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AI Management Beyond Myth and Hype: A Systematic Review and Synthesis of the Literature

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Abstract

Background: *AI management has attracted increasing interest from researchers rooted in many disciplines, including information systems, strategy, and economics. In recent years, scholars with interests in these diverse fields have formulated similar research questions, investigated similar research contexts, and even often adopted similar methodologies when studying AI. Despite these commonalities, the AI management literature has largely evolved in an isolated fashion within specific fields, thereby impeding the development of cumulative knowledge. Moreover, views of AI's anticipated trajectory have often oscillated between unjustifiably optimistic assessments of its benefits and extremely pessimistic appraisals of the risks it poses for organizations and society.*

Method: *To move beyond the polarized discussion, this work offers a systematic review of the vast, interdisciplinary AI management literature, based on analysis of a large sample of articles published between 2010 and 2022.*

Results: *We identify four main research streams in the AI management literature and associated, conflicting discussion, concerning four (data, labor, critical, and value) dimensions.*

Conclusion: *The review conceptually and practically contributes to the IS field by documenting the literature's evolution and highlighting avenues for future research trajectories. We believe that by outlining four key themes and visualizing them in an organized framework the study promotes a holistic and broader understanding of AI management research as a cross-disciplinary effort, for both researchers and practitioners, and provides suggestions that extend the framing of AI beyond myth and hype.*

Keywords: AI Management, Big Data, Systematic Literature Review, Value Creation, Ethics.

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Introduction

In efforts to exploit the increasing possibilities of AI systems, increasing numbers of firms across the globe are incorporating AI management as an integral part of their strategic agenda. AI systems go beyond previous technologies by approximating human cognitive functions and providing capacities to search, analyze and use large datasets, and learn (Li et al., 2021; Waardenburg et al., 2021). Specifically, Machine Learning (ML) technologies have greater autonomy, opacity but also deeper learning capability than previous 'IT types' (Baird & Maruping, 2021; Berente et al., 2021). In addition, IT and AI management differ due to the higher complexities associated with AI. According to Berente et al. (2021), AI is not a technology, or even a bundle of technologies, but rather an evolving frontier of computational advances. This raises questions regarding the adequacy of traditional managerial and organizational frameworks for managing AI and addressing new and emerging associated challenges (Neeley & Leonardi, 2022). It also clearly highlights the need to manage AI systems carefully, taking into consideration all the diverse associated challenges and opportunities for organizations and society (Berente et al., 2021; Fosso Wamba et al., 2021; Waardenburg et al., 2021).

Although the AI phenomenon has received significant attention from both researchers and practitioners, its framing in the literature is problematic for three main reasons. First, the framing oscillates between two extreme poles: the fear of AI linked to deterministic technological dystopias and the hype of AI linked to overly optimistic utopias (Borges et al., 2021). A need to overcome this naïve anxiety, or exaggerated admiration, of the power we assign to AI technologies has been noted (Huysman, 2020), and some attempts have been made to progress beyond overly optimistic views and cemented pessimism (Benlian et al., 2022). However, there is still a need for further investigation. Second, the literature on AI is scattered and diverse, demonstrating a lack of cumulative building of knowledge and reflecting a lack of maturity in today's AI research (Collins et al., 2021) and a holistic view of AI scholarship (Fosso Wamba et al., 2021). Recently some authors, for instance Campbell et al. (2020), have documented the new opportunities associated with AI. Researchers have scrutinized the positive impact on AI on designing intelligent products (Huang et al., 2019), reshaping business processes (Tarafdar et al., 2019), inventing new business models and adopting new organizational forms (Faraj et al., 2018). However, these new opportunities are accompanied by a set of complex emerging challenges. These concerns are associated with risks of work displacement (for examples, see Frey & Osborne, 2017; Kaplan & Haenlein, 2020), the adaptation of AI in the workplace (Wibowo et al., 2022), the development of AI and sustainability issues (Bracarense et al., 2022) and trust (Glikson & Woolley, 2020; Kumar et al., 2021). Current literature also captures issues related to decision-making for complex problems (Johnson et al., 2022), big data (Constantiou & Kallinikos, 2015), responsible use (Fosso Wamba & Queiroz, 2021) and security risks (Martin, 2015; Dwivedi et al., 2021). There are also concerns that AI's implementation may impair "unique human knowledge" and turn "humans in the loop" into borgs (Fügener et al., 2021). Clearly, to embrace the possibilities and meet the challenges that accompany new AI technologies a multi-dimensional perspective is required, but the socio-technical processes involved are often examined through a narrow, polarized lens.

Lastly, there is a lack of clarity and misunderstanding of what constitutes AI, which may derive partly from snapshot theorizing of AI, treating AI as an umbrella term or equating AI with data (Ågerfalk et al., 2022). In efforts to avoid such misconceptions, we need to distinguish between data and AI, while acknowledging their intersection and co-dependence. In this discourse, Paschen et al. (2020, p. 147) argue that "*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*". As already noted, Berente et al. (2021) have defined AI as an evolving frontier while Crawford (2021, p.8) extrapolates that "*artificial intelligence is both embodied and material, made from natural resources, fuel, human labour, infrastructures, logistics, and classifications*". In efforts to address the abovementioned challenges, we have formulated the following research question: What is the current state of AI management literature?

To address this question and tackle the issues emerging from problematizing shortcomings in the literature, we present here a systematic investigation of AI management literature. In total, 109 articles and highly cited books published between 2010 and 2022 are synthesized and discussed. The starting date marks the beginning of a resurgence in AI research after several 'AI winters' (Wamba-Taguimdje et al., 2020). In order to bridge the dichotomy between social and technical aspects of AI, and respond to calls for a more comprehensive and cohesive approach in IS research, we adopt a socio-technical perspective (Sarker et al., 2019). Such an approach may be crucial for grasping "*the essence of IS*" (Sarker et al., 2019, p.9) as it considers not only the technical artifacts involved but also the individuals involved and society wherein the artifacts are developed. We recognize the importance of acknowledging not only the roles of both social and technical aspects of AI, but also the interactions between them. The approach is also valuable for investigating both instrumental and humanistic outcomes of AI (Benbya et al., 2021; Mumford, 2006; Sarker et al., 2019). We identified four key themes in AI management literature. Inspired by the results of our review and the dominant discourses in the field, as described by Berente et al. (2021), we define AI management as a constantly evolving socio-technical process of organizing tasks, decision-making and managing data through human-AI coordination to seize business value in accordance with relevant regulatory and ethical imperatives.

The study presented here, based on our systematic literature review (SLR), offers three distinct theoretical contributions and practical implications. First, by documenting how the literature on AI management has evolved and its current state we map the polarized discourse around AI research, and present more holistic possibilities and limitations of AI management. Second, we outline four key research themes in the literature and visualize them in an organized framework, thereby improving its accessibility and understanding for both practitioners and researchers. Lastly, we highlight several understudied areas of AI management, thus highlighting potentially fruitful avenues for future research trajectories.

The rest of the paper is structured as follows. In section 2, we present the theoretical background and acknowledge previous SLRs of AI within the interdisciplinary IS spectrum. In Section 3, we elaborate on our systematic methodological approach. Section 4 synthesizes and discusses the four identified research streams. Section 5 provides discussion of the findings, and their implications for AI management research and practice. Finally, section 6 presents the conclusions and limitations of the study.

Theoretical Background

In this section, we first elaborate on the socio-technical perspective as the theoretical framework chosen for our study. Then we provide a brief overview of previous scholarly endeavors to capture systematically the AI management literature while highlighting the differences with our work.

Theoretical Framework

In this study we apply a socio-technical framing of AI management, which offers a powerful, multi-faceted approach that helps transcendence of simple or reductionist views of AI management. According to Sarker et al. (2019, p. 3), the sociotechnical perspective "*considers the technical artifacts as well as the individuals/collectives that develop and use the artifacts in social (e.g., psychological, cultural, and economic) contexts*". Framing with this perspective, with consideration of both social and technical aspects, offers a richer understanding of the complexities involved in managing AI systems than consideration of either set of aspects alone.

A reductionist view of AI management focuses solely on technical aspects, such as algorithms, hardware, and software, or solely on social aspects. While these elements are undoubtedly vital, a narrow focus on either the technical or social aspects may miss important aspects of the broader context in which AI systems operate. In contrast, the socio-technical perspective recognizes that AI systems are embedded in complex social, economic, legal, and ethical contexts (Sarker et al., 2019), which inevitably both influence and are influenced by AI management. This is important for at least three reasons.

First, the social dimension recognizes the importance of human actors within AI management. Human users, developers, managers, regulators, and other stakeholders are all parts of the ecosystem that interacts with AI. The socio-technical perspective acknowledges the importance of understanding human needs, values, biases, and socio-cultural norms. By recognizing these factors, AI management can more effectively align AI systems with human interests, promoting responsible use and mitigating potential harms (e.g., Grønsund & Aanestad, 2020). Second, the socio-technical framing emphasizes the interconnectedness between technology and society. For instance, AI algorithms may inadvertently perpetuate social biases if they are trained on biased data. A narrow technical focus might miss these dynamics, whereas the socio-technical perspective incorporates consideration of the broader societal implications of AI, and hence is more likely to identify such biases and possible steps to mitigate them (e.g., Jussupow et al. 2021). Third, the socio-technical framing recognizes that AI is not merely a neutral tool but is shaped by and shapes the society in which it operates. The values and norms embedded in AI systems can have significant societal impacts. By considering these interactions, AI managers can take a more proactive role in guiding the development and uses of AI in ways that align with societal goals (e.g., Coeckelbergh, 2022).

In conclusion, the socio-technical perspective of AI management provides a powerful framework that can help us move beyond simple accounts of AI management. By acknowledging the complex interplay between social and technical factors, it offers a more nuanced understanding of the challenges and opportunities of AI. This comprehensive perspective allows for more responsible, ethical, and effective management of AI systems, considering not just the immediate technical requirements but also the broader social context in which these systems operate. It also promotes a holistic approach, which is crucial as AI is not an isolated technological phenomenon but an integral part of the social world.

Mapping Previous Systematic Reviews of AI Literature

The polarized discussion of AI may have been amplified by dispersal of the AI literature and failure to integrate the disparate strands (Collins et al., 2021). Additionally, few studies provide a holistic view of scholarly work on AI (Fosso Wamba et al., 2021). Building on these claims, we seek to explore and provide a holistic, cross-disciplinary framing of AI management research. In so doing, we acknowledge previous systematic reviews of AI studies while highlighting their distinctive differences from our work.

A systematic review by Dwivedi et al. (2021) exemplifies a shift towards a more multidisciplinary approach to AI by addressing manifold aspects of AI, including associated challenges, opportunities, and policies while providing suggestions for future research trajectories. The review is extensive and covers diverse dimensions of AI. However, it does not follow the systematic steps of a SLR. In contrast, Collins et al. (2021) provide a SLR with an informative synopsis of previous reviews of AI research, but only cover recent IS literature. Juxtaposing the 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. In the same vein, a wide spectrum of literature aims to uncover the implementation, use, opportunities, and impact of AI in various sectors. For example, Di Vaio et al. (2020), Mariani et al. (2022) and Zuiderwijk et al. (2021) respectively explore AI's use and implications in creation of sustainable business models, marketing and public governance. A systematic review by McKinnel et al. (2019) and meta-analysis of the AI literature identifies research challenges and opportunities related to penetration testing and system vulnerability assessment. In addition, Toorajipour et al. (2021) systematically investigate the role of AI in supply chain management (SCM), the main AI techniques involved, and the elements of SCM that AI could potentially improve. Radhakrishnan et al. (2022) review literature and draw conclusions regarding organizations' AI implementation and the challenges that firms may encounter. In contrast to previous studies, they investigate AI "implementation journeys" beyond a specific domain. Di Vaio, Hassan, D'Amore et al. (2022) systematically address responsible innovation in the Asian fashion industry, seeking to reveal the "how" and "when" and "what" of a responsible innovation governance framework that may enable transition from a traditional fashion industry to an "*ethical and environmentally sustainable industry*" (p.1).

Our review differs from those of Dwivedi et al. (2021) and Collins et al. (2021) in terms of the nature of technology covered and disciplinary scope. We do not limit our analysis to any particular AI technology, and a major objective is to capture the interdisciplinary nuances of AI management research. Thus, we cover a broader field than the previous reviews. Moreover, all the cited reviews except the one by Radhakrishnan et al., (2022), address AI implementation in a specific context, domain, and industry (see Di Vaio, Hassan, D'Amore et al., 2022), while we have aimed throughout our study to maintain a holistic approach to broaden understanding of the management and organizational implications of AI beyond the boundaries of any specific industry. Moreover, a major objective of our review has been to capture the interdisciplinary nuances of AI management research. Thus, we cover a broader field than some previous authors, such as Collins et al. (2021), and adopt a holistic approach for understanding, managing, and organizing AI generally, rather than addressing its implementation in a specific domain and industry. Radhakrishnan et al. (2022) also applied an interdisciplinary approach, but focused on AI "implementation journeys", whereas we focus on unpacking the polarized discussion in extant AI management literature.

Research Design

In this section we elaborate on the evidence-based SLR approach we adopted. 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). We chose to examine the literature in a systematic manner in efforts to establish and apply rigorous search criteria (Mallett et al., 2012) and thus allow us to identify as many relevant and emerging streams of AI management literature as possible. Noted advantages of SLR include its ability to increase transparency (Paré et al., 2016), improve quality (Templier & Paré, 2015), minimize biases (Snyder, 2019) through transparency and allow for methodological replicability. A systematic approach also facilitates identification, summarization and synthesis of large quantities of knowledge (Fink, 2005; Templier & Paré, 2015), which we deemed important given the disparate nature of AI management literature. Moreover, according to Snyder (2019), SLR is a suitable research method for addressing emergent topics in the literature. Our SLR could be categorized as a 'specific theorizing review' intended to provide theoretical filling of identified knowledge gaps in the AI management literature, following the polylithic framework of Leidner (2018). In this review, we draw on and are inspired by the guidelines presented by Okoli (2015) for constructing a stepwise SLR framework. In the following sections we present in detail our systematic approach to the literature.

Process and Stages of the Literature Review

Pilot Search and Planning Phase

When starting our review, we identified a problem. Despite the abundance of AI literature intended to elucidate various aspects of challenges and opportunities associated with AI, as exemplified by Dwivedi et al. (2021), AI research has evolved in isolated one-sided traditions with equally polarized and diverse logics, hindering the emergence of cumulative knowledge. Hence, a major aim of our review was to systematically explore the full spectrum of relevant literature to address the formulated research question and meet the previously stated objectives. In the first phase of exploration, the pilot search, we used Web of Science (WoS), Scopus and Google Scholar databases to review academic literature and identify the main themes (see Martín-Martín et al.,2018; Denyer & Tranfield, 2009; Di Vaio et al., 2023), considering the breadth of our research question and diverse nature of our topic.

In this stage, following Di Vaio et al. (2023), no limit was imposed when exploring the subject. Thus, we tried multiple possible keywords before focusing on more specific, but broad keywords in the next (planning) stage. This exploratory stage allowed us to acquire a preliminary understanding of the coverage of extant literature, and "*define the concept or constructs at the heart of the synthesis*" (Templier & Paré, 2015, p. 115). This is consistent with stipulations that while planning a review authors should justify the need for a standalone literature review (Keele, 2007; Webster & Watson, 2002), identify the review's purpose (Okoli & Schabram, 2010), and define the concepts or constructs at the heart of the synthesis (Cooper, 2009; Webster & Watson, 2002). It is essential to specify the research questions being addressed (Keele, 2007) because they guide the entire study design as they govern the type of information that is required, inform the search for and selection of relevant literature, and guide the subsequent analysis (Jesson et al., 2011).

This primary/pilot search of the literature during the planning phase led to discovery of important keywords ("ethics", "labor", "value", "big data"), which were combined in various strings in the next phase in efforts to capture and delineate distinct streams of AI management literature. The choice of these keywords (and their combinations) was based on the frequency of their appearance in the searches and dimensions required to cover the interdisciplinary nature of AI embraced in our broad socio-technical framework. Thus, keywords such as "digital transformation" were deliberatively excluded to avoid deviation of the discussion. A condition we imposed was that the selected keywords had to be in the title, abstract, or keywords of papers identified by the search.

Lastly, from the pilot search and planning phase onwards, throughout the entire process, both authors discussed potential keywords and reached agreement (in each phase) about the inclusion/ exclusion criteria in efforts to ensure that the study was rigorous and the results reliable. Both authors were involved in screening the articles, the coding process and decisions regarding emerging dimensions and subthemes.

Selection, Extraction and Execution Phases

In the selection phase, we systematically searched for relevant literature. We identified most of the relevant articles by screening entries in the WoS, Scopus, and Google Scholar databases, following guidelines formulated by Levy and Ellis (2006) for a well-rounded SLR. The criterion for database selection was that each database had to provide a wide range of sources and references (see Di Vaio, Hassan, Chhabra et al., 2022). Therefore, strategically, we chose the WoS and Scopus databases since they are traditionally used for reviews of IS-related literature, as illustrated by SLRs by Gupta et al. (2018) and Collins et al. (2021). Following suggestions by Di Vaio, Hassan, Chhabra et al. (2022) we included the Google Scholar database as it is perceived as the most extensive database to identify recent articles in the focal subject areas. In alignment with the purpose of our study to delineate current literature and discussion on AI management, we selected 2010 as a baseline year. Since the inception of AI concept in the 1950s, there have been several "summers and winters" of research attention to it, and AI management. The year 2010 marks the start of a rejuvenation of AI literature due to significant improvements in computing possibilities and access to vast amount of data (Collins et al., 2021; Duan et al., 2019; Wamba-Taguimdje et al., 2020). Our search strategy included entries up to the time of searching (December 2022). An aspiration was to encapsulate the interdisciplinary nature of the IS field concerning AI management, following guidelines by Webster and Watson (2002). In efforts to avoid missing valuable sources and obtain accurate information regarding development of the relevant 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 (Table 2). We applied the same dyadic combinations of keywords in the additional search of the Google Scholar database and 'went backward' and 'forward' by reviewing citations in identified studies in an attempt to identify prior relevant work that we should consider (Webster & Watson, 2002). Application of this strategy resulted in identification of 6,873 relevant studies from the search of the WoS database, together with 6,184 and 189 from searches of the Scopus and Google Scholar databases, respectively. The high number of identified studies was not surprising, since the search of the Scopus database with our keyword string yielded 1,307 and 2,043 entries published in 2021 and 2022, respectively (Table 1). Next, we imported the results into an Excel worksheet. To restrict our review to manageable numbers of studies, we imposed strict inclusion and exclusion criteria during this phase. For inclusion, articles had to have been published in English between 2010 and the time of searching, on topics categorized as elements of Social Sciences, IS, Management or Business domains. From an initial scanning of abstracts, we removed 10,345 articles that were deemed irrelevant due to association with a topic and journal outside the focal disciplines (e.g., articles on social ramifications of AI rather than its management, or focusing merely on technical aspects of AI). The studies included were mainly peer-reviewed articles, but highly cited books (with at least 200 citations) listed in the Google Scholar database were included to broaden and deepen coverage of the discourse on AI management.

Table 1 – Strings Applied in Database Searches

Database	String
WoS	AK= ("Artificial Intelligence" OR "Machine learning" OR "Big Data" AND "ethics" OR "labor" OR "value") and 2010 or 2011 or 2012 or 2022 or 2021 or 2020 or 2019 or 2018 or 2017 or 2016 or 2015 or 2014 or 2013 (Publication Years) and Article (Document Types) and English (Languages) and Article (Document Types) and Business (Web of Science Categories)
Scopus	TITLE-ABS-KEY ("Artificial Intelligence" OR "Machine Learning" AND "ethics" OR "labor" OR "value") AND PUBYEA> 2009 AND LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English")) AND(LIMIT-TO (SUBJAREA,"SOCI") OE LIMIT-TO (SUBJAREA, "BUSI"))

To expand the dialogue and reduce risks of missing relevant aspects we also included prominent books focused on critical dimensions of AI and big data (see Eubanks, 2018; O'Neil, 2016). We also cautiously incorporated studies recently published in top-tier journals that may lack high citations but may encapsulate the most recent trends in views and understanding of AI management. We then removed duplicated articles, which left 2901 that met our inclusion and exclusion criteria. After the selection process, we moved to the <u>extraction phase</u>, in which we expanded the search and scanned abstracts of retrieved articles. To avoid overlooking articles, we also read the introduction section in cases when the abstracts were insufficiently clear regarding the nature of covered AI, scope, and objectives. Moreover, to ensure that the selected literature had sufficient quality and relevance, we applied similar exclusion and inclusion criteria, seeking to retain articles that: clearly focused on AI and/or big data and/or ML; addressed phenomena related to our research question and broader aspects of AI management; and were published in top-tier journals. First, adopting a socio-technical perspective, we excluded studies that did not address strategic aspects of AI in organizations or society. Then, we removed studies that merely emphasize the technological role or foundations of a particular AI system as we aimed to avoid the technical-social dichotomy. We also excluded studies merely exploring the impact of AI systems in a particular industry. After applying these criteria, 465 articles remained. Lastly, after reading them thoroughly, we selected 109 that met all the mentioned criteria (Figure 1). In the last (<u>execution</u>) phase of the review we analysed, synthesized and integrated findings, which are presented in detail below.

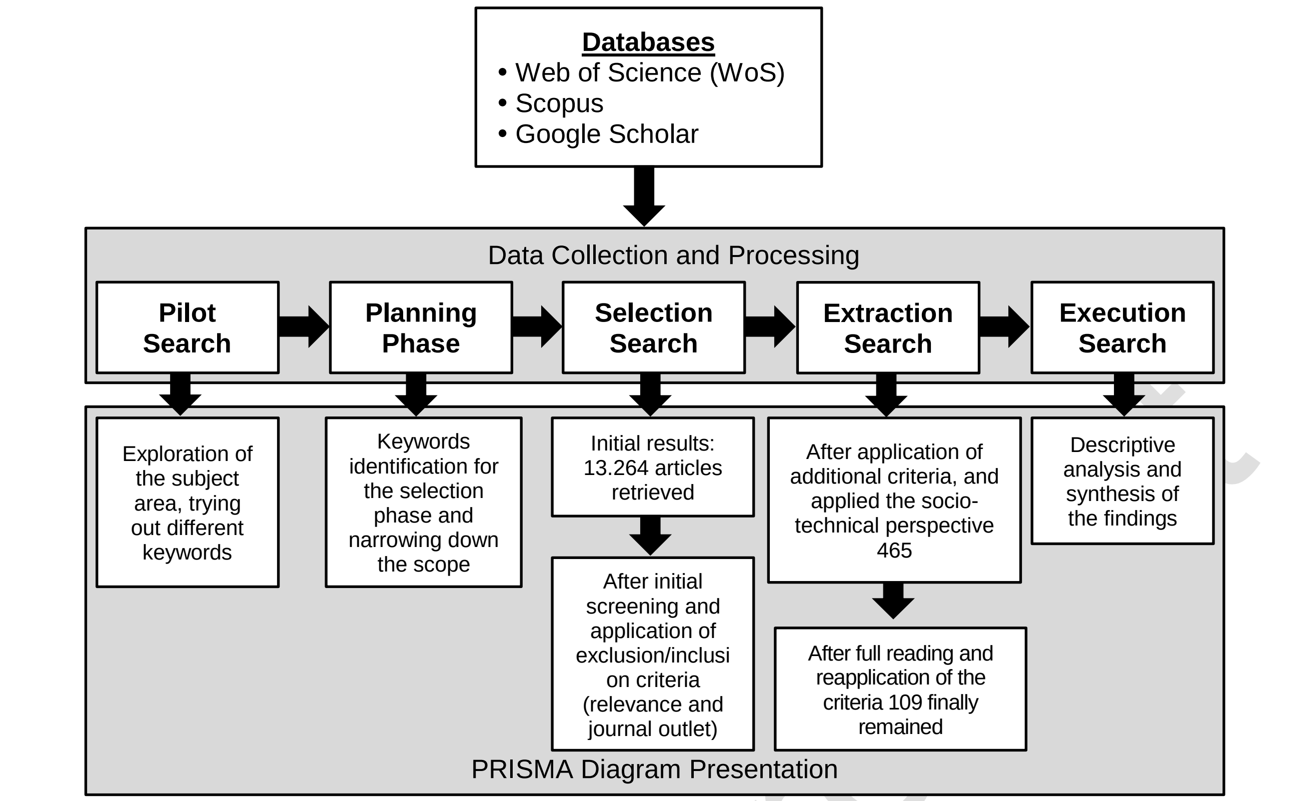

Figure 1 – Illustrative Diagram of the SLR Process

Analysis and Literature Synthesis

We conducted a four-stage iterative analysis of the final 109 articles. First, we read through all the articles to identify key concepts, inspired by the concept-centric matrix of Webster and Watson (2002). During this stage we followed the recommendation of Wolfswinkel et al. (2013) and highlighted portions of articles for deeper and further analysis. In the second stage we read and coded each article independently, making extensive notes and interpretations. For generating first-order themes, open coding was employed and therefore the codes emerge from the articles text. Some of the open codes, such as "*we always had big data problem*" (Yoo, 2015, p. 63) or "*data is the sensing arms of algorithms*" (Alaimo & Kallinikos, 2022, p. 20), were extracted directly form the articles. Open coding was employed, so the codes emerged from the articles' texts. We constantly compared the codes and during the third stage independently grouped them into categories. Two examples of the categories were: (Big) data's ambivalent nature and Data governance: fallacies and concerns. During the last stage of coding, we revisited the original articles, read each article in each category, the concepts we identified and our notes. We removed overlapping and grouped together conceptually related categories, as illustrated in Table 2.

Table 2 – Example of Coding Table

Open Codes	Categories	Key Themes
"Data is increasingly the phenomenon"; "Data is the oxygen"; Data-driven decisions; "We always had a big data problem"; Improving customers´ needs through data; Improve decision-making through data; Performance optimization; Data affects innovation; Transforming organizations through data; Data and business model renewal; Value generation; Value capture; Data as a socio-technical phenomenon; Enhancing organizational learning curve; Minimize strategic failures; Data nature; Data liquidity; Data contextualization; Data democratization; Data is a non-rivalrous good; Data as a strategic resource; Data increases competitive advantage.	***(Big) Data´s ambivalent nature***	***The (Big) Data Dimension***
Data enthusiasm; Overestimating data applicability; Hyperbolic reliance on data; High expectations for data possibilities; Failures of strategic decisions due to data; Complexity of data monetization; AI and data generate managerial concerns; Rising of issues of privacy and concern; Data mistrust; Data injustice; Data generates discriminatory biases; Employees´ scepticism; Data law fails to protect data object; Data generates novel risk; Data aspects should be viewed through an ecosystem perspective; Concerns of data sharing; Issues of data use.	***(Big) data governance: Fallacies and concerns***	

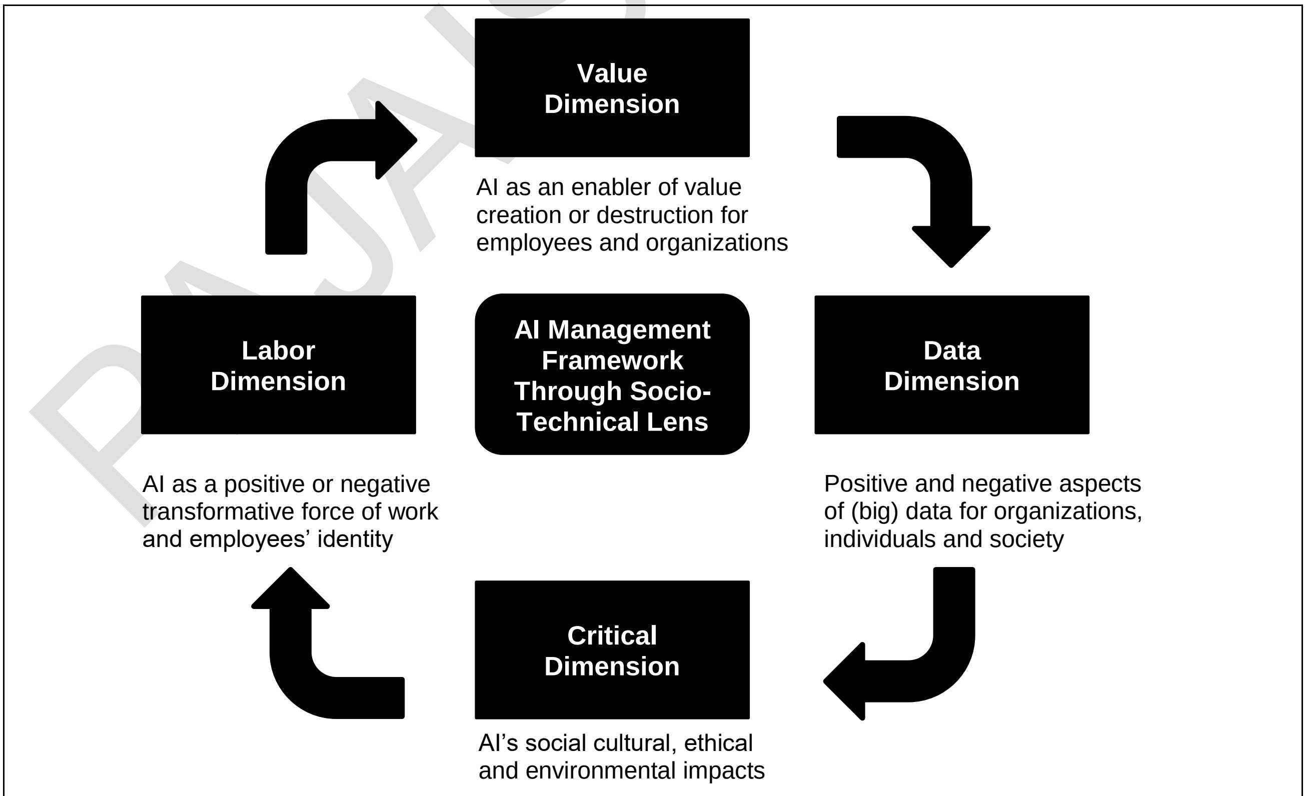

Figure 2 – Dimensions of AI Management Literature Identified Using Our Socio-technical Approach

The key themes that emerged from our analysis are designated the data, labor, value, and critical dimensions of AI management (Figure 2). We extrapolate that the themes are conceptually and empirically interdependent and interconnected, since they constitute and influence AI management. However, the associated streams are dispersed in the literature, and in some cases the themes are only treated as underlying factors. In the following text we synthesize literature streams on these four key dimensions and present the main findings regarding them.

The Data Dimension: (Big) Data and Big Challenges

The stream of literature on this dimension depicts the importance of managing data as a building block of holistic AI management. The overarching discussion captures the challenges and opportunities that organizations need to address when seeking to exploit data (and data analytics). The following sections emphasize subthemes covering two poles of discourse: one underscoring big data's depiction as a strategic asset for organizations, and one problematizing the energizing concerns associated with issues of privacy, mistrust, and misuse.

(Big) Data's Ambivalent Nature

Recent AI studies highlight the importance of datasets, describing them as the "fuel and oil of AI" (Crawford, 2021), "the sensing arms of algorithms" (Alaimo & Kallinikos, 2022), and "the new oxygen" (Svensson & Poveda Guillén, 2020). The importance of data is epitomized by a statement by Chen et al. (2017, p. 19), 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*". These quotations highlight the revolutionary impact of big data on organizations (Aversa et al., 2018; Shrestha et al., 2019) and validate an argument by Monteiro (2022) that "*data are increasingly the phenomenon*" (p. 11). In response to this and in order for organizations to seize new opportunities, current business practices aim to expand the use of data while also developing tools, models and techniques (Kallinikos & Constantiou, 2015). Hence, the availability of data with increasingly enormous velocity, variety, veracity and volume has increasingly validated assertions such as "data-driven decisions are better decisions" (McAfee et al., 2012) and stressed the 'big impact of big data'. Interestingly, as Yoo (2015) underscores in this discourse, positioning the pervasive importance of big data only on the quantitative aspect of '4 Vs' may be myopic. Solely focusing on the size and context of big data may diminish its strategic importance. After all, as he continues, "*we always had a big data problem*" (p. 63).

Big data adds an analytics dimension to existing organizational capabilities (Bhimani, 2015), and hence introduces new needs, opportunities and challenges, as highlighted by Constantiou and Kallinikos (2015). Accordingly, big data is entangled with performance optimization (Chen et al., 2012), increasing productivity (Loebbecke & Picot, 2015), predictability of potential failures (Grover et al., 2018), effectivization of organizational learning (Hagiu & Wright, 2020) and expedition of decision-making processes (Ghasemaghaei, 2020; Schildt, 2017; Shrestha et al., 2019; Von Krogh, 2018). Bhimani (2015) expands the discussion by noting positive impacts of big data including enrichment of customer bases and enhancement of the understanding of customers' needs. In this manner, big data can provide strategic competitive advantage by enabling organizations to act on data insights before their rivals, as described for example by Chen et al. (2016). Other authors stress the impact of big data on: innovation (Mikalef et al., 2020); organizational transformation in terms of process, scope, and scale (Baesens et al., 2016); business models (Günther et al., 2017; Loebbecke & Picot 2015; Parvinen et al., 2020) value capture (Zeng & Glaister, 2018); and value generation (Burton-Jones, 2014; Wamba-Taguimdje et al., 2020; Zeng & Glaister 2018). Within the spectrum of value generation and capture, research also indicates that sociotechnical characteristics of data such as portability (the possibility to transfer digitized data from one context to others), non-rivalrous nature (the ability of multiple actors to exploit a single dataset at the same time without the value disappearing), and interconnectivity (the ability to synthesize data from diverse sources) have increasingly influenced organizations' perceptions of value (Günther et al., 2017; Parvinen et al., 2020). Another attribute that distinguishes big data from traditional resources, is an agnostic nature, as it can be repurposed and reused in different contexts (Aaen et al., 2022). It also has high liquidity, i.e., "*ease of data asset reuse and recombination*" (Wixom et al., 2021, p. 1). This is regarded as a substantial step towards its monetization, i.e., the process and outcome of capturing data value (see also Parvinen et al., 2020). The profound impact of (big) data on strategy-making is not a new aspect of the literature either. For instance, Constantiou and Kallinikos (2015) noted that a key element of its utility is updatability, which massively extends the timeframe of data's relevance. We extrapolate that these attributes affect norms and rules related to strategy-making and big data management, enabling managers to democratize, contextualize, and experiment with big data, and exploit insights acquired from it to create value (Zeng & Glaister, 2018).

(Big) Data Governance: Fallacies and Concerns

In addition to the unprecedented opportunities offered by big data, as outlined above, there are major challenges and assumptions associated with its management and organization. Although some challenges of managing big data are rooted in practical impediments, our findings demonstrate that major sources are high expectations and over-optimism associated with AI (Dwivedi et al., 2021). In many cases these may lead to misunderstanding of the applicability of data and real practices involved, and hence not necessarily to value generation (Günther et al., 2017). For example, Aversa et al. (2018) describe how big data may not improve strategic decisions due to hyperbolic reliance on the data in complex and turbulent circumstances. Questioning the hype of expectations, a diverse research stream, exemplified by Pentland (2014), problematizes the management challenges and importance of data governance in the era of AI. The challenges reflect the scope of its implementation, difficulties of extracting value and data management issues. For instance, Mikalef et al. (2019) recognize that big data may also hurt organizations, and that despite the hype few organizations manage to fully seize value from their big data investments in reality. Thus, generating value from big data may be more complex than often thought, as accentuated by Grover et al. (2018) and Wixom et al. (2021), who refer to difficulties of "data monetization". Reflecting on the hindrances of extracting strategic value from big data, authors such as Kitchens et al. (2018) and Grover et al. (2018) highlight issues including insufficient data quality, integration, and security along with challenges that may emerge when processing and interpreting big data described, for example, by Günther et al. (2017). Time constraints, skepticism of employees (Makarius et al., 2020), historical legacies, and inappropriate team composition (Günther et al., 2017) are some of the hindrances that may impede successful exploitation. In alignment with this discussion, scholars have noted that mistrust of data and AI generally may generate major managerial concerns (Glikson & Woolley, 2020), thus raising serious privacy and security concerns (Dwivedi et al., 2021), while fostering discriminatory biases, as discussed by various authors (e.g., Svensson & Poveda Guillén, 2020; Wachter & Mittelstadt, 2019).

In a contribution to the discussion on data biases and privacy issues in collection and dissemination of information, Martin (2015) highlights the associated risks of the "big data industry". In addition, 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*". Specifically, they highlight that inferential analytics methods are used for predicting users' behaviors and preferences for marketing purposes or inferring sensitive attributes and political stances (Ibid.). Interestingly, 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.). An important conclusion is that key attributes of big data, including its value, cannot be estimated in isolation as they are intertwined with other aspects of ecosystems in which diverse agents collect, use, and share data. To varying degrees, data then loses its agnostic quality in accordance with the virtues and problems of the social systems in which the ecosystems are embedded (Aaen et al., 2022). This issue is further considered in the section on the critical dimension stream.

The Value Dimension: Value Creation and Value Destruction

Literature on this dimension concerns AI's potential power to transform organizations, its impact on value creation and organizational performance, as well as factors that may constrain such transformation. As outlined below, it encompasses studies concerning both AI's potential for business value creation and its fallacies. This stream substantively differs from the stream centered on big data, its strategic value and associated concerns, seeking to provide a broader and more nuanced discourse on value creation and destruction, extending beyond the role of data.

AI Capabilities and Business Value Generation

Recent research has started to explore and deepen the understanding of AI's capabilities for value creation (Shollo et al., 2022). The introduction and deployment of AI technologies (Li et al., 2021) in an organizational ecosystem can enable creation of economic value and optimization of business processes (Coombs et al., 2020), flexibility of operations (Wamba-Taguimdje et al., 2020), innovation management (Kakatkar et al., 2020; Haefner et al., 2021) and business models (Günther et al., 2017), through new ways of managing information (Haefner et al., 2021; Wamba-Taguimdje et al., 2020). Enthusiastic optimism regarding value-generating opportunities expressed in this steam embraces possibilities AI may generate for customers (Davenport et al., 2020).

Further benefits of AI include its potentials to increase revenues (Davenport et al., 2020) while reducing costs (Haefner et al., 2021), minimize decision-making time (Haefner et al., 2021; Von Krogh, 2018), and hence enhance long-term competitiveness (Hagiu & Wright, 2020). In a similar vein, according to a review by Haefner et al. (2021), it is important for innovation managers to find ways to apply AI technologies in efforts to support human organized innovation, and provide capacity for explorative initiatives within the innovation spectrum. The cited authors present key potentials of AI in innovation processes, including abilities to generate creative ideas by overcoming information-processing barriers and restrictions of local search routines (Ibid.). Similarly, researchers such as Kakatkar et al. (2020) highlight three ways that AI can enhance innovation analytics (visualization, generation of data-driven insights, and construction of models in innovation processes) as venues of value creation. In particular, they suggest that AI can allow innovation teams to leverage large volumes of data. By doing so, innovation managers can collaborate with data scientists, enhance creativity, and constantly improve questions asked by those involved in innovation processes.

AI Beyond the Hyperbolic Confidence in Value

Recent statistics show that many organizational efforts fail to generate value (Canhoto & Clear, 2020; Fountaine et al., 2019; Frick et al., 2021), resistance to (behavioral) change (Frick et al., 2021), managers' apprehension of new technologies, myopic vision (Kolbjørnsrud, et al., 2017; Rinta-Kahila et al., 2022), and organizational lack of AI readiness (Holmström,2022) are some of the emerging challenges identified and discussed in current AI literature.

Beyond the romanticization of data-driven learning, authors such as Hagiu and Wright (2020) add an interesting nuance by stressing that it is not true that "more customers entail more data that when analyzed with machine learning will lead to competitive advantage". Accordingly, the perils associated with AI that may lead to value destruction, and thus competitive disadvantage, are highlighted by authors such as Canhoto and Clear (2020) and Rana et al. (2022). For example, a revelatory case study by Rinta-Kahila et al. (2022) extends the discussion to "social destructive systems", focusing on an algorithmic decision-making (ADM) program, "that was designed to automatically calculate and collect welfare overpayment debts from citizens but ended up causing severe distress to citizens and welfare agency staff" in Australia. It also caused financial and reputational damage to the government. In addition, other AI-related systemic problems may be related to ethical concerns, associated (for instance) with the increasing pressure on consumer-oriented firms to collect and exploit information in rapidly changing markets' regulatory contexts (Martin, 2015).

The Labor Dimension: Racing with or Against the Machines

This stream encompasses the debate and diverse narrative related to the transformative impact of AI-driven technologies on organizing logics and workforces. Specifically, it presents the ongoing challenges and opportunities associated with AI implementation related to labor, task delegation, and management, encompassing conflicting views. New technologies and their deployment can engender progress towards industrial goals, such as automation and acceleration of production processes, but also (according to some organizational theorists) lead to fragmented work (Barley, 1990), deskilling of labor forces and lurking dangers for the future trajectory of labor (Brynjolfsson & McAfee, 2017). However, a wide sub-stream of the literature emphasizes the potentially positive impacts of AI. Additionally, emerging literature addresses the potentially drastic impact of AI on employees' identities and organizational control.

Describing the Two Extremes: AI as a Panacea or Job Destroyer

There has been ongoing debate regarding reconstitution of the work order due to implementation of technologies (Alaimo & Kallinikos, 2021), dating back to 'computerization' (Zuboff, 1988). This has been so extensive that Orlikowski and Scott (2016), for example, refer to work practices that have been reconfigured, inter alia, through algorithms as 'digital work'. The discussion has been fluctuating between conflicting and polarized arguments. As nicely depicted by Willcocks (2020), there is a clear dichotomy in the literature on AI's anticipated impact on workforces as a 'Robot-Apocalypse' or 'Automotopia'. One portrays AI as a technological panacea (Kelly, 2017), blessing for management (Lindebaum et al., 2020) and job creator (Wright & Schultz, 2018), while the other portrays it as an agent of 'job destruction' that leads to increases in unemployment rates (see for example, Brynjolfsson & McAfee, 2017; Frey & Osborne, 2017; Kaplan, 2016). The assumption, and fear, of 'technological unemployment' (Wladawsky-Berger et al., 2020) also reflects fictional and sensational treatments of ML abilities that exceed any currently conceivable capacities (e.g., superintelligence).

The argument that technology enables creative destruction is not new (see, for example, Autor, 2015; Frey & Osborne, 2017). However, it remains more extensively explored and discussed in the literature than the job creation potentials, despite contributions on positive aspects by Wilson et al. (2020), for example. It should be mentioned that instances of job creation mediated by technological improvement have probably received relatively little research attention because this effect is rarely immediate (see Kaplan, 2016). Furthermore, AI technologies also have capacity to encroach on workers' skills that is unprecedented in the history of technological development and innovation (Faraj et al., 2018; Kelly, 2017). This literature tends to emphasize the challenges posed by automation replacing skills, rather than replacing jobs. Thus, as Kaplan (2016) elaborates, to assess whether AI will put an employee out of a job, it is important to understand the nature of skills, whether these abilities are separable from the rest of the work, and "*how susceptible those skills are to automation*" (p.115). Continuing and expanding this discussion, some authors extrapolate that this may initiate a vicious cycle leading to increases in employees' vulnerability, by starting with automation and gradually degrading employees' skills and making them obsolete. Such situations are prominent in cases where the skills are mostly associated with repetitive tasks requiring relatively low levels of creativity (Kaplan, 2016), decision-making (Lindebaum et al., 2020) and human learning abilities (Lyytinen et al., 2020).

Bridging the Extremes: Augmented Intelligence and Human-AI Collaboration

Beyond the polarized extremes, emerging literature has started shaping a more pragmatic view (Coombs et al., 2020) of challenges, perils, potentials of human-AI symbiosis (Seidel et al., 2018; Seidel et al., 2020), or assemblages (Jarrahi et al., 2021), meta-humans (Lyytinen et al., 2020), machines as teammates (Seeber et al., 2020), collaboration (Fountaine et al., 2019; Seidel et al., 2020) and augmentation in workforces and organizing tasks (Grønsund & Aanestad, 2020; Raisch & Krakowski, 2021). The importance of a more realistic depiction of the constraints and possibilities of AI systems is outlined by Jarrahi et al. (2022), the mentioned analysis by Willcocks (2020), and Huysman (2020), who adopts a sociotechnical perspective (2020).

First, in a contribution to the discussion on collaboration, a longitudinal case study by van den Broek et al. (2021) addressed human-ML hybrid practices, i.e., ML and domain experts working together. They concluded 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). Similarly, Seidel et al. (2020) considered a concrete example of interaction between autonomous design tools and human designers, concluding that such tools can generate designs that may not be expected by human designers using them. However, despite the increasing level of autonomy, human designers still play a fundamental role as control units and 'tutors' of the tools. Broadening the discourse of AI-employee collaboration, Makarius et al. (2020) focused on aspects of implementation, and stressed that important aspects to consider include when, what and how such integration should be implemented to obtain competitive advantage. Hence, managers need to consider various factors, including aspects of technological readiness, the types of employees involved and the nature of the work itself.

The narrative on augmentation involves the controversial and 'paradoxical tensions' between automation and augmentation (Raisch & Krakowski, 2021). The cited authors extrapolate that automation and augmentation are closely associated and interdependent, because augmentation is both a trigger and outcome of automation. Thus, the impacts of automation on employment and organizing are multifaceted and extend beyond those postulated in a simple replacement and substitution narrative (Autor, 2015; Brynjolfsson & Mitchell, 2017). Accordingly, without ignoring the inevitability that AI will reconstitute organizations (Faraj et al., 2018; Grace et al., 2018), change skills, reconfigure work and control (Kellogg, 2020), and optimize working morale through people analytics (Gal et al., 2020), research showcases that managers and employees should set realistic expectations (Huysman, 2020) to adapt to the current AI landscape (Jarrahi, 2018).

Researchers have outlined the significant advantages of AI for information processing, analytical tasks (Kelly, 2017), abductive reasoning (Von Krogh, 2018), and 'augmented formal' rationality (Lindebaum et al., 2020). However, the delegation of decision-making solely to AI can jeopardize the validity of results (Von Krogh, 2018). Specifically, in circumstances where decision-making requires imagination, intuition, social skills and creativity, it is argued that humans still have competitive advantage. For instance, Lee (2018) found that participants (residing in the USA, at least 18 years old and meeting an intelligence criterion) felt that algorithms are less capable of evaluating workers' performance or identifying appropriate candidates as they lack human intuition. Interestingly, a contrary argument is expressed by Huang et al. (2019), who note that AI both replaces and augments. However, the key differentiator is that feelings and emotions are more difficult for AI to emulate, so feeling-based tasks are becoming increasingly significant for human workers. Continuing this discussion and juxtaposing today's Thinking Economy and the Feeling Economy, Huang et al. (2019) emphasize that employees must be more people-oriented than data-oriented to seize the benefits of Thinking AI. According to Von Krogh (2018), AI is less likely to mimic or replicate abstract thinking, especially in conditions of high complexity and equivocality. Following these arguments, some scholars conclude that the significance of algorithms lies in their ability to augment or complement ('upskill') employees' activities (Davenport et al., 2020; Grønsund & Aanestad, 2020), and bounded rationality (Lindebaum et al., 2020) since "*learning algorithms require humans to ensure accountability*" (Faraj et al., 2018, p. 66).Thus, organizational decision-making should be handled by the combined forces of employees' intuitive capabilities and machines' analytical abilities (Brynjolfsson & McAfee, 2014; Lindebaum et al., 2020; Wright & Schultz, 2018). In this discourse, Jarrahi et al. (2020) also contend that AI systems can provide "augmented human intelligence", referring to their ability to support, amplify or extend human capabilities rather than replacing them.

(Emerging) Roles and Competencies

Beyond the perceptions of AI as a destroyer of work, recent literature discusses new roles for addressing the emerging challenges of algorithmic management. Jarrahi et al. (2021) highlight the importance of building algorithmic competencies, with active engagement of employees, as an avenue towards human-machine collaboration. In this discussion, Gal et al. (2020, p. 10) propose use of the term 'algorithmists' for employees who are "*not just data scientists, but the human translators, mediators, and agents of algorithmic logic*". Similarly, Kellogg et al. (2020) and Waardenburg et al. (2022) proposed use of the term 'algorithmic brokers' for human agents with roles resembling those of 'knowledge brokers', that is reducing the opacity of algorithms by interpreting, filtering, and translating the results for users (Waardenburg et al., 2021). Another role resembling that of algorithmic brokers, recognized by Wilson et al. (2017), is that of 'the explainer' who bridges the gap between technology experts and business leaders. Wilson et al. (2017) also recognize 'trainers' and 'sustainers', who respectively aim to educate employees about how AI systems work and avoid adverse unintended consequences of AI systems.

Algorithmic Management, Employees' Identities, and Organizational Control

This emergent sub-stream of literature describes how AI-human symbiosis reconfigures work and organizational practices. It includes an account by Jarrahi et al. (2021) of two poles of task delegation in algorithmic management. One, over-reliance on algorithmics, can amplify power dynamics and control over employees. The other, excessive delegation of tasks to algorithms, may undermine agency and the generation of managers' tacit knowledge. Similarly, Strich et al. (2021) present mechanisms through which substitutive decision-making AI systems can influence employees' professional role identities individually and collectively. They contend that substitutive decision-making AI systems may affect entire work processes, limit employees' interaction capabilities, and lead to unprecedented but also less transparent work outcomes. The epitome of identity change may be the notion of 'algorithmic leadership' (Jarrahi et al., 2021), referring to cases where algorithms are assigned or acquire key roles in leadership, motivation, and support activities. Moreover, several recent studies emphasize 'the dark side' of people analytics for organizations and employees (Giermindl et al., 2022) and organizational control that is deemed to be challenging for 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. (2019) address the potentially drastic impact of algorithmic 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. Algorithmic control has also been described, by Cram et al. (2022), as a novel source of technostress. 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 human agency in decision-making. An interesting and nuanced riposte by Möhlmann (2021) and Benlian et al. (2022) is that algorithmic nudges are not unethical by default and that algorithmic control does not inherently correspond to the dark side of AI.

The Critical Dimension: Ecological Dimension, Socio-political Underpinnings, and Ethical Parameters

This theme concerns the ecological, social, political, and ethical underpinnings of the AI literature and it is included to provide a holistic overview. The stream focused on these aspects also outlines the emerging social expectations regarding sustainable AI and its potentials and limitations, as well as the socio-political or ethical challenges posed by (and implications of) the availability of big data and AI management.

The Ecological Dimension

Some studies in this stream have discussed the potential capacity AI to address major challenges not only to increase growth and productivity but also to enhance equality, inclusion (Vinuesa et al., 2020), and reliability (Taddeo & Floridi, 2018), as well as diminishing negative impacts of environmental crises (Di Vaio et al., 2020; Nishant et al., 2020). This is highly important as 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). In a contribution to the sustainability discourse, van Wynsberghe (2021) argues that sustainable AI is still at an embryonic stage, juxtaposes two branches (concerning "AI for sustainability" and the "sustainability of AI") and stresses the importance of integrating them. She notes that according to some authors AI has unfathomable potentials for mitigating climate crises, meeting other socio-economic challenges and, for instance, generating a 'sharing economy' that makes major contributions to a more sustainable future

(Flyverbom et al., 2019). However, she argues that this view fails to account for the environmental repercussions of AI's development (see also Crawford, 2021) in terms of the sustainability of the data sources, power supplies, and infrastructure involved, and hence needs to measure and reduce the carbon footprints of training or tuning the algorithms applied.

The Socio-technical Underpinnings: Datafication and Algorithmic Justice

Recent research outlines a plethora of socio-political and ethical concerns associated with the prevailing role of data and algorithms, despite the optimistic aspects of AI possibilities and implementation. Data-related challenges could arise even without AI. However, as noted by Taddeo and Floridi (2018), AI can exacerbate these challenges and risks. Specifically, technology is neither good nor bad, but not neutral either (Crawford, 2021; Lindgren & Holmström, 2020); it is political and embedded in social contexts (Crawford, 2021). In this discussion, Zuboff (2019) highlights that data should not be regarded as a technology, an inevitable effect of technology, or an autonomous process. Datasets are a form of power (Iliadis & Russo, 2016), originating in social (Zuboff, 2015) and cultural (Boyd & Crawford, 2012) contexts: data and algorithms are not cultural per se but are shaped by, and shape, culture (Seaver, 2017). Stemming from critical data studies, Iliadis and Russo (2016), in alignment with other scholars, argue that datasets are never 'raw' but always 'cooked'. Seaver (2017, p. 4) also describes these effects using the metaphor of a rock in a stream, which "*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). Similarly, data has an immanent instrumental nature (Hoffmann, 2019). In this dialogue, authors such as Sadowski (2019) and Crawford (2021) have noted and criticized the notion 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 reveals imperative considerations for current organizations' data extraction and ways to generate value from data. Consequently, concerns related to questions regarding "*how the data is produced, who owns it and what uses it can be put*" (Svensson & Poveda Guillén, 2020, p. 5) are not rhetorical but rather crucial concerns for AI management and governance. Adding to the critical discussion on AI landscapes, Lindgren and Holmström (2020) provide an interdisciplinary study and advocate an integrated view of AI management, encompassing social, historical, and political aspects, while underscoring the need to go beyond the materiality and code. In the socio-political sphere, the discourse is geared around datafication (Dignum, 2021; Sadowski, 2019), with conceptualizations of the degradation of democracy following the rise of the economic system called surveillance capitalism (Zuboff, 2019).

According to Flyverbom et al. (2019), the concept of datafication includes 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 defined and approached as a result of contemporary organizations' needs that go beyond extracting all relevant data, from all relevant sources and by all possible means, to production of data (Sadowski, 2019). Similarly, Iliadis and Russo (2016, p. 3) have introduced the concept of "data assemblages", as big data may encompass "*systems of thought, forms of knowledge, finance, political economy, governmentalities and legalities, materialities and infrastructures, practices, organizations and institutions, subjectivities and communities, places, and the marketplace where datasets are constituted*".

Additionally, issues related to ownership (Taddeo & Floridi, 2018), task delegation (Martin, 2019), erosion of privacy and security, transparency, (Günther et al., 2017; Vinuesa et al., 2020), agency and sovereignty (Mittelstadt, 2019), are emerging in the context of algorithms and applications (see Vinuesa et al., 2020). Interestingly, in an Orwellian scenario Zuboff (2015) describes this new form of information capitalism as translating human experiences into behavioral data. This enables agents of surveillance capitalism to not only know and foresee customer behavior (Flyverbom et al., 2019), but also to shape, affect, modify and manipulate it (Mittelstadt, 2019). An apt example is big nudging, i.e., use of big data analytics and AI to exploit psychological weaknesses and influence direct decisions (Vinuesa et al., 2020).

The literature also covers aspects of the socio-technical phenomenon of algorithmic biases, by highlighting ramifications of reproducing biases in the data used to train AI algorithms. Biases may be integrated into algorithms in different phases of operations or generated through "*incomplete, unrepresentative, and poorly selected input data*" (Kordzadeh et al. 2022, p. 3). This includes profiling and data-based discrimination towards less privileged groups, according to Eubanks (2018, p. 11), who refers to Automated Algorithmic Decision Making (AADM) as "*tools for digital poverty management*". These discriminatory effects of algorithmic decision-making on various (individual, group, and society) levels are described by Marjanovic et al. (2021) as 'algorithmic pollution' that lead to 'cumulative disadvantage'. A small but growing number of researchers counterbalance this view by recognizing the potentially anti-discriminatory effects of "algorithmic justice as a framework that (1) makes visible the injustices related to the "what", "who", and "how" of AADM in transformative services, and (2) provides further insights into how we might address and resolve these algorithmic injustices" (Marjanovic et al., 2022).

Emerging AI Ethics and Regulatory Concerns

Ethical frameworks and regulations intended to protect human rights also have crucial roles in AI management, with accompanying needs for organizational teams involved in deploying, designing, and developing AI to accept professional responsibility for its effects (Fjeld et al., 2020). The topicality of the discourse is clearly illustrated by increasing interest in these aspects since 2016 (Jobin et al., 2019; Mittelstadt et al., 2016). However, the problematization and ethical complexities reflect the absence of a universal practical regulatory framework to enforce ethical rules and principles (Jobin et al., 2019; Mittelstadt, 2019; Taddeo & Floridi, 2018). Furthermore, there is strong criticism of codification efforts, highlighting issues of vagueness in theoretical frameworks that promise action in principle, but in practice do not thoroughly address the normative and political tensions (Mittelstadt, 2019). In addition, Hagendorff (2020) notes both a need for engineers to consider ethical aspects in their decision-making and the limited potency of ethical guidelines and codes, which thus fail to transform the behavior and conceptions of professionals in the tech sector. These problems are multifaced and may derive partly from the absence of adequate education to enable developers and engineers to consider ethical issues robustly, but also from the lack of positive reinforcement from organizational structures and culture (Ibid.)

Another feature of AI that raises major ethical concerns is autonomy (Floridi et al., 2018), particularly in cases where we delegate substantial decision-making power to AI agents (Fjeld et al., 2020; Martin, 2019; Taddeo & Floridi, 2018). Some authors, such as Jobin et al. (2019), broaden the discussion by arguing that transparency and predictability can assist the acceptance of AI's autonomy and maintenance of a more desirable balance, partly through "*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). In contrast, others strongly emphasize a need for AI systems to be designed and implemented in ways that enable oversight of their operations (see, for example, Fjeld et al., 2020; Mittelstadt et al., 2016). Mittelstadt et al. (2016) also recognize an ethical need for a connection between data and accessible conclusions. Further, they show that lack of knowledge and understanding of the data being used, or the scope and amount of data used by ML systems, generates causal and principled constraints (Ibid.).

AI also has important socio-political implications for justice (Floridi et al., 2018). Research indicates that it can be used to eliminate instances of (social) discrimination and prevent dissemination of harmful results while enabling shared benefits (Floridi et al., 2018). As mentioned by Jobin et al. (2019), equality and fairness are also required for realization of justice. Nevertheless, to sustain realistic expectations, achieving complete fairness may not be feasible (Dignum, 2021), and thus as argued by Teodorescu et al. (2021), maintaining fairness requires balancing action between machines and humans as neither can ensure fairness alone.

Table 3 – Representation of Current AI Management Research Streams

Dimensions of AI management literature	Brief Description	Representative articles
Data Dimension	Discourse regarding effects, challenges and opportunities associated with (big) data in organizational contexts.	Aaen et al. (2022); Alaimo & Kallinikos (2021); Alaimo & Kallinikos (2022); Aversa et al. (2018); Baesens et al. (2016); Bhimani (2015); Chen et al. (2012); Constantiou & Kallinikos (2015); Glikson & Woolley (2020); Grover et al. (2018); Günther et al. (2017); Günther et al. (2022); Iliadis & Russo (2016); Kallinikos & Constantiou (2015); Kitchens et al. (2018); Loebbecke & Picot (2015); McAfee et. al. (2012); Mikalef et al. (2019); Parvinen et al. (2020); Pentland (2014); Schildt (2017); Shrestha et al. (2019); Wixom et al. (2021); Zeng & Glaister (2018)
Value Dimension	Discourse on the possibilities and limits of the transformative power of AI to generate business value and maximize firm performance.	Canhoto & Clear (2020); Coombs et al. (2020); Fountaine et al. (2019); Frick et al. (2021); Haefner et al. (2021); Hagiu & Wright (2020); Holmström (2022); Kakatkar et al. (2020); Kolbjørnsrud et al. (2017); Li et al. (2021); Rana et al. (2022); Rinta-Kahila et al. (2022); Von Krogh (2018); Wamba-Taguimdje et al. (2020)

Table 3 – Representation of Current AI Management Research Streams		
Dimensions of AI management literature	**Brief Description**	**Representative articles**
Labor Dimension	Discourse on AI-driven workforce transformation (e.g., job gain/loss, upskilling, deskilling, boundary change, decision-making) and new organizing logics.	Autor (2015); Benlian et al., (2022); Brynjolfsson & McAfee (2014); Brynjolfsson & McAfee (2017); Brynjolfsson & Mitchell (2017); Cram et al. (2022); Davenport et al. (2020); Faraj et al. (2018); Frey & Osborne (2017); Gal et al. (2020); Giermindl et al., (2022); Grace et al. (2018); Grønsund & Aanestad (2020); Huang et al. (2019); Huysman (2020); Jarrahi (2018); Jarrahi et al. (2021); Jarrahi et al. (2022); Kaplan (2016); Kellogg et al. (2020); Kelly (2017); Lee (2018); Lindebaum et al. (2020); Lyytinen et al. (2020); Makarius et al. (2020); Möhlmann (2021); Newlands (2021); Orlikowski & Scott (2016); Raisch & Krakowski (2021); Seeber et al. (2020); Seidel et al. (2018); Seidel et al. (2020); van den Broek (2021); Waardenburg et al. (2021); Waardenburg et al. (2022); Willcocks (2020); Wilson et al. (2017); Wood et al. (2019)
Critical Dimension	Discourse on the current dialogue of the impact of (big) data algorithms on social/cultural, political and ecological factors.	Boyd & Crawford (2012); Crawford (2021); Di Vaio et al. (2020); Dignum (2021); Dwivedi et al. (2021); Eubanks (2018); Fjeld et al. (2020); Floridi et al. (2018); Flyverbom et al. (2019); Hagendorff (2020); Hoffmann (2019); Jobin et al. (2019); Kordzadeh et al. (2022); Lindgren & Holmström (2020); Marjanovic et al.(2021); Marjanovic et al. (2022); Martin (2015); Martin (2019); McAfee et al., (2012); Mittelstadt et al. (2016); Mittelstadt (2019); Nishant et al. (2020); O'Neil (2016); Sadowski (2019); Svensson & Poveda Guillén (2020); Taddeo & Floridi (2018); Teodorescu et al. (2021); van Wynsberghe et al. (2021); Vinuesa et al. (2020); Wright & Schultz (2018); Wachter & Mittelstadt (2019); Zuboff (2019)

Discussion and Contributions

Current AI literature oscillates between utopian, hyped anticipation (Dwivedi et al., 2021; Willcocks, 2020) and dystopian rhetoric (Hagiu & Wright, 2020). Here, we extrapolate that, despite interest in AI from both researchers and practitioners, AI management research has mostly evolved in isolated sub-streams. However, neither the extremely optimistic nor postapocalyptic pessimistic contributions can provide pragmatic guidance for AI research and its management. In efforts to overcome the isolation barriers and move beyond the monochromatic black or white statements, we ascertain themes and dimensions that not only map the terrain of AI management, but also highlight the extreme scattering of the literature and thus a clear need for an integrated, holistic view (see Figure 2). This includes requirements for a socio-technical perspective to strengthen the comprehensiveness and cohesion of AI management literature by considering not only AI but also the individuals and societies involved (Sarker et al., 2019). We recognize the need to apply the socio-technical perspective (in accordance with fundamental premises of the IS discipline), and argue that it provides explanations of the interactions of social and technical components that enable progress beyond utopian and dystopian speculations regarding AI to more realistic views of AI management. Moreover, AI management theorists and practitioners need to consider equally the instrumentalist and humanistic implications of AI in all four of the identified dimensions. Specifically, researchers, managers and policy-makers need to recognize that behind the promised gains in efficiency and productivity associated with AI's rapid development and implementation lurk severe ethical and critical concerns for employees, society and the environment (Giermindl et al., 2022; Nishant et al., 2020; Sarker et al., 2019).

Our study provides a snapshot of current AI management research (see Jiang et al., 2019 on literature review) and thus conceptually contributes to the fervent and emerging discussion on AI management (see Berente et al., 2021; Crawford, 2021; Waardenburg et al., 2021) and calls for framing AI as an interdisciplinary phenomenon that requires researchers to move beyond idealized myths and nightmares (Benlian et al., 2022; Collins et al., 2021; Huysman 2020). The organized framework visualizes the iterative and interdependent relations between the dimensions of AI. As AI is fundamentally changing organizations and our society, the way we understand and manage its evolution will affect and determine the flux of developments, opportunities, and outcomes (Di Vaio et al., 2020).

To contribute to such awareness, we addressed the following research question: "What is the current state of the AI management literature?" in efforts to elucidate the evolution of the AI management 'terrain' and its current state through a SLR of recent AI management literature. Our findings show that analyses of four major AI management dimensions (data, labor, critical and value), are currently dispersed in the research literature. Echoing emerging arguments that AI management should not be perceived as a one-dimensional road or monolithic concept (Jarrahi et al., 2022; Kaplan and Haenlein, 2020), we argue that AI management dimensions must be collectively and iteratively considered, as demonstrated below, and that AI management should be treated as a multilevel process with multiple dimensions in both research and practice. In the following text we elaborate on implications for theory and practice, study constraints, and future research trajectories.

Theoretical Implications

This study provides insights that contribute to the emerging AI management discourse and answers recent calls for a comprehensive, holistic approach (Fosso Wamba et al., 2021), embracing a socio-technical perspective. First, our study expands and complements current literature and findings on AI management, as summarized in Table 4.

Table 4 – Representation of the Pervious Work on AI Management in Relation to Our Work

Comparison Element	Study Objectives/ Focus	Our work
Fosso Wamba et al. (2021)	To evaluate past and current 'AI for social good'.	Applies a socio-technical perspective and expands the discussion to AI management in organizations while referring to the impact on society and individuals.
Dwivedi et al. (2021)	Aspects of AI such as challenges, opportunities, and policies	Explores socio-technical aspects of AI beyond generally rather than a specific AI technology.
Di Vaio et al. (2020)	AI use and implementation in sustainable business models in the Asian fashion industry	Explores socio-technical aspects of AI generally rather than a specific AI technology with discussion of sustainability within the critical ecological dimension of AI.
Mariani et al. (2022)	AI in the marketing domain, consumer research and psychology. The authors identify eight clusters and 42 theoretical lenses. However, the discussion focuses largely on the role of big data in marketing.	We emphasize discussion within IS research. Our work moves beyond data, as data is considered only one of the multiple socio-technical dimensions of AI.
Zuiderwijk et al. (2021)	Findings regarding AI in public data governance identified in 26 articles.	Our findings are not constrained to one domain or industry.
McKinnel et al. (2019)	Research challenges and opportunities identified in AI literature related to penetration testing and system vulnerability assessment.	Our findings are not limited to a specific industry.
Toorajipour et al. (2021)	AI in supply chain management	Our findings are not limited to a specific industry.
Radhakrishnan et al. (2022)	AI facilitators, barriers, trends and strategies for AI adoption/ journeys.	We extend findings by addressing the underlying dimensions of AI management. The paper focuses on AI implementation, whereas we focus on overall views of AI management.
Collins et al. (2021)	Synopsis of current AI literature (emphasis on AI definition, methodology, AI functions, frequency of publications)	Expands the socio-technical view and emphasizes the key dimensions of managing AI.

The potential opportunities offered by AI have been hyperbolically depicted in recent literature (Borges et al., 2021). Similar hyperbolic views have also been expressed recently about big data (Yoo, 2015) and environmental aspects of AI (Di Vaio et al., 2020; Nishant et al., 2020). We have identified instances of data evangelists equating data with revolutionary technological change offering unlimited opportunities (Hagiu & Wright, 2020). However, our study also shows that although big data and algorithms provide unprecedented possibilities for strategy-making and competitive advantage (Parvinen et al., 2020; Willcocks, 2020), their realization depends on various other factors beyond the 'bigness' of the data, such as trust (Glikson & Woolley, 2020), understanding of AI systems' types of intelligence (Jarrahi et al., 2022), and workers' skills. We have followed scholars who treat data and AI as socio-technical phenomena (Berente et al., 2021; Crawford, 2021; Günther et al., 2017; Lindgren & Holmström, 2020) that can lead to either vicious or virtuous outcomes (Frey & Osborne, 2017). Thus, our work provides holistic and summative insights into the immense AI literature, seeking a balanced view of its value and how researchers should address associated challenges and opportunities. Our review also synthesizes findings regarding the labor dimension, weighing productivity, autonomy flexibility and efficiency against the 'dark side' of algorithmic control, and potential technostress (see e.g., Cram et al., 2022). By illuminating issues related to algorithmic leadership, we also add insights on "algorithmic management" literature (see Benlian et al., 2022; Möhlmann, 2021), presenting arguments from both sides to help efforts to understand how to exploit the opportunities while mitigating risks.

Our review also considers the critical, social, ethical, cultural and ecological factors that are crucial for managing AI successfully and generating value. We extend arguments that outline how AI can potentially promote equality, sustainability, transparency and explainability, but also note criticisms of 'datafication' and 'surveillance capitalism' (Svensson & Poveda Guillén, 2020; Zuboff, 2019) due to associated concerns regarding privacy, security and discrimination. To mitigate the risks, our review shows that researchers should be aware of the multiple dimensions of the AI phenomenon to shape the future research agenda by adopting a holistic view of AI management research, encompassing both societal and managerial concerns. Thus, for instance, researchers should focus on the balancing activities required to address issues related to AI's sustainability effectively and realize the potential of Responsible AI to contribute to sustainable development. We extrapolate that despite the progress made, for instance, in the potential contributions of AI to sustainability there is a need to move beyond technical issues and address more sociological, psychological and cultural aspects (see Bracarense et al., 2022; Nishant et al., 2020). Hence, AI management researchers need to more cohesively study both the social and technical implications.

Implications for Practice

Echoing an argument by Gélinas et al. (2022) that AI will have more practical relevance if it is aligned with practitioners' interests, we stress some essential practical implications of our review. First, by presenting an organized framework of the four key dimensions, we highlight the importance of managers, policy-makers and decision-makers considering and bridging elements of all four dimensions when organizing or formulating AI management strategies. Similarly, by depicting the fallacies and exaggerated expectations related to AI capabilities, we stress the importance of setting realistic expectations that reflect the opportunities and perils of AI, particularly those emerging in the wake of technological advances of Generative AI (GAI). For this our framework may be useful for evaluating and managing GAI's potential roles, and pitfalls, in decision-making within organizations.

To move beyond the myth, 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. Moving beyond the extreme poles and associated speculations may be crucial for informing and helping managers to improve the strategies for AI's adaptation, implementation and management. This may also contribute to understanding of the social-technical challenges and opportunities associated with AI. Since issues such as whether and when to implement an AI system are not merely technical but also have major managerial ramifications, emerging roles must be tailored to meet needs of both users and developers (Waardenburg et al., 2021). We also stress that as concerns about the prospects of a "good AI society" emerging are rising (Fosso Wamba et al., 2021), a social and technical perspective that considers the benefit of organizations, individuals and society is necessary to address the complex and emergent AI challenges. In particular, the findings reveal that the outcomes of implementing AI for different sets of stakeholders may vary enormously, so policy-makers must evaluate its value and responsibility accordingly.

Starting with data and its value, following previous authors, we recognize that datasets are created, and historically situated (Günther et al., 2022; Parvinen et al., 2020). Therefore, we argue that it is also important for managers and strategists to consider (in all stages) big data's contexts or social embeddedness (Martin, 2019) and associated factors while continuously and transparently experimenting with it (Pentland, 2014; Zeng & Glaister, 2018). The value of big data lies not only in the data itself but also the actions of managers and other agents (Zeng & Glaister, 2018). Thus, it is important for organizations to design realistic AI strategies and set feasible objectives for AI management by considering the sensitivity of the context. To mitigate concerns, and generate value while preserving trust, managers should also reflect on their professional responsibility, as well as skills and education to address emerging ethical and social concerns. For instance, managerial but ethically-laden questions related to agency, such as "Who has the responsibility?" and "Who owns data?" (see Svensson & Poveda Guillén, 2020) are constantly relevant and potentially complex but increasingly important.

Implications for the Asia-Pacific Region

This study has several implications for the Asia-Pacific region and the need to approach AI management holistically with a socio-technical perspective. First, our work aligns with emerging indications of needs to address aspects of social responsibility and sustainability concerns in Asian countries (Di Vaio, Hassan, D'Amore et al., 2022). Following a suggestion of the cited authors, who drew examples from the Asian fashion industry facing issues related to technological advances, we stress the need for researchers to investigate frameworks for Responsible AI in the specific contexts of Asian countries. Following a suggestion of the cited authors, who drew examples from the Asian fashion industry facing major issues related to technological advances, we stress the need for researchers to investigate frameworks for Responsible AI in the specific context of Asian countries, including diverse aspects that are important for addressing issues in complex contexts (Jiang et al., 2019). Such aspects that require further exploration include personal data protection, governance and regulatory frameworks, and standards for human-AI symbiosis. Accordingly, managers and policy-makers need to apply clear ethical frameworks and design sustainable business models for implementation of AI (see also Di Vaio et al., 2020). Our study also extends findings regarding the labor dimension, including both challenges and opportunities presented by AI. Following recent research, we pinpoint the importance of educating workforces not to fear and instead collaborate with AI. Although improvements have been made, for instance in the Indian context (see Gélinas et al., 2022), there is still a need to educate the workforce to obtain skills for successful and holistic AI management. Lastly, our work expands the discussion on data as well as the ethical aspects of AI, such as biases. As data are shaped by, and shape, the context, researchers and policy-makers who focus on the Asia-Pacific region should investigate how biases are formed and amplified in Asian countries.

Study Constraints

This study has some limitations inherent to methodology and the study scope (Collins et al., 2021; Okoli, 2015). First, limitations exist due to inclusion/ exclusion criteria and the search string used in selecting relevant articles. Specifically, we excluded search words (such as "digital transformation") after the pilot study. Although keywords as such seem relevant, they were not merely focusing on AI-related technologies and therefore they diverge the discussion. Future research could include different combinations of "digital transformation" keywords to broaden the discussion, and bridge these two research streams. Second, there is a natural bias that favors older publications as they tend to receive more citations. Also, although our study covers a broad spectrum of IS and management literature, we acknowledge that publication bias is one of the potential limitations. Specifically, we focus on a number of IS and management studies and highly cited books, excluding grey literature, non-IS outlets and IS conferences. Additionally, some publications have not been included in our analysis if they were not present in our selected databases, namely WoS, Scopus or Google Scholar. Lastly, we approach and interpret the results under the lens of a socio-technical perspective. Therefore, our research design is influenced and driven by the aim to identify studies that adhere to this perspective, and as a result it excludes work that emphasize on the technical artifact or merely the social parameters.

Future Research Directions

Several open avenues are worth noting for future research that addresses both opportunities and threats associated with AI management. First, the findings of our SLR and analysis clearly highlight needs for more socio-technically oriented research on AI management (Sarker et al., 2019). Embracing both social and technical perspectives in a synergistic manner is important for mitigating the perpetuation of myths, fears and extreme enthusiasm, which may lead to blinkered views of its management. We propose that future research, both empirical (e.g., case studies) and theoretically oriented, should embrace research methods, approaches, and theories in a manner that facilitates investigation of both sets of aspects. Application of the socio-technical perspective may also be crucial for countering the scattering of AI literature and providing robust foundations for cohesive, cumulative knowledge (Collins et al., 2021) in IS literature (Sarker et al., 2019).

In addition, our review highlights the possibilities offered by big data and the opportunities for generating value through data and algorithms, while acknowledging their 'dark side'. We suggest that future researchers should investigate the roles of data in the context of new technological frontiers. Important aspects here include the management of data content by GAI, potential unintended consequence of GAI implementation for organizations, employees and wider society, and the types of data management that are appropriate for capturing value from GAI without amplifying injustice.

Our findings also demonstrate a need to expand the discussion on the labor dimension and algorithmic management, which has been mainly studied in the context of platform-mediated gig work (Jarrahi et al., 2021). However, as we have started to witness the development of algorithmic management in more standard settings (Ibid.), we stress the need for future investigation of the phenomenon in more traditional settings, including the differences in challenges and opportunities for managers and workers. Hence, further attention to the dependence of the human-AI role on contextual factors is warranted to extend the discussion of Glikson and Woolley (2020), and the implications of 'algorithmic leadership' especially the associated impacts, risks and opportunities for humans and their organizational roles and identities (Jarrahi et al., 2021). In addition, our findings reveal a need for deeper understanding of critical AI landscapes, especially elements of the ethical dimension. Outlining this as a potential research avenue, we stress that further research is needed to identify the kinds of adaptability required in terms of education, leadership characteristics and skills. More interdisciplinary exploration of the required leadership abilities and organizational skills is needed to build on and extend insights into emerging roles provided by Kellogg et al. (2020) and Waardenburg et al. (2022), among others. This should include investigation of the skills that 'algorithmic brokers' need to implement ethical and Responsible AI in organizations.

Lastly, our findings indicate a nascent interest in AI governance (Papagiannidis et al., 2023; Schneider et al., 2023). However, the literature on AI governance and its relation to AI management is still in its infancy. Therefore, future research should unveil the socio-technical mechanisms and activities that constitute the building blocks of AI governance that can facilitate AI management. We regard AI management as the making and implementation of decisions related to AI and its uses, while AI governance refers to 'who' makes decisions. Thus, management is influenced by governance (Alhassan et al., 2016). Our comprehensive, integrated framework provides a first step towards adding AI governance to AI management literature, but further research is needed to characterize AI governance in relation to the four key dimensions of AI management and investigate their interplay.

Conclusion

This systematic literature review provides a structured view of and integrative approach to the evolving AI management literature, going beyond the pessimism and optimism of the current dominant discourses. To support a holistic view of AI management in research and practice, we adopted the socio-technical perspective when selecting articles to scrutinize, analyzing them, and synthesizing our findings. Through the identification of 109 articles out of 13,264 published in a 12-year period (2010-2022), four key dimensions (data, labor, critical, and value dimensions) emerged and we have considered them in relation to the hype and myth narratives associated with AI. Furthermore, from our findings we deduce that although the themes are interlinked, co-dependent and thus should be synergistically considered in AI management research and practice, they are still treated in isolation in the vast majority of published studies. The socio-technical perspective is still applied in very little research on AI. Hence this study contributes to the IS field by documenting the evolution of AI research, unpacking the cemented AI narratives, and providing an organized framework for applying this perspective in more holistic investigations.

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