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AI MANAGEMENT BEYOND THE NARRATIVES OF DYSTOPIAN NIGHTMARES AND UTOPIAN DREAMS: A SYSTEMATIC REVIEW AND SYNTHESIS OF THE LITERATURE

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Research Paper

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Abstract

Over the years, AI management has attracted significant interest from researchers rooted in diverse disciplines, including information systems, computer science, strategy, and economics.Despite scholars in these fields addressing many similar research questions and empirical contexts, often applying similar methodologies, the literature has largely developed in an isolated fashion. Moreover, AI's anticipated trajectory has often been painted in deeply optimistic or pessimistic terms. This article offers a systematic review of the AI management literature, based on analysis of a sample of articles published between 2010 and 2021. The review contributes by: documenting the literature's evolution, outlining four key research themes in the literature, and highlighting several areas for future research. The aim is to foster broader understanding of AI management research that helps to advance our knowledge of AI and its management beyond dystopian nightmares and utopian dreams.

Keywords: AI management, big data, interdisciplinary research, systematic literature review, value creation, ethics, integrative framework.

1 Introduction

AI management has emerged on the strategic agenda for firms across the globe due to AI's increasing importance in today's organizations. However, AI management differs from IT management because of the higher complexities associated with AI. First, for instance, the Machine Learning (ML) technologies at the core of contemporary AI have greater autonomy, deeper learning capacity, and are more opaque than other 'IT types' that have come before (Baird and Maruping, 2021; Berente et al., 2021).

Second, as research highlights, AI is not a technology or even bundle of technologies, but rather an evolving frontier of computational advances (Ibid). Thus, traditional managerial and organizational solutions may not be adequate to tackle the new emerging challenges of AI (Raisch and Krakowski, 2021). Hence, AI must be carefully managed as it presents hosting organizations with new sets of challenges and opportunities (Berente et al., 2021).

For the same reasons, AI is strongly debated, and the debate often oscillates between two poles of hyper fear linked to technological dystopias and hype linked to optimistic technological deterministic utopias (Borges et al., 2021). The new opportunities associated with AI are well documented, for instance by Campell et al. (2020). AI may provide organizations with myriads of opportunities for designing intelligent products, devising novel service offerings (Huang and Rust, 2018), inventing new business models and adopting new organizational forms (Faraj et al., 2018). The opportunities of AI are also related with value generation for custumers and organizations (Davenport et al., 2020; Chui et al.,

2018) and the increase of performance (Chen et al., 2012). However, these new opportunities are accompanied by a set of emerging and complex challenges associated with work displacement (see, e.g., Frey and Osborne, 2017; Kaplan and Haenlein, 2020), trust (Glikson and Woolley, 2020), big data (Constantiou and Kallinikos, 2015), and security risks (Martin, 2015; Dwivedi et al., 2019),or concerns on how AI implementation can negatively affect humans´ unique knowledge (Fügener et al., 2021). Inspired by Berente et al. (2021) and by the outcomes of our review, we define AI management as a "constantly evolving socio-technical process of organizing tasks, making decisions and managing data through human-AI coordination to seize business value, in accordance with relevant regulatory and ethical imperatives". As such, AI management needs to embrace both these possibilities and challenges that accompany new AI technologies.

However, while the AI phenomenon has drawn attention from both researchers and practitioners, huge extend of the current literature emphasizes either the technical aspects associated with AI technologies *per se* (Lindgren and Holmström, 2020), and thus pays less attention to human and organizational aspects or focuses mainly on the human aspects while downgrading the nature of AI technologies. As noted by Paschen et al. (2020),"the range of topics and the opinions expressed on artificial intelligence (AI) are so broad that clarity is needed on the field's central tenets, the opportunities AI presents, and the challenges it poses" (p.147). The lack of cohesion and cumulative building of knowledge of AI as an organizational phenomenon reflects a lack of maturity in today's AI research (Collins et al., 2021). Therefore, an integrative view of AI management that allows for a sociotechnical approach is needed. In efforts to address this issue, we have formulated the following research question: *What is the current state of AI management literature?*

To do so we conducted a Systematic Literature Review (SLR) in an effort to elucidate the scattered streams of AI literature, and their evolution, thereby acquiring a more coherent overview and providing a more holistic approach to AI management for both researchers and practitioners. To bridge the dichotomy between either social or technical aspects, in this review we adopt a socio-technical aspect. In particular, we analyzed work published between 2010 (when a resurgence in AI research started after several 'AI winters') (Wamba-Taguimdje et al., 2020) and 2021. Specific objectives were to sample and analyze the relevant literature systematically in order to: identify and describe key portrayed dimensions of AI and its management; synthesize potential benefits, challenges and opportunities associated with its management; and identify fruitful future avenues for AI management research. The study presented here, based on the SLR, offers three distinct contributions. First, we document how the literature on AI management has evolved. Second, we outline four key research themes in the literature, thereby improving its accessibility to both practitioners and researchers. Lastly, we highlight several areas that warrant future research. The rest of the paper is structured as follows. In section 2, we acknowledge previous SLRs of AI within the interdisciplinary IS spectrum. Section 3 presents in detail the research methodology we applied. Section 4 presents the analysis and four identified research streams. Finally section 5 provides discussion of the findings, and their implications for AI management research and practice.

2. Previous systematic literature reviews of AI

The AI literature in IS remains dispersed and largely unexplored, as noted, for example, by Collins et al., (2021). However, recent scholarly work includes efforts to contribute to a broader AI management discourse and cover its interdisciplinary spectrum. For instance, a study by Dwivedi et al. (2021) exemplifies a shift towards a more multidisciplinary approach to AI. It addresses manifold aspects of AI, including associated challenges, opportunities, and policies while providing suggestions for future agenda. However, although it is extensive and covers diverse dimensions, it does not address the body of acquired knowledge systematically, as in a SLR. In contrast, a SLR by Collins et al. (2021) provides an informative synopsis of previous reviews of AI research, but only in recent IS literature. Juxtaposing strands of this literature, the cited authors focus on identifying practical implications of AI and opportunities it provides. They evaluate these strands in terms of definitions, AI functions, frequency of publications, data collection, methodological approach, and business value. Furthermore, a wide spectrum of literature aims to uncover the implementation, use, opportunities, and impact of AI in various domains (*inter alia*, marketing, manufacturing, supply chains, and the public sector).

Our review differs from the abovementioned studies in the following ways. First, it does not target any particular AI technology. Second, a major objective is to capture the interdisciplinary nuances of AI management research and as such our review covers a broader field than some previous authors, such as Collins et al. (2021). Lastly, most of the presented reviews were domain-specific and thus focused on AI implementation in a single industry, while we aim to provide a holistic approach for thinking and managing AI beyond any specific industry.

3. Research Methodology

This section describes the evidence-based SLR approach adopted in this study. SLR is defined as an "explicit, [comprehensive,] and reproducible method for identifying, evaluating, and synthesizing the existing body of completed and recorded work produced by researchers, scholars, and practitioners" (Okoli, 2015, p. 43). A traditional narrative review often lacks thoroughness in appraising and portraying the literature, as discussed by various authors (e.g., Tranfield et al. 2003; Tate et al., 2015; Snyder 2019). In contrast, in a SLR explicit, rigorous criteria are established and applied (Mallett et al., 2012) to minimize bias (Snyder, 2019) and increase transparency (Paré et al., 2016). Moreover, as Snyder (2019) highlights, SLR is a suitable research method for addressing emergent topics in the literature. In this study, a systematic approach was chosen for its abilities to: identify, summarize and synthesize large quantities of literature (Fink, 2005) rigorously and transparently identify relevant and emergent reference materials on focal phenomena; and maximize scientific rigor and methodological replicability while minimizing bias.

Following a polylithic framework for review and development presented by Leidner (2018) our SLR could be categorized as a 'specific theorizing review' with the objective to provide theoretical filling of identified gaps. Our systematic approach to literature was inspired by guidelines presented by Okoli (2015) for constructing a stepwise SLR framework and the SLR by Collins et al. (2021). In the following section we outline stages of the literature review process in detail.

3.1 Stages of the Systematic Literature Review

Despite the plethora of AI literature intended to elucidate various aspects of challenges and opportunities associated with AI, as exemplified by Dwivedi et al. (2019), AI research has evolved in diverse isolated traditions with equally diverse logics. Hence, the overall review explores the full spectrum of relevant literature systematically to address the formulated research question and meet the previously stated objectives. In accordance with the breadth of our research question and diverse nature of AI, we first conducted a pilot search on Web of Science (WoS), Scopus and Google Scholar databases to acquire a preliminary understanding of the coverage of extant literature. This primary search in the literature conducted during the planning phase, also led to discovery of the targeted keyword ("ethics", "labor", "value", "big data") combinations. Those keywords were applied in search strings in the coming phase. Specifically, the keywords chosen for the SLR to delinate the different nuances of AI management literature.

During the next stage, namely the selection phase, we approached the literature systematically and a searched for relevant sources within and beyond the 'AIS basket-of-eight' journals following specific inclusion and exclusion criteria. Initially, we identified most of the relevant articles by screening entries in the WoS, Scopus, and Google Scholar databases, following the guidelines of Levy and Ellis (2006) for a well-rounded SLR. WoS and Scopus are traditionally used for reviews of IS-related literature, as illustrated by SLRs by Gupta et al. (2018) and Collins et al. (2021), while while according to Martín-Martín et al. (2018) Google Scholar provides greater coverage, including some of their weak spots. In alignment with the purpose of our study to delineate the AI management process, we selected the year 2010 as the baseline for the search to gain sturdy insights into the recent discussion of AI and development of associated literature (Duan et al., 2019), to 2021.The aspiration was to encapsulate the interdisciplinary nature of the IS field concerning the AI process, following guidelines by Webster and Watson (2002). In efforts to avoid missing valuable sources and obtain accurate information regarding development of the AI management literature, we first searched for appropriate keywords then applied them using Boolean operators. Specifically, the OR operator was used between combinations of words, and quotation marks, following Collins et al. (2021), to search exclusively for a specific term. AI and related terms were the main keywords (see Table 1). We applied the same dyadic combination of keywords in the additional search in Google Scholar and also went backward in an attempt to identify prior relevant work that we should consider (Webster and Watson, 2002). First, we searched the Scopus database, focusing on the AIS 'basket-of-eight' journals to retrieve articles published in them showing how prominent channels of IS research depict the evolution of AI management. Then, we applied the search string with the same keywords in searches of all three mentioned databases, expanding our focus beyond the AIS 'basket-of-eight' journals. By doing so, we capture the different nuances of the interdisciplinary nature of AI management research. This led to 1748 'hits': 96 from our Scopus search of the AIS 'basket -of-eight' journals, 336 from the WoS database, 891 from Scopus, and 425 from Google Scholar. Then, we imported the records into the Mendeley reference management system and converted them to Excel worksheet format. In this primary search the initial inclusion and exclusion criteria were as follows (Table 1). Included articles had to be published, in English (on topics categorized as elements of Social Sciences, IS, Management or Business domains) between 2010 and 2021. They were mainly peer-reviewed articles, but highly cited books (with citation rate 200 and above) included in the Google Scholar database were included to broaden and deepen coverage of the discourse on AI management.

Source	String
SCOPUS "Basket-of-eight"	((TITLE-ABS-KEY ("Artificial Intelligence" OR "AI" OR "machine learning" OR "big data" AND "ethics"OR "labor" OR "value") AND SRCTITLE ("MIS Quarterly: Management of Information Systems Quarterly" OR " EUROPEAN JOURNAL OF INFORMATION SYSTEMS" OR " INFORMATION SYSTEMS JOURNAL" OR "JOURNAL OF INFORMATION TECHNOLOGY" OR "JOURNAL OF THE ASSOCIATION FOR INFORMATION SYSTEMS"))AND PUBYEAR >2009 AND PUBYEAR< 2022)
SCOPUS	KEY(" Artificial Intelligence" " big data" OR " machine learning" AND "ethics" OR "labor" OR "value") AND PUBYEAR>2009 AND PUBYEAR < 2022 AND (LIMIT-TO (PUBSTAGE, "final")) AND (LIMIT-TO(DOCTYPE. "ar")) AND "LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (SUNJAREA, "SOCI")OR "LIMIT-TO (SUBJAREA, "BUSI"))
Web of Science (WoS)	"Artificial Intelligence" OR "machine learning" OR "big data" (Author Keywords) and "ethics" OR "labor" OR "value" (Author Keywords) Refined by: Document Types: Article, Publication Years: 2010 or 2011 or 2012 or 2013 or 2014 or 2015 or 2016 or 2017 or 2018 or 2019 or 2020 or 2021, Language: English, Web of Science Categories: Business or Management or Computer Science Information Systems or Computer Science Artificial Intelligence or Social Issues

Table 1. Strings applied in the database search

Furthermore, in the searches we included prominent books that focused on critical dimensions of AI and big data (see Eubanks, 2018) and expanded the dialogue. We then removed duplicated articles, which left 1024 that met our inclusion and exclusion criteria. After the selection process, we moved to the extraction phase. During this phase, we expanded the search and scanned abstracts of retrieved articles. To avoid overlooking relevant articles, we also read the introduction section when abstracts were insufficiently clear. Moreover, to ensure that the selected literature had sufficient quality and relevance, we also considered for further review: articles that clearly focused on AI and/or Big data and/or ML; studies addressing phenomena related to our research questions and broader aspects of AI management; and articles published in top-tier journals.We excluded studies that do not focus on strategic aspects of AI in organizations or society (adopting socio-material perspective), or merely the technological role and foundations of a particular AI system as we aim to avoid the dichotomy between technical and social. After applying these criteria, 330 articles remained. Lastly, after reading them thoroughly, we selected 84 articles that met all the mentioned criteria and their citation rate was 100 and above depending also on the year of publication (Figure 1). In the last phase of review, (the execution phase) we synthesized findings of our SLR, which are presented in the following section.

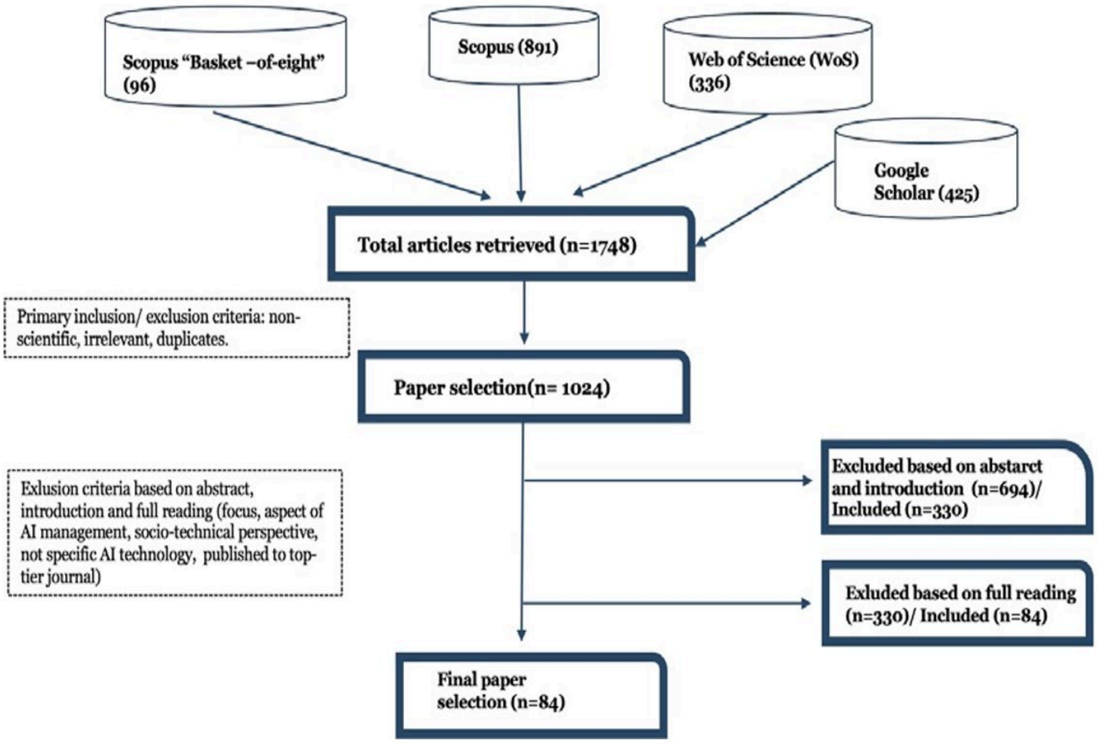

Figure 1. Schematic diagram of the SLR process inspired by Collins et al. (2021).

4. Descriptive Analysis and Literature Synthesis

In the following section, we describe and synthesize the four key themes, or research streams, identified by the SLR, which map the current sociotechnical view of AI landscape. These themes each concern a specific dimension of AI management, and they are designated: *the data dimension: big data and big challenges; the labor dimension: racing with or against the machines*; *the critical dimension:*

ecological aspects, socio- political underpinnings and ethical parameters; and the *value dimension: value creation or value destruction*. They are interdependent and interconnected but dispersed in the literature.

4.1 The Data dimension: Big data and big challenges

This stream discusses the challenges and opportunities that organizations face when seeking to exploit big data (analytics).The following sections address subthemes covering two poles of discourse: one highlighting big data's utility as a source of value creation, and one problematizing associated concerns with privacy and misuse.

4.1.1 Big Data as a value-enabling source

Recent AI research studies have described data as the "fuel and oil of AI' (Crawford, 2021) and the new oxygen (Svensson and Guillén, 2020). Chen et al. (2017, p.19) further argue that big data has triggered "one of the most significant technology disruptions for businesses since the meteoric rise of the Internet and the digital economy". The availability of data with increasingly enormous velocity, variety and volume has increasingly validated assertions such as "data-driven decisions are better decisions" (McAfee et al., 2012) and underscored the 'big impact of big data'. Moreover, sociotechnical characteristics of big data such as portability (the possibility to transfer digitized data from one context to others) and interconnectivity (the ability to synthesize data from diverse sources) have increasingly influenced organizations' perceptions of value (Günther et al., 2017). Hence, the role of (big) data and analytics is entangled with performance optimization (Chen et al., 2012), productivity (Loebbecke and Picot, 2015), predictability of potential failures (Grover et al., 2018), innovation (Mikalef et al., 2020), business value generation (Wamba-Taguimdje et al., 2020), organizational transformation in terms of process, scope, scale (Baesens et al., 2016), business models (Loebbecke and Picot 2015; Günther et al., 2017), and strategic competitive advantage (Chen et al., 2016).

The potent impact of (big) data on strategy making is not a new aspect of the literature either. For instance, the usefulness of big data lies in their ability of being updatable, which subsequently minimizes the timespan that data are relevant (Constantiou and Kallinikos, 2015). Accordingly, these attributes affect norms and rules related to strategy-making. The roles of data and analytical tools in effectiv of organizational learning (Hagiu and Wright, 2020) and expedition of decision-making processes (Schildt, 2017; Von Krogh, 2018; Shrestha et al., 2019; Ghasemaghaei, 2020) have also been highlighted.

4.1.2 Big Data fallacies, drawbacks and concerns

Big data may have had revolutionary effects (Shrestha et al., 2019; Aversa et al., 2018, p. 2) and provide unprecedented opportunities, as outlined above, but it is accompanied by major challenges for management and organizing. The high expectations and optimism associated with AI (Dwivedi et al., 2019) do not ensure value generation and may lead to misunderstanding about the applicability of data and real practices involved (Günther et al., 2017). A diverse research stream highlights the management challenges associated with big data (Pentland, 2014). For instance, Mikalef et al. (2019) mention that big data may hurt organizations instead of helping them and stress that despite the hype few organizations manage to fully seize value from their big data investments. Similarly, Grover et al. (2018) accentuate the difficulties of 'data monetization', while Aversa et al. (2018) attribute a case of big data failing to enhance strategic decisions to hyperbolic reliance on the data in complex and turbulent circumstances. The inadequate data quality, integration and security can all hinder extraction of strategic value from data (Kitchens et al., 2018; Grover et al., 2018), while challenges may emerge when processing and interpreting big data (Günther et al., 2017). Other potential hindrances to successful adaptation include time constraints, skepticism of employees (Makarius et al., 2020), historical legacies and inappropriate team composition (Günther et al., 2017). Mistrust of the data and AI generally may also pose major managerial problems (Glikson and Woolley, 2020). Although the cited studies highlight a number of emergent challenges in AI management, problems linked to privacy and security (Dwivedi et al., 2019) and discriminatory biases (Wachter and Mittelstadt, 2019; Svensson and Guillén, 2020) still receive more attention. Martin (2015) refers to the "big data industry" in an effort to underline the risks of data biases and privacy issues in the collection and dissemination of information. In accordance with this view Wachter and Mittelstadt (2019, p. 497) assert that AI and big data analytics draw on "non- intuitive and unverifiable inferences and predictions about the behaviors, preferences, and private lives of individuals". In particular, they note, inferential analytics methods are used for predicting users' behaviors and preferences for marketing purposes or inferring sensitive attributes and political stances (Ibid). An important conclusion is that data protection law is meant to protect people's privacy, identity, and autonomy, but it is currently failing to protect data subjects from the novel risks of inferential analytics (Ibid).

4.2 The Labor dimension: Racing with or against the machines

Research on this theme encapsulates the diverse narrative of the impact of AI-driven technologies on workforces and organizing logics. Ongoing debate on the challenges and opportunities associated with AI implementation on labor and management encompasses conflicting views. The deployment of new technologies that enable progress towards industrial goals such as automation and acceleration of production processes, but also lead to deskilling of labour forces, and fragmented work, (Barley, 1990), and lurking dangers for the future direction of labor (Brynjolfsson and Mcafee, 2017) have been described by organizational theorists. However, we also identified a wide stream of literature that extensively highlights AI's positive potential (see, for example, Lindebaum et al., 2020). In addition, emerging organizational literature addresses its impact on employees' identities and organizational control.

4.2.1 AI as a magic bullet and job destroyer

Willcocks (2021) describes the polarized discussion in the literature of AI's impact on workforces as a dichotomy between the 'Robot-Apocalypse' and the 'Automotopia'.The arguments have been fluctuating between fallacious perceptions of AI as a technological panacea (Kelly, 2017), blessing for management (Lindebaum et al., 2020) and job creator (Wright and Schultz, 2018) on one hand, and as an agent of 'job destruction' that leads to increases in unemployment rates (Kaplan, 2016; Frey and Osborne, 2017; Brynjolfsson and Mcafee, 2017) on the other. The latter assumption of 'technological unemployment' (Wladawsky-Berger et al., 2020) also reflects sensational and fictional approaches to ML abilities that surpass. Although technology's role as a trigger of creative destruction is not a new concept (David, 2015; Frey and Osborne, 2017), it is still more intensively explored than its job creation potential, despite exceptions such as a study by Wilson (2020). Moreover, AI technologies have capacity to encroach on workers' skills that is unprecedented in the history of technological development and innovation (Kelly, 2017; Faraj et al., 2018), and the literature tends to focus on the challenges posed by automation replacing skills rather than displacing jobs. Hence employers are shifting from recruiting workers *per se* towards seeking workers or machines that can provide gains associated with targeted skills according to Kaplan (2016). This may create a vicious cycle that increases employees' vulnerability, starting with automation gradually degrading employees' skills and making them obsolete, especially those that are tightly associated with repetitive tasks (Kaplan, 2016), human learning abilities (Lyytinen et al., 2020) and decision-making (Lindebaum et al., 2020).

4.2.2 The golden point of the two extremes

Moving beyond the monochromatic black or white statements and towards a more pragmatic view (Coombs et al., 2020), emerging literature has started to set out more realistically both the challenges and potentials of human-AI symbiosis (Seidel et al., 2018; Seidel et al., 2020), collaboration (Fountaine et al., 2019; Seidel et al., 2020) and augmentation in organizing tasks and workforces (Grønsund and

Aanestad, 2020; Raisch and Krakowski, 2021). First, regarding collaboration, Seidel et al. (2020) consider a concrete example of interaction between autonomous design tools and human designers.

They conclude that such tools can generate designs that may not be expected by human designers using them, but human designers still play a fundamental role as control units and 'tutors' of the tools. Accordingly, in a longitudinal case study Van den Broek et al. (2021) found evidence of human-ML hybrid practices involving ML and domain experts working together. They found that in such cases ML-based knowledge production in organizations "involves managing a dialectic tension between independence and relevance in which ML developers iterate between excluding domain expertise from the tool and including it" (p. 1573). In this discourse of AI-employee collaboration, Makarius et al. (2020) note that important factors to consider include *when*, *how* and *what*: for such integration to lead to competitive advantage, managers must consider the types of employees involved, technological readiness, and nature of the work itself.

Second, regarding augmentation, Raisch and Krakowski (2021) elaborate on the controversy and 'paradoxical tensions' between automation and augmentation. They conclude that automation and augmentation are tightly interdependent, and that augmentation is both a trigger and outcome of automation. Hence, effects of automation on employment and organizing are multifaceted and extend beyond those postulated in a simple replacement and substitution narrative (David, 2015; Brynjolfsson and Mitchell, 2017). In a similar vein to this and the mentioned analysis by Willcocks (2021), Huysman (2020) adopts a sociotechnical perspective and calls for 'breaking open'(2020, p. 308) the realistic depiction of the constraints and possibilities of AI technology. Accordingly, without denying or neglecting that AI will change skills (2020), reconfigure work and control (Kellogg, 2020), and transform organizations (Grace et al., 2018; Faraj et al., 2018), managers and employees should set realistic expectations (Huysman, 2020) to adapt to the current AI landscape (Jarrahi, 2018). AI has significant advantages in terms of information processing, analytical tasks (Kelly, 2017), abductive reasoning (von Krogh, 2018) or as Lindebaum et al. (2020) stated the 'augmented formal' rationality. However, the delegation of decision-making to merely AI can jeopardize the validity of results (von Krogh, 2918), and humans still have competitive advantage in cases where decision-making requires intuition, imagination, social skills and creativity. An interesting position is also expressed by Huang et al. (2019), who argue that AI both replaces and augments. However, the key differentiator is that feeling is more difficult for AI to emulate, so the feeling tasks are becoming more important for human workers. Juxtaposing the Feeling Economy and today's Thinking Economy, Huang et al. (2019) emphasize that employees will need to be more people-driven than data-oriented to seize the benefits of Thinking AI. AI is less likely to mimic or replicate abstract thinking, especially under conditions of uncertainty, complexity and equivocality (von Krogh, 2018). Hence, the significance of algorithms lies in their ability to complement or augment employees' activities (upskilling) (Davenport et al., 2020; Grønsund and Aanestad, 2020), and bounded rationality (Lindebaum et al., 2020) since "learning algorithms require humans to ensure accountability" (Faraj et al., 2018, p.66). Therefore, organizational decision-making should be handled by the combinatory forces of employees' intuitive capabilities and machines' analytical advantage (Brynjolfsson and McAfee, 2014; Wright and Schultz, 2018; Lindebaum et al., 2020).

4.2.3 AI, employees' identities and organizational control

This emergent substream of research describes how AI-human symbiosis reconfigures work and organizational practices. For instance, Strich et al., (2021) presents mechanisms through which substitutive decision-making AI systems can influence employees' professional role identities. Moreover, several recent studies emphasize 'the dark side' of people's analytics for organizations and employees (Giermindl et al., 2021) and organizational control that is deemed to be challenging for the employees. Kellogg et al. (2020) extend this analysis by providing a thorough review of ways that employers direct workers by restricting, evaluating, and replacing or rewarding them. In addition, drawing examples from the gig economy, Wood et al. (2020) address the drastic impact of algorithmic management control on job quality. They conclude that although it can provide flexibility, autonomy and task variation, it can also lead to overwork, sleep deprivation and social isolation.

4. 3 The Critical dimension: Ecological aspects,socio-political underpinnings and ethical parameters

This theme concerns the social, political, ethical and ecological underpinnings of the AI literature in order to provide a holistic overview. The stream focused on these aspects also depicts social expectations regarding sustainable AI and its potentials, as well as the sociopolitical or ethical challenges posed by (and implications of) the availability of big data and AI management.

4.3.1 Ecological Aspects of AI

AI is anticipated, by some authors, to increase productivity, growth, equality, inclusion (Vinuesa et al., 2020), and reliability (Taddeo and Floridi, 2018), while diminishing negative impacts of environmental crises (Nishant et al., 2020; Di Vaio et al., 2020). Contemporary organizations are increasingly facing challenges to improve the sustainability of their operations and products in efforts to enhance the scope of innovations (Di Vaio et al., 2020). According to authors who hold these views, AI has unfathomable potentials for addressing these challenges, mitigating climate crises and, for instance, generating a 'sharing economy' that makes significant contributions to a more sustainable future (Flyverbom et al., 2019).

4.3.1 **Socio-political aspects of AI**

Despite the optimistic aspects of AI implementation, recent research outlines a plethora of sociopolitical and ethical concerns associated with the prevailing role of data. Data-related challenges could arise even without AI. However, AI can exacerbate these challenges and risks (Taddeo and Floridi, 2018). As noted by Zuboff (2019), data should not be regarded as a technology, an inevitable effect of technology, or an autonomous process. Data originates in social (Zuboff, 2015) and cultural (Boyd and Crawford, 2012) contexts. Adding to this discourse, Saever (2017) recognizes that data and algorithms are not cultural *per se*, but are shaped by and shape culture. Saever (2017, p. 4) also uses the metaphor of a rock in a stream for data, stating that "the rock is not part of the stream, though the stream may jostle and erode it and the rock may produce ripples and eddies in the stream" (p. 4). This bestows data with an immanent instrumental nature (Hoffmann, 2019). In this dialogue, authors such as Sadowski (2019) and Crawford (2021) have noted that big data has started to be perceived as a form of capital, and in association with broader neoliberal market trends, a primary form of organizing value. According to Sadowski (2019), framing and understanding data as a form of capital (rather than just a commodity) clearly shows that imperative considerations for today's organizations data extraction and ways to generate value from data. Consequently, issues such as "how the data is produced, who owns it and what uses it can be put" (Svensson and Guillén, 2020, p. 5), are not rhetorical but rather crucial concerns for AI governance. Hence, in a recent interdisciplinary study on the AI landscape, Lindgren and Holmström (2020) advocate an integrated view of AI management, encompassing social, historical and political aspects, and highlighting the necessity of going beyond the materiality and code.

Technology is neither good nor bad, but not neutral either (Lindgren and Holmström, 2020; Crawford, 2021); it is political and embedded in social contexts (Crawford, 2021). In alignment to this discourse, Crawford (2021) recently used a vivid metaphor of an atlas to map the forces that shape AI and show that planetary networks of materials, natural sources, fuels, classification and logistic systems are involved. In the sociopolitical sphere, the discourse is centered around datafication (Sadowski, 2019; Dignum, 2021) and the degradation of democracy following the rise of the economic system called surveillance capitalism (Zuboff, 2019). The concept of datafication, according to Flyverbom et al. (2019), encompasses the masses of digital traces generated by users and technologies online, together with the propagation of tools for analysis and integration of data patterns. Thus, datafication is a result of contemporary organizations' needs not only to extract all relevant data, from all relevant sources and by all possible means, but also to create data (Sadowski, 2019). Increasingly detailed information and reams of data are needed to improve the AI algorithms and applications (Vinuesa et al., 2020), raising corresponding concerns regarding ownership (Taddeo and Floridi, 2018), transparency, erosion of privacy and security (Günther et al., 2017; Vinuesa et al., 2020), agency and sovereignty (Mittelstadt et al., 2019). Specifically, Zuboff (2015) describes an Orwellian-like scenario, in which this new form of information capitalism translates human experiences into behavioral data (Zuboff, 2015).This enables agents of surveillance capitalism to not only know and foresee customer behavior (Flyverbom et al., 2019), but also shape, affect, modify and manipulate it (Mittelstadt et al., 2019). For instance, big data analytics and AI may be used to exploit psychological weaknesses and direct decisions through *big nudging* (Vinuesa et al., 2020). Broadening the discourse of surveillance and control, Newlands (2021) refers to the notion of 'algorithm surveillance', and drawing examples from gig economy platforms such as Foodora, discusses a so-called multimodal surveillance assemblage that incorporates managerial and customer surveillance. This goes far beyond merely generating data, evaluating work behavior and performance, and assigning labor activities, replacing both human observation in organizational contexts and decision-making.

The literature also highlights ramifications of reproducing biases in the data used to train AI algorithms. For example, Eubanks (2018, p.11) refers to Automated Algorithmic decision-making (AADM) as "tools for digital poverty management", providing an apt example of profiling and data-based discrimination towards poor and middle-class Americans. Such unjustified, discriminatory, and unfair harmful effects of algorithmic decision-making on individuals, groups and society, are described by Marjanovic et al. (2021) as 'algorithmic pollution' and lead to 'cumulative disadvantage'.

4.3.2 Emerging AI ethics and regulatory concerns

AI ethics and regulations intended to protect human rights play a significant role in AI management. A surge in interest in AI ethics and regulation after 2016 (Jobin et al., 2019) clearly illustrates the topicality of the discourse (Mittelstadt et al., 2016). However, the absence of a universal regulatory framework to enforce ethical rules and principles (Taddeo and Floridi, 2018; Jobin et al., 2019; Mittelstadt, 2019) highlights the ethical complexities. Moreover, initiatives to codify ethics have been strongly criticized for vagueness and theoretical underpinnings that promise action, but in practice do not thoroughly address the normative and political tensions (Mittelstadt, 2019). Accordingly, Hagendorff (2020) presents an example of ethical decision-making for engineers and deduces that ethical guidelines and codes have limited efficacy and thus do not transform the behavior and conceptions of professionals in the tech industry. These problems may be at least partly rooted in the absence of fully-fledged education that enables developers and engineers to consider ethical issues robustly and lack of positive reinforcement from organizational structures and culture (Hagendorff, 2020). However, there is also a crucial need for organizational teams involved in deploying, designing, and developing AI to accept professional responsibility for its effects (Fjeld et al., 2020).

Autonomy is another feature of AI that has major ethical implications (Floridi et al., 2018), particularly regarding the balance between the power we retain for ourselves in decision-making and delegate to the AI agents (Taddeo and Floridi, 2018; Fjeld et al., 2020). Jobin et al. (2019) broaden the discussion and state that transparency and predictability can help acceptance of AI's autonomy and maintenance of a more desirable balance by "increasing people's control over their lives and their surroundings" (Fjeld et al., 2020, p. 55). Furthermore, increases in transparency are widely and quite fervently advocated for improving AI, encompassing efforts to enhance its explainability, predictability (Fjeld et al., 2020) and interpretability (Jobin et al., 2019). The belief that AI systems should be designed and implemented in such a way that they enable and allow oversight of their operations, is continuously highlighted in the literature (Mittelstadt et al., 2016; Fjeld et al., 2020). Another example is presented by Mittelstadt et al. (2016), who refer to ethical need for a connection between data and accessible conclusions. They further show that lack of knowledge and understanding regarding the data being used, or the scope and the amount of data used by ML, generates causal and principled constraints (Ibid).

Lastly, AI has important sociopolitical implications for justice (Floridi et al., 2018). It can potentially be used to eliminate (social) discrimination and prevent dissemination of harmful results while creating share benefits (Floridi et al., 2018). According to Jobin et al. (2019) realisation of justice also requires efforts to promote equality and fairness. However, achieving complete fairness may not be possible

(Dignum, 2021), and Teodorescu et al. (2021) maintain that neither humans nor machines can ensure fairness alone.

4.4 The Value dimension: Value creation or value destruction

This theme concerns the possibilities and hindrances of AI's transformative power and its impact on value creation and organizational performance. The following sub-themes unpack both AI's potential for business value creation and its fallacies.

4.4.1 AI and business value creation

According to von Krogh (2018), understanding of AIs' functions and roles in organizational contexts is needed to explore AI's possibilities, and for this a phenomenon-based theorizing approach and abductive reasoning are required. This is because AI technologies are used to perform tasks that entail data input, processing (by algorithms) and outputs (decisions), which are clearly affected by organizational factors. Moreover, the adoption of AI-driven technologies as parts of an organizational ecosystem can engender economic value (Chui et al., 2018), business process performance (Coombs et al., 2020), flexibility in operations (Wamba-Taguimdje et al., 2020), innovation management (Kakatkar et al., 2020; Haefner et al., 2021) and business model innovation (Günther et al., 2017), through new ways of managing information (Wamba-Taguimdje et al., 2020; Haefner et al., 2021). AI's potentials to reduce costs (Haefner et al., 2021), increase revenues (Davenport et al., 2020), and minimize decision-making time (von Krogh, 2018) are also recognized as key advantages. Thus, AI can lead to long-term competitive advantage (Hagiu and Wright, 2020). In a review of AI and innovation management, Haefner et al. (2021) highlight the importance of innovation managers finding ways to apply AI technologies in efforts to support human-organized innovation. Key functionalities of AI in innovation processes they recognize include its capacities for developing and generating ideas by overcoming information processing limitations and both generating and developing ideas by overcoming restrictions of local search routines. Similarly, Kakatkar et al. (2020) describe three ways that AI can enhance innovation analytics (generation of data-driven insights, visualization, and construction of models in innovation processes) to generate value. They specifically suggest that AI can allow innovation teams to leverage large volumes of data, thereby enabling innovation managers to corroborate with data scientists, augment creative processes, and improve questions asked by those involved in innovation processes.

4.4.2 AI beyond the hype of value

Despite the enthusiasm and optimism regarding value-generating opportunities that AI may generate for both customers (Davenport et al., 2020) and organizations (Chui et al., 2018), recent statistics show that many organizational efforts fail to generate value (Fountaine et al., 2019). Culture (Fountaine et al., 2019), resistance to (behavioral) change (Frick et al., 2021), managers' apprehension towards new technologies, leadership (Kolbjørnsrud et al., 2017; Frick et al., 2021; Canhoto and Clear, 2020) and AI readiness of organizations (Holmström, 2021) are some of the challenges recognized in recent AI literature. Moreover, there is a romantization related to the possibilities of data-enabled learning, according to Hagiu and Wright (2020), who argue that it is not true that "more customers entail more data that when analyzed with machine learning will lead to competitive advantage". In the same vein, Canhoto and Clear (2020) recognize AI perils that may lead to value destruction and thus competitive disadvantage. These may include systemic problems associated with ethical issues, related (for instance) to the increasing pressure on consumer-oriented firms to gather and exploit information (Martin, 2015) in opaque and rapidly changing markets and regulatory contexts.

Research Dimensions	Brief description	Representative Articles
Data Dimension	Discourse regarding effects, challenges, and opportunities associated with (big) data in organizational context.	McAfee et al. (2012); Chen et al. (2012); Pentland (2014); Constantiou and Kallinikos, (2015); Martin (2015); Loebbecke and Picot (2015); Baesens et al. (2016); Günther et al. (2017); Schildt (2017); Saever, 2017; Shrestha et al. (2019); Aversa et al. (2018), Grover et al., (2018), Kitchens et al. (2018); Mikalef et al. (2019); Glikson and Woolley (2020)
Labor dimension	The narrative on AI-driven workforce transformation (e.g., job gain/ loss, upskilling, deskilling, boundary change, decision-making) and new organizing logics.	Brynjolfsson and McAfee, (2014) David (2015); Kaplan (2016); Brynjolfsson and MacAfee, (2017); Frey and Osborne (2017); Kelly, 2017; Brynjolfsson, and Mitchell (2017); Seidel et al. (2018); Jarrahi (2018); Faraj et al. (2018); Grace et al.,(2018); Huang et al., (2019); Wood et al., 2019; Huysman, 2020; Davenport et al.,(2020); Willcocks, 2020; Kellogg et al.,(2020); Lindebaum et al., (2020);Lyytinen et al. (2020); Seidel et al. (2020); Makarius et al. (2020); Grønsund and Aanestad (2020);Huysman, 2020; Seeber et al. (2020); Raisch and Krakowski, 2021; van de Broek et al. (2021)
Critical Dimension	Discourse on the current dialogue of the impact of big data and algorithms on the social/ cultural, political, and ecological factors.	Boyd and Crawford (2012); McAfee and Brynjolfsson (2012); Martin, 2015; Mittelstadt et al. (2016); O'neil, C. (2016); Taddeo and Floridi, (2018);Noble (2018); Eubanks (2018); Wright and Schultz,(2018); Floridi et al. (2018);Hoffmann, 2019; Flyverbom et al. (2019); Jobin et al. (2019); Mittelstadt (2019); Dwivedi et al.(2019); Wachter and Mitteltadt (2019); Vinuesa et al., (2020); Fjeld et al. (2020); Sadowski (2019); Zuboff (2019); Lindgren and Holmström (2020); Hagendorff, 2020; Svensson and Guillén, (2020); Nishant et al., (2020);Di Vaio et al., (2020); Crawford, 2021; Dignum (2021); Newlands (2021); Marjanovic et al., 2021; Teodorescu et al. (2021).
Value Dimension	Discourse on the possibilities and limits of the transformative power of AI to generate business value and maximize firm performance.	Kolbjørnsrud et al. (2017); von Krogh, 2018; Chui et al. (2018) Fountaine et al. (2019); Wamba Taguimdje et al. (2020); Hagiu and Wright, (2020); Coombs et al., (2020); Canhoto and Clear, (2020); Kakatkar et al. (2020);Haefner et al., (2021); Frick et al. (2021); Holmström, 2021.

Table 2. Representation of current research streams of AI management

5 Discussion

Recent AI literature oscillates between utopian, hyped anticipation (Dwivedi et al., 2019; Willcocks, 2020) and dystopian rhetoric (Kaplan, 2016; Hagiu and Wright, 2020). However, neither the extremely optimistic nor the post-apocalyptic pessimism strands can facilitate successful AI management research. Moreover, despite the nascent interest in AI from both researchers and practitioners, AI management research has mostly evolved in isolated fashion in their respective subthemes. The dimensions and subthemes ascertained here not only map the terrain of AI, but also highlight the extreme scattering of the literature, and thus clear need for an integrated, holistic view. AI is changing our society, so the way we manage its evolution will determine the flux of the development, the opportunities and the outcomes (Di Vaio et al., 2020). Hence, objectives of the presented study were to identify key dimensions of AI management research, highlight associated challenges and opportunities, and outline future research directions. Therefore, we posed the following research question: "What is the current state of the AI management literature?", and addressed it in efforts to elucidate the evolution of the AI 'terrain' and its current state through a SLR of recent AI management literature. We then identified and synthesized four major research dimensions (data, labor dimension, critical and value dimensions) that are interdependent and must be considered to acquire an integrated view of AI management. Specifically, the interdependence of these dimensions is demonstated by the fact that all dimensions contribute and affect AI management, as it is showcased by our results. To avoid the hype and misconceptions, AI management research should not be perceived as a one-dimensional road or monolithic (Kaplan and Haenlein, 2020), but as a multilevel process with multiple dimensions. As such, the elements of all four dimensions should be considered when organizing or formulating strategies for AI management.

First, big data has been hyperbolically presented in contemporary research, with several data evangelists equating big data with a revolutionary technological change that offers unlimited opportunities (Hagui and Wright, 2020). However, although big data and algorithms provide possibilities for strategy-making and competitive advantage (Willcocks, 2020), their realisation depends on several other factors such as trust (Glikson and Woolley, 2020) and workers' skills, beyond the 'bigness' of the data. To avoid science fiction statements and expectations both practitioners and researchers need, first and foremost, to understand that AI and big data are not 'silver bullets', go beyond to the "big impact of the big data" and be aware of barriers and risks. On the contrary, data and AI should be approached as sociotechnical phenomena (Günther et al., 2017; Lindgren and Holmström, 2020; Berente et al., 2021) that can lead to either value generation or value destruction (Frey and Osborne, 2017). This understanding could shape realistic expectations of what AI is able to achieve and how big data may lead to both creation and desctruction.

Out of context, data loses its meaning (Dwivedi et al., 2019) and as Pentland (2014) notes, continuous and transparent experimentation with big data is a necessity. Thus, understanding of social, cultural, ecological and ethical factors is crucial to manage AI successfully and generate value. AI can potentially promote equality, sustainability, transparency and explainability. It is also accompanied by constant risks of increasing 'datafication', 'surveillance capitalism', losses of privacy and security, and discrimination (Svensson and Guillén, 2020).

However, between these utopic and dystopic extremes there is the middle ground of managing the challenges and opportunities. To mitigate the risks, researchers should to be aware of the different dimenions that constitute the AI phenomenon and research. In such a way, researchers can shape the future research agenda by considering a holistic view of AI management research that captures both societal and managerial concerns. In the same vein, to minimize concerns, generate value and preserve trust, managers should reflect on their professional responsibility, leadership and understand how to address emerging social and ethical concerns. Thus, the ethical guidelines should reflect realistic and practical implications and not have merely theoretical applicability. To overcome the myths of optimism and pessimism, AI managers should adopt an integrated view with understanding and equal consideration of data, value possibilities and labor impacts, as well as social, cultural, ethical and ecological factors.

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