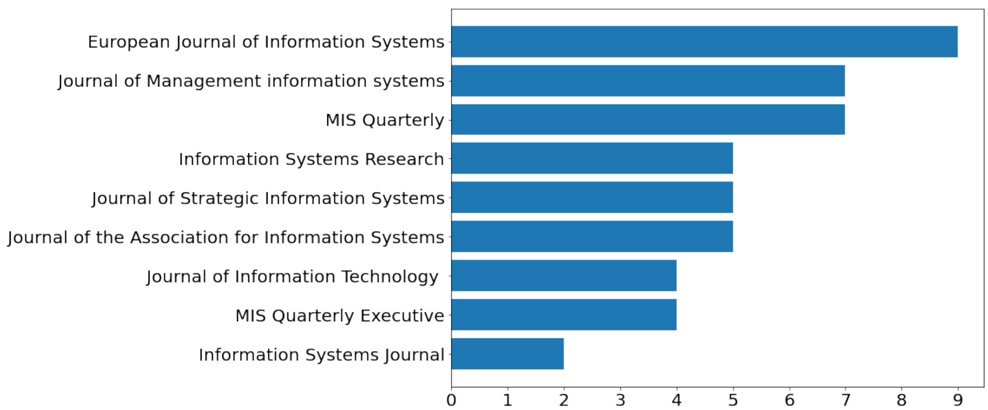

Figure 3: Articles per journal included in the systematic review

environment are included in the review. The results of the coding process followed in Atlas.ti are summarised in Table 1.

Table 1: Manual topic classification of 48 articles reviewed.

Topic	**Articles**
Social - Actors	[63, 83, 44, 11, 50, 72, 68, 75, 12, 87, 14, 65, 3, 51, 17]
Social - Structure	[15, 65, 44, 54, 85, 11, 86, 68, 74, 71, 37, 76, 41, 70, 53, 23, 17]
Technical - Physical	[6, 76, 5, 23, 4, 15, 38, 3, 17]
Technical - Task	[6, 47, 15, 65, 44, 61, 35, 50, 26, 2, 17]
Environment	[50, 54, 46, 47, 4, 15, 65, 44, 68, 44, 11, 79, 17, 52]
Interaction	[44, 54, 38, 30, 85, 35, 11, 44, 54, 11, 5, 40, 70, 74, 45, 65, 83, 60, 49, 3, 75, 80, 17, 42].

On the social side, different actors play a role in organisational AI adoption. It is not only the technical experts [68] that are important, but managers and executives [12, 75, 87], customers [72, 44, 50, 75, 68] and suppliers [50] play a role. These are all stakeholders [44] without which AI adoption in an organisation cannot exist. The main social related focus areas were "business requirements and value" [15, 37, 72, 3] and "fairness, accountability, transparency and explainability" [70, 54]. Most of the business value to relate to improved decision-making [37, 76, 41]. Other focus areas that stood out were "knowledge" about AI [37], "governance and compliance" [15, 53] and "strategy" [40]. "Trust" and "expectation management" [65, 23] were also focus areas in some literature. Expectations about AI's capabilities must be managed, or trust in AI will diminish. Therefore, it is unsurprising that knowledge is one of the main focus areas. Knowledge relates not only to the tools and the algorithms that make AI possible [37], but also the capabilities of AI, which assist in expectation management [4]. Specific aspects such as training can increase knowledge, however, other elements such as a data-driven culture and absorptive capacity also play a role [71]. The requirement for knowledge on AI relates not only to the operational requirements of implementing AI today but also to enable people to deal with the future, where AI will be more integrated into business and daily life [47] and also its impact on society [51].

From a technical perspective, "data" is one of the most prominent areas of focus in the literature that were reviewed [6, 47, 15, 65, 44, 3], with data quality [61], data engineering [61] and data labelling [65] emerging as subtopics. Other areas of research include the design [35], implementation [50] and use [26] of AI in organisations. AI is perceived as both an old and new technology [6], with the recent development in AI also allowing for some augmented creative capabilities [76]. Newer technical aspects such as "conversational AI" [5, 23], "text analytics" [5], "big data" [4], "technology integration" [15], "platforms" [23] and data ecosystems [2] are also covered. Certain aspects of AI, like being human like [23] and using people analytics [38], are also focused topics and are specifically important when AI is making decisions that might impact people.

The social and technical aspects do not exist in isolation. According to sociotecnical theory, social and technical and technical systems exist in a complex environment. The predominant theme in the literature regarding "environment" was the impact of systems on each other and the environment. This includes the impact of the transformation of organisations into data-driven on employees [47], data privacy [4], regulatory guidelines on the social impact of AI [15], considering the external effects of AI [65], the implications of AI on the organisations [44], customers [50], suppliers [50], competitors [68], institutions [50] and society as a whole [44]. In the context of responsible organisations, the implementation of AI can also be used to promote sustainability [54]. To manage the interaction between the environment and the AI system, environment envelopment can be used [11]. Environment envelopment defines clear boundaries between the AI system and its environment. Furthermore, the impact of AI on society and how it should be managed is a research area that is covered [44, 52]. Another way to manage the interaction is to bring the benefits and knowledge of AI to more people in the organisation, empowering people by democratising AI [54, 79]. Although many studies have conceptually discussed these aspects, a limited number have empirically examined them [46].

It is not only the environment and the sociotechnical systems that impact each other but also the social and technical interactions with each other that plays a role [59]. The articles covering the interaction between the social and technical often mentioned the importance of ethical and responsible AI [44, 54, 38, 30, 85, 35, 11]. For example, Jain et al. highlight the need to build knowledge on how to navigate the ethical challenges of AI [44], Mikalef et al. cover responsible AI [54] and Asatani et al. create a framework to help organisations to deploy AI systems without causing ethical problems [11]. Furthermore, there is a focus on human and machine interaction [5, 40, 70, 74, 45] and how adaptions are taking place because of these interactions and how resistance to adoption can be reduced [65, 83, 60, 49]. Creating data assets by people and the use of data assets [3, 75] by AI are research areas that support human and machine collaboration. The interaction cannot be discontinued, as the continuous interaction between the social and technical is what leads to the realisation of value from data [42]. Therefore, the monitoring of AI systems and how it uses data [44] and human oversight over AI solutions and AI-based decisions [40, 11, 68] are other important topics of research. Moreover, the critical topic of AI and control over people is also covered [45, 80, 38].

4.2 Topic modelling

In addition to the manual coding done in Atlas.ti, the topic modelling was done on the abstracts of the 48 articles. Topic modelling was used to uncover underlying themes that may not be readily apparent by simply reading the text [57]. During the topic model process, the number of topics must be manually defined. Topic coherence is a measure that can be employed to evaluate the quality of the topic model output [66]. Essentially, it assesses how understandable the topics are to human beings by gauging the similarity among the topic's top N words. Topic coherence was used to establish the most suitable number of topics for every factor corpus. Also, LDA identifies the topics with keywords related to the topic. However, the topic label or name needs to be inferred. Figure 4 summarises the topic modelling process results. In the figure, the four topics are represented by Q0, Q1, Q2 and Q3 and stack the 5 top words for each topic. The blue bar depicts the probability or weight of connecting the specific word with a topic. For example, in Q2, the word "Business" holds the top position and is represented by a higher weight as shown by the darker shade. By using Figure 4 and with the background of manually coding all 48 articles, the following topics' names were inferred: The first (Q0) topic relates to AI to support decision-making and its effect on AI-supported decision-making on the social side. Moreover, according to the LDA analysis, Q0 has the largest marginal topic distribution. It is interesting to observe that the word "Decision" is part of every topic. AI-supported decision-making and the impact thereof is one of the main underlying themes in information systems AI-related research. This is also evident in the high number of articles that were manually coded and linked to decision-making. Some examples include converting data, to information, to knowledge to decision [4], the automation of this decisions [15] and the growing evidence of the unintended potentially harmful impact of automated decision-making on society [51]. The second topic (Q1) relates to the design of technology. The design topic related to AI and organisations ranges from how to design AI solutions [50] to the impact of introducing AI in the design process on designers' design strategies [49]. The third topic (Q2) relates to business or the organisation and the relationships with humans, users, management, and customers. This confirms the importance of technology and social interaction in using AI in organisations [59]. The last topic (Q3) relates to the challenges organisations practice face. AI offers novel opportunities to organisations; however, it also poses significant challenges [17]. The challenges include aspects such as development challenges [87], AI project-related challenges [68] and socially related risks related to AI implementations [38].

5 Discussion

Two methods were used to conduct the systematic literature review, the first was a manual process where the data was coded, and the second was using topic modelling. Using topic modelling to assist with a literature review is a novel approach [13]. This paper combined the technique as an augmented solution with a detailed manual analysis of the same text corpus. Even though there is still some discussion required on the theoretical validity of using topic modelling in literature reviews [33] topic modelling viewed as an efficient method for an exploratory literature review for management research [22]. This study found the technique

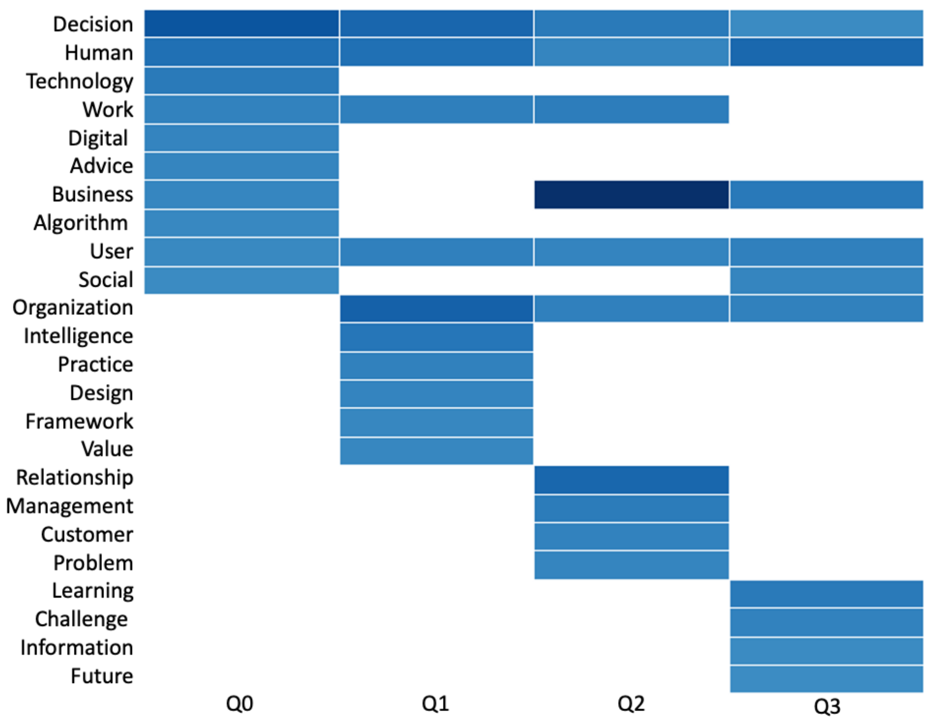

Figure 4: Topic modelling results (Q0 = AI to support decision making and its effect on the social side, Q1 = Design of technology, Q2 = Bringing value to business and humans, Q3 = Challenges in business/practice

valuable and efficient in identifying underlining research topics in AI that did not emerge from the manual literature review.

From the systematic literature review, a high-level view of the state-of-the-art information systems research on organisational AI adoption and how to embed AI in organisations were created. The overview can be useful to researchers to understand the important aspects in the field, it can also be used by organisations in understanding what the elements are that play a role in the organisational adoption of AI. Almost a third of the articles produced frameworks related to organisational AI adoption. These frameworks range from social aspects, such as the ethical considerations in organisational AI adoption [35] to how to change data into data assets (or commodities) [3]. From the 48 articles included in the study, 13 articles developed frameworks that are in some form related to organisational AI adoption [4, 5, 44, 83, 3, 50, 53, 85, 23, 75, 35, 84, 11].

On the interaction between social, technical and the environment, Jain et al. (2021) created a framework to guide research on the important implications of the future of work, organisations and society [44]. One of the implications is that big data availability is providing organisations with new AI-supported opportunities. However, some organisations struggle to turn data into value [42]. To address this, Abbasi et al. (2016) propose a framework for research agenda to support the data to information value chain [4] and Aaltonen et al. (2021) provides a procedural framework for making data commodities, where data is turned into what the organisations would view as an asset [3]. Furthermore, the use of omnichannel data, as explained by Sun et al. (2022), can improve the deep learning outcomes and bring more value to organisations [75].

Using data and AI can benefit organisations, but AI-enabled automation of decisions can potentially negatively impact people. The framework by Gal et al. (2022) provides a basis for ethics in the case of algorithmic decision-making [35]. Furthermore, to assist with the explainability of algorithmic decision-making, Asatiani et at. (2020) provide a framework and recommendation to address the many challenges related to algorithmic decision-making [11]. You et al. (2022) propose a collaborative decision-making process between algorithmic and humans [85]. As resources in organisations are typically not unlimited, McFowland et al.'s (2021) framework on addressing the need of the constrained decision-maker supports the processes of embedding AI in the organisation [53]. Furthermore, to assist organisations in having a realistic view of the capabilities and pitfalls of data science and AI solutions, Cybulski et al. (2021) created a framework to explain what types of problems are likely to be addressed in the future [26]. Marabelli et al.'s (2021) framework add to this by providing ways to design, implement and use algorithmic decision-making systems in practice [50]. In the same theme, Chandra et al. (2022) go deeper into the idiosyncrasies of conversational AI [23], whereas Abbasi et al. (2018) look at how text analytics can support the sense-making of data [5]. In terms of design, the impact of introducing AI is not only on the users but also on the designers. Lastly, Xie et al. (2021) created a framework with design principles for social media analytics, therefore addressing that the technology should be shaped to fit the social [83].

These frameworks are valuable, but none provide a holistic view of the organisational requirements, with few providing information on enabling AI adoption and embedding it into an organisation. The closest to a holistic view is Jain et al. (2021) framework on the important implications of the future of work, organisations and society [44]. Jain et al.'s framework is valuable in providing researchers insight into the possible implications of AI and organisations information on the essential aspects of AI in organisations. Nevertheless, it does not provide details on embedding AI in organisations. It is also the case when referencing academic articles outside the basket of eight and MIS Quarterly Executive. For example, Bettoni et al. provides a practical AI adoption model with an organisational focus that provides an AI maturity model to measure maturity [19]. Although the framework helps obtain information on the maturity of organisations, the framework's scope is different from how to get there. Another example is Chatterjee et al.'s study on understanding AI adoption, which highlights important technical, organisational and environmental considerations. However, the study focuses on AI acceptance, not adoption enablement [24]. This is similar in the case of other studies [29, 19, 7]. From an industry perspective, large organisations such as Google and AWS provide frameworks for enabling AI adoption. For example, Amazon AWS' cloud adoption framework [8] and Google cloud's AI adoption framework [39] provide information on how to enable AI adoption on their platforms, which is relevant and useful in the correct context. However, these frameworks are focused on the hyperscalers' specific AI offerings. Moreover, sustainability and environmental impact should also be in scope.

6 Conclusion and future research

This paper provides an overview of state-of-the-art research on organisational AI adoption and how to embed AI in organisations. The articles were mapped to the sociotechnical aspects and discussed in the context of what research is available to assist organisations in implementing AI as part of their analytics portfolio. The systematic literature review confirms that an AI-supported method to conduct a literature review is efficient, but human insight is still required.

From the topic modelling analysis, four underlying research themes emerged: AI to support decision-making and its effect on the social side, design of AI solutions, bringing value to business and humans, and lastly, the challenges of embedding AI in organisations. Furthermore, the systematic literature review indicated that the state-of-the-art research on organisational AI adoption is extensive, leading to different AI adoption frameworks. These frameworks are helpful as focussed areas of adoption, but they need to provide a holistic view on enabling AI adoption in organisations. Future studies can look for enablers for adoption and value [72]. This study, like all studies, has limitations. The study's scope was on information systems research and the basket of eight together with MIS Quarterly Executive. Moreover, we do not claim it to be an exhaustive literature overview but instead, focus on specific top journals. Future studies can build on the frameworks and combine and empirically test the results to create a more holistic sociotechnical adoption framework.

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