Algorithmic Decision-Making Systems: A Conceptualization and Agenda for Green IS Research

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Abstract

Algorithmic decision-making systems (ADMSs), consisting of the two distinct but related concepts of artificial intelligence (AI) and big data analytics (BDA), represent the most current computing advances for decision-making. ADMSs are associated with significant opportunities and challenges in a wide range of high-impact application areas. However, the conceptual confusion around ADMSs limits information systems (IS) research in comprehensively studying them and their impacts within a clearly defined cumulative tradition. This literature review develops an inclusive conceptualization of ADMS through the ideas of AI and BDA to mitigate such shortcomings. The conceptualization of ADMS is inductively generated following a grounded theory approach used to analyze the content of 54 IS articles. The resulting conceptualization includes eleven key aspects representing the intricate socio-technical nature of current computing processes for decision-making. Lastly, a green IS research agenda is proposed to illustrate the applicability of the ADMS conceptualization to IS scholarship.

Keywords: Algorithmic decision-making, artificial intelligence, big data analytics, green IS

Introduction

Advances in algorithmic decision-making systems (ADMSs – Newell and Marabelli 2015), currently consisting of the two distinct but related concepts of artificial intelligence (AI) and big data analytics (BDA), herald unprecedented opportunities and challenges for high-impact application areas (Akter and Wamba 2016; Berente et al. 2021; Dwivedi et al. 2021; Marjanovic et al. 2021; Rana et al. 2021). ADMS, meaning information systems that collect, process, and analyze data through algorithms for the purpose of improving (data-driven) decisions, is an umbrella concept encompassing current computing advancements that inform, augment, and automate human decisions and actions to realize value (Grønsund and Aanestad 2020; Newell and Marabelli 2015). However, there exists confusion around ADMS and related terms such as "artificial intelligence" (Monett et al. 2020) and "big data analytics" (Favaretto et al. 2020), limiting their conceptual exploration and potentially threatening the identification and realization (/reduction) of their expected benefits (/drawbacks) given their complexity and breath (Akter and Wamba 2016; Collins et al. 2021). This lack of conceptual clarity undermines the capacity of the information systems (IS) community to (1) identify the key aspects of ADMS, (2) understand the intricate relationships among ADMS components and their contexts and the resulting outcomes, (3) comprehensively research key aspects of ADMS, and (4) build a cumulative tradition of knowledge under a clearly defined umbrella (Favaretto et al. 2020; Thorisson 2020). In other words, the lack of conceptual clarity poses a threat to content validity

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within IS scholarship and limits our ability to specify and test the nomological network of current computing advancements for decision-making (Podsakoff et al. 2016; Straub et al. 2004).

As definitions affect the way phenomena are studied, it appears highly advisable for the IS field to develop a definition of ADMS to guide future efforts. However, formal definitions tend only to capture relatively stable aspects of concepts, and it may be premature to restrict the intricate and moving computing advancements for decision-making to concise statements (Wang 2019). Formal definitions of ADMS, AI, and BDA could misrepresent their constantly evolving nature as a static concept soon to be outdated and exclude some of their key aspects due to their complexity and breath (Berente et al. 2021; Collins et al. 2021). The situation is thus contradictory: the IS field would profit from greater conceptual clarity around ADMS, but such a clarifying attempt could hinder our scholarly progress by misrepresenting the object of our research. "And yet, to study any phenomenon scientifically requires making some assumptions about that phenomenon [...]. How can this conundrum be addressed?" (Thorisson 2020, p. 7).

Instead of a penultimate definition, a working definition might be useful when there is no accepted standard for concepts (Wang 2019). Such a conceptualization of ADMS and its components would highlight their critical issues and key aspects, aim for comprehensiveness rather than conciseness, embrace their complex and integrative nature, and respect the need for future improvements and modifications (Thorisson 2020). It should also relate to the concepts' common usage, draw boundaries around them, represent their complex nature simply, and serve as a beacon for research (Wang 2019).

Providing the IS field with the key aspects of ADMS is critical for three reasons. First, data and algorithms in decision-making are multidisciplinary ideas as their opportunities and challenges span across a wide diversity of high-impact application areas such as economics, ethics, politics, business, science, technology, and society (Chen et al. 2012; Chen et al. 2016; Dwivedi et al. 2021). A conceptualization inspired by working definitions' properties would allow for a holistic approach to understanding ADMS' multidisciplinary computing processes and provide a flexible framework for collaboration within and between fields. Instead, the current conceptual confusion leads to each stakeholder working with their own understanding, which could complicate the design, development, and evaluation of desirable systems, global accumulation of knowledge, prediction and assessment of future impacts, establishment of goals, avoidance of misunderstanding based on false implicit assumptions, and interdisciplinary collaboration (Favaretto et al. 2020; Wang 2019). For instance, Raisch and Krakowski (2021) explain that the concept of AI is mainly framed and applied as automation in computer science, whereas social scientists essentially understand AI as an augmentative capability. With such narrow views of computing processes for decision-making and the inability to build upon automation's and augmentation's complementarities, Raisch and Krakowski (2021) suggest that we risk nourishing vicious cycles where humans become redundant and deskilled or where outcomes are biased, inconsistent, and unreliable. Similarly, whereas some consider big data as a lever for AI, others argue that understanding the training of intelligent machines as a function of data volume restricts their potential for solving novel tasks (Zhu et al. 2020). In sum, the efforts of the plethora of ADMS researchers will be of little avail unless we know precisely what we are targeting as a scientific community. Second, several authors report a lack of theoretically grounded research in ADMS as the focus primarily lies in problem-solving and technical solutions (Chen et al. 2016; Collins et al. 2021; Nishant et al. 2020). Given the ubiquity of digital technologies and their rate of change, there is a pressing need for innovative theorizing around ADMS for IS scholarship to demonstrate leadership and contribute to practice (Grover and Niederman 2021). As conceptual clarity is a central element of any theoretical work, clarifying the key aspects of ADMS and its components is central to knowledge progression and accumulation in IS (Rivard 2014). Third, extant research has mainly focused on the positive outcomes of data and algorithms and often embraced a technical perspective with little regard for human-related implications (Chen et al. 2016; Marjanovic et al. 2021; Raisch and Krakowski 2021; Rana et al. 2021). This highlights the need for a more comprehensive approach to studying ADMS, as our knowledge only pertains to specific aspects of these complex computing processes. The conceptualizations this paper aims to produce may help scientists broaden the scope of their investigations and better equip them to comprehensively study the relationships among ADMS' components and their contexts.

To recapitulate, this paper draws inspiration from the properties of working definitions to propose an inclusive conceptualization of ADMS to encourage a comprehensive and cumulative research tradition (Paré et al. 2015). To develop a conceptualization useful to IS scholarship, this paper takes the form of a theoretical literature review. More precisely, the IS literature is systematically reviewed in a concept-centric fashion (Webster and Watson 2002) to identify papers containing conceptual elements about AI and BDA (i.e., the current foundations of ADMS). By focusing on IS research that contributes to understanding these concepts, the review builds on 54 papers about ADMS that are subsequently coded following a grounded theory approach (Myers 2019). By iteratively generating and refining coded elements, the coding process highlights eleven interactive, key aspects that together form an inductive, non-restrictive conceptualization of ADMS. The conceptualization attempts to identify ADMS components, how they interact, and how they contribute to the emergence of outcomes.

To show the value of the conceptualization and its applicability to high-impact application areas, a green IS research agenda is elaborated. Green IS represents a relevant area to showcase how researchers can apply the conceptualization, as ADMS is among the most promising solutions to effectively deal with wicked problems such as environmental sustainability (Nishant et al. 2020; Song et al. 2017). However, these technological trends may also cause a decrease in environmental performance (Vinuesa et al. 2020), which highlights the need for a more balanced and comprehensive view of ADMS for sustainability. Because environmental sustainability has been described as wicked, it requires a wide variety of contributors for efficient mitigation and adaptation (Grundmann 2016), which renders the use of the conceptualization even more valuable in terms of capturing all the potential interactions between these intricate technological and environmental concepts. Lastly, similar to the AI and BDA areas, sound theoretical development about computing advancements for sustainability is scant but warranted to extend knowledge related to green IS solutions (Nishant et al. 2020). The rest of the paper describes extant research, presents the methodology and results, discusses each of ADMS' key aspects, and develops a green IS research agenda. The paper concludes with contributions and limitations.

Background

ADMS is a difficult construct to conceptualize considering its multidisciplinary, multifaceted nature and the use of various labels to describe it (e.g., "data-driven decision-making" - Giermindl et al. 2021). Despite this conceptual ambiguity, recent research consistently identifies two central components of ADMS: AI and BDA. However, AI and BDA are two concepts for which no definitional consensus exists, despite significant research interest (Favaretto et al. 2020; Monett et al. 2020). Of particular relevance, the literature review by Collins et al. (2021) provides a list of 28 distinct AI definitions within the IS field alone. Among these definitions, AI is understood in many different ways, such as a science, an engineering or design practice, human-like capabilities, a computer system, information technology, machine, or a collection of them, an algorithm, a process, and finally an agent. While the review by Collins et al. (2021) represents an excellent overview of the AI literature published in IS, it does not include an analysis of the AI definitions (nor BDA definitions), diminishing the overlap between their review and the present one. Similarly, IS research defines BDA in many ways: it has been described as a data set and related storage, management, analysis, and visualization technologies, a technique, a tool, a system, an application, a strategic or tactical initiative, an organizational capability, an asset, an industry, a process, an algorithm, an array of functions, and a managerial approach (Boldosova 2019; Božič and Dimovski 2019; Chen et al. 2015; Chen et al. 2012; Chiasson et al. 2018; Giermindl et al. 2021; Grover et al. 2018; Koch et al. 2021; Martin 2015; Mikalef and Krogstie 2020; Parmiggiani et al. 2022; Shi et al. 2022).

In addition to definitional plurality, ADMS is historically associated with different sets of technologies and applications. AI designates autonomous and self-improving machines (Berente et al. 2021) and includes technologies like machine learning, natural language processes, robots, various automation technologies, and rule-based expert systems (Benbya et al. 2021). BDA is associated with voluminous data, which is not necessarily a precondition for AI (Zhu et al. 2020), and refers to a wide range of processing and analytical technologies such as descriptive, predictive, and prescriptive analytics (Chen et al. 2021; Giermindl et al. 2021). Meaning, ADMS is an evolving concept representing the applications of advanced forms of computing to decision-making at a given point in time. Indeed, BDA has been branded as the "new frontier of data science" (Akter and Wamba 2016, p. 178) and the advances in data storage, management, analysis, and visualization required to match the ever-growing complexity and size of data (Chen et al. 2012). Similarly, AI is "the frontier of computational advancements that references human intelligence" (Berente et al. 2021, p. 1435) and "the culmination of a long tradition devoted to creating machine capabilities [...] equivalent to or better than human abilities" (Schuetz and Venkatesh 2020, p. 461).

In sum, we understand ADMS as an umbrella idea encompassing the most recent computing advancements (i.e., AI and BDA) applied to decision-making problems. This stance is aligned with our intention to clarify what ADMS is without restricting its intricate and moving nature to a concise statement, the apparent plurality of views about ADMS, and the wide range of concepts accumulating under AI and BDA. Framing AI and BDA as two components of ADMS advancements signals two things. First, despite the plurality of views about them, AI and BDA are ultimately related to informing, augmenting, and automating decisions and actions. Indeed, BDA is core to the cyclical generation, capture, and conversion of large and complex data into information and knowledge to facilitate informed decisions with predictions and/or causal inferences (Abbasi et al. 2016; Baesens et al. 2016). Similarly, "AI is fundamentally about making decisions" (Berente et al. 2021, p. 1435) with varying degrees of automation (Raisch and Krakowski 2021). Because of their ability to incorporate voluminous, complex data and make decisions autonomously, new computing processes for decision-making can be distinguished from conventional systems (Chen et al. 2012; Li et al. 2021). Second, although AI and BDA are not one and the same, they are related and interconnected computing concepts (Ågerfalk 2020). Regrouping AI and BDA under the ADMS banner makes sense as the merging of their capabilities is now increasingly recognized by researchers (e.g., Giermindl et al. 2021; Rana et al. 2021; Watson 2017). The two concepts are also interweaving in practice as BDA uses AI-related technologies such as machine learning to master the ever-increasing amount of complex data and inform decisions (Goes 2014). In sum, an algorithmic decision-making system (ADMS) refers to both AI and BDA.

Looking at AI and BDA as common categories for computing processes for decision-making highlights the importance of adopting a holistic approach when studying them and their impacts (Chen et al. 2016; Dwivedi et al. 2021). For instance, ADMS stresses the relevance of addressing the human and ethical aspects of data and algorithms to understand their imbrication within human-machine hybrid systems (Lyytinen et al. 2021) and the attribution of accountability for poor decisions (Marjanovic et al. 2021). Similarly, ADMS emphasizes the active role of AI and BDA within complex and high-impact processes in areas like economics, ethics, politics, business, science, technology, and society (Chen et al. 2012; Chen et al. 2016; Dwivedi et al. 2021). So far, research has mostly adopted a narrow perspective of AI and BDA by focusing on its technical aspects (Chen et al. 2016; Nishant et al. 2020) and positive outcomes (Rana et al. 2021). Such a focus could result in adverse consequences like an overly instrumental reality (Berente et al. 2021) and actions based on biased or inaccurately represented digital data leading to poor decisions with critical negative consequences (Clarke 2016; Giermindl et al. 2021; Marjanovic et al. 2021). There is therefore a need for the IS discipline to engage in a more comprehensive investigation of ADMS.

Methodology

This theoretical review follows a concept-centric approach (Webster and Watson 2002) to conceptualize ADMS, which refers to the collection, processing, and analysis of data by algorithms for the purpose of (data-driven) decisions. The review focuses on AI and BDA as its most central components. AI and BDA are represented via various means within extant research, such as through formal definitions (e.g., Collins et al. 2021), conceptualizations and theorizations (e.g., Marjanovic et al. 2021), operationalizations (e.g., Rana et al. 2021), descriptions of facets and dimensions (e.g., Berente et al. 2021), typologies (e.g., Benbya et al. 2021), and so on. Hence, the present review does not focus solely on conceptual papers; it aims to extract the conceptual elements embedded within the representations of AI and BDA regardless of their formality. That is, conceptual elements can be found within words, sentences, passages, tables, figures, etc. Extracting these elements in this way avoids restricting the inductive conceptualization process to formal definitions, which could limit ADMS to static and overly concise statements (Wang 2019). Conceptual elements capture the essence of the ADMS concept by focusing on the key aspects of its underlying computing processes and techniques (Thorisson 2020). Key aspects are defined as those that, if omitted, will negatively and significantly affect the way ADMS research is conducted and the progress of that research.

In February 2022, we searched the IS basket of eight (plus *MIS Quarterly Executive* because of its high-quality practice-based research) using Scopus (see Appendix A, available upon request). Scopus' coverage is excellent but not comprehensive, and a manual search was therefore conducted to cover missing periods for each journal. The recent literature review by Collins et al. (2021) was also included. While ADMS reaches beyond the boundaries of the IS field, this review focuses on top IS journals for two reasons. First, theoretical reviews should only include high-quality conceptual and theoretical research (Paré et al. 2015). Targeting journals considered of the highest caliber increases the likelihood of including high-quality conceptual elements in the review. Second, it is extremely challenging, if not impossible, to extract all the conceptual elements related to ADMS if one concentrates on all related fields. This comes as no surprise considering the number of areas affected by AI and BDA (Dwivedi et al. 2021) and the long history of these concepts (Chen et al. 2012; Collins et al. 2021). To illustrate, a topic search of "artificial intelligence" or "big data analytics" conducted on April 8, 2022 using Web of Science resulted in 93,735 papers.

The AI-related keywords were inspired by Keding (2021), who "deliberately excluded more specific search terms and used 'artificial intelligence', 'AI' and 'machine learning' as aggregated umbrellas, to keep the review focused on the general influence of AI [...] and to ensure a coherent synthesis of the articles" (p. 97). The BDA-related keywords followed the same principle: "big data" and "analytics" are umbrella terms (Chen et al. 2021) for more specific applications and types of voluminous and complex data set. The strategy of a recent review by Wiener et al. (2020) supports this approach. Hence, without any year restriction, the search string used for the search was as follows:

> TITLE-ABS-KEY("big data" OR analytics OR "artificial intelligence" OR AI OR "machine learning") AND SRCTITLE("Journal title")

In total, 363 articles were identified (see Figure 1). First, papers' titles, abstracts, and keywords were reviewed in combination with a quick manuscript scan when necessary: 92 papers were retained. At that stage, the sole inclusion criterion was that a paper focused on AI and/or BDA. Papers (1) using AI and/or BDA as methods while not providing insights about AI or BDA per se or (2) including AI and/or BDA in a broader set of technologies were excluded. The second screening stage corresponds to an in-depth analysis of each manuscript. It aimed to identify articles likely to provide conceptual elements. Conceptual elements are any contribution to what ADMS represents (i.e., not necessarily a precise and concise definition). Fifty-four papers containing conceptual elements were retained during this second stage.

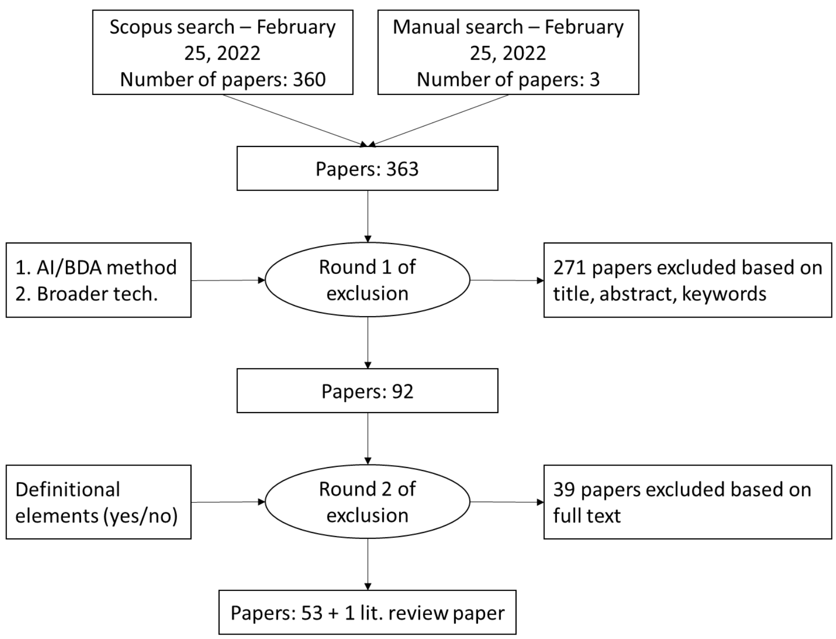

Figure 1 - Search process for ADMS conceptual elements

The coding of the conceptual elements is inspired by Curtis and Lehner (2019), who follow a qualitative content analysis approach to review and analyze the literature to define the sharing economy for sustainability. More precisely, the analysis of the 54 papers follows a data-driven approach falling under the grounded theory umbrella to inductively develop the conceptualization. Borrowing from grounded theory is appropriate for a theoretical review, which can organize existing knowledge to discover patterns and commonalities, leading to novel conceptual insights (Paré et al. 2015). As shown in table 1, the coding process started with open coding and then proceeded with axial coding (Myers 2019). Open coding is a descriptive attempt to understand the qualitative data and the first step in analyzing it. "Open codes are descriptive: that is, they identify, name, and categorize phenomena found in the text" (Myers 2019, p. 110). Hence, open coding happens directly in the text and uses words, sentences, and passages to identify categories. As the researcher constantly and iteratively compares the coded elements, the categories are refined and sub-categories start to emerge (Schreier 2012). Hence, similarities and differences are made salient and guide the definition of categories. Interpreting the categories and sub-categories and their respective properties is the second stage of grounded theory and is often referred to as axial coding (Myers 2019). The core categories resulting from axial coding represent the key aspects of AI and BDA (Thorisson 2020), which together form the conceptualization of computing advancements for decision-making. NVivo 12 was used to conduct the two qualitative analytical steps. As the review focuses on defining a concept rather than generating causal explanations, our process does not include theoretical coding. The review's final sample and the conceptual elements extracted from it are available from the authors upon request.

Table 1 – Illustration of the coding process

Passage example (underlines and superscripts added)	Codes	Key aspects
"Machines that learn <u>interact adaptively with their environment</u> [1, 2] while <u>increasing their capabilities through experience</u> [3]. [...] [They are] being <u>embedded in apps, news feeds, video streaming services, and email filters</u> [4]." (Lyytinen et al. 2021, p. 427)	1. Interaction [a] 2. Context [a] 3. Improve [b] 4. System [a]	a. Systemic nature b. Ambivalent regulation

Developing a Conceptualization of ADMS

Open coding started with AI-related conceptual elements and then transitioned to BDA. The qualitative analysis process resulted in 996 (AI: 548/ BDA: 448) coded pieces of data (i.e., words, sentences, and paragraphs). More precisely, the grounded theory approach generated 204 (AI: 79/ BDA: 125) different codes. During axial coding, these were aggregated into eleven categories (i.e., the key aspects of ADMS) by paying attention to their commonalities and dissimilarities and keeping ADMS as the core concern. While the AI and BDA data were coded separately, many nodes and categories were found to relate to both phenomena, indicating a strong link between them and the broader ADMS concept.

Figure 2 represents our ADMS conceptualization, the arrangement of its eleven key aspects (numbered from 1 to 11), and their interactions with their broader context (i.e., natural and artificial reality). Based on a socio-technical system logic (Leonardi 2012), our model attempts to support future efforts in (1) identifying the relevant aspects of the system under study, (2) reflecting on the intricate relationships within and beyond it, and (3) comprehensively exploring the emergence of outcomes by considering all the relevant connected elements. We use Uber as a running example to describe the model's flow as follows. Natural and artificial realities are to some extent mediated by technologies (Figure 2: 5), meaning the collection of data and the (un)faithful representation (Figure 2: 2) of empirical phenomena by algorithms (e.g., Uber relies on big data, analytics, and AI to represent the demand and supply within its market in real-time[2]). First, data (Figure 2: 5), and increasingly "big" data (Figure 2: 11), are collected via a connected infrastructure (e.g., drivers' and passengers' smartphones). This data representing objects, processes, and events is processed and analyzed via different functions (Figure 2: 7), such as descriptive, predictive, prescriptive, and autonomous analytics (Giermindl et al. 2021), executed by algorithms (Figure 2: 5) with various degrees of "intelligence" (Figure 2: 10). For instance, Uber now uses predictive analytics and machine learning to automatically improve passenger demand forecasting models and rely on computer vision to validate driver identities[2]. The technological mediation means that humans act based on direct interactions with the empirical world (e.g., a taxi driver picking up a passenger as (s)he drives by) and/or indirect, partially understood interactions with machines (Figure 2: 4), such as when Uber algorithms allocate drivers to passengers without them being aware of the inputs and processes behind that decision. Some machines also act autonomously (Figure 2: 9) without human supervision or collaboration (e.g., Uber algorithms autonomously setting fares). Hence, while human agents (Figure 2: 6) might contribute in important ways to value co-creation with algorithms (Lyytinen et al. 2021), some decisions are made either by humans or algorithms alone. These decisions (Figure 2: 8) generate more data and contribute to shaping natural and artificial realities (Figure 2: 2). For instance, Uber passengers evaluate their driver after a trip, which may impact their digital profile and how algorithms allocate them to passengers in the future. The new world

[2] Please refer to "Uber AI in 2019: Advancing Mobility with Artificial Intelligence," by Z. Ghahramani, 2019 (https://www.uber.com/en-CA/blog/uber-ai-blog-2019/?uclick_id=e04882de-ef4f-4756-a8eb-d46dcd763ae6).

states and associated data are used to improve algorithmic models with or without human supervision so that they can better reflect the reality they aim to represent and predict (Figure 2: 3). In sum, an ADMS is a complex, continuous arrangement of technological and social elements within which parts and "key aspects" are interrelated and interdependent (Figure 2: 1). The next sub-sections detail each key aspect.

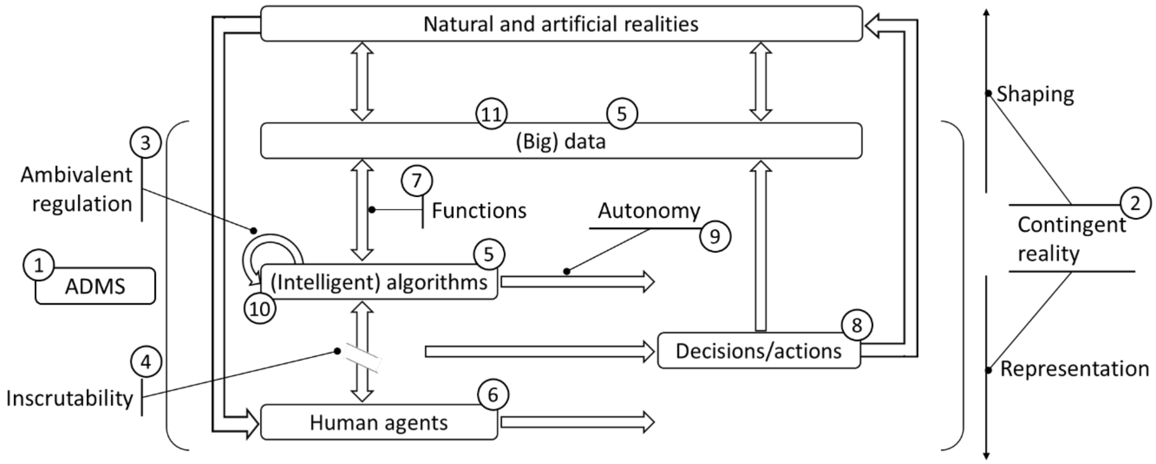

Figure 2 – Key aspects of algorithmic decision-making systems

Key Aspect 1: Systemic Nature

The first key aspect of ADMS is its systemic nature, meaning it can be best represented by a complex arrangement of technological and social elements within which parts are interrelated and interdependent. Computing advancements combine various elements such as techniques, technologies, applications, data sources, processes, people, contextual events, and rules that interact to inform, augment, and automate decisions and actions (Ågerfalk 2020; Božič and Dimovski 2019; Schuetz and Venkatesh 2020; Wixom et al. 2013). As put by Lehrer et al. (2018), the systemic aspect is at the core of ADMS' value proposition as it combines "digital artifacts that are part of a wider ecosystem, and they derive their utility from the functional relationships they maintain" (p. 447). These functional relationships are nourished by an ever-increasing amount of data points, forming a globally connected network supported by five major sources of data: enterprise systems, online social platforms, mobile, internet-of-things, and open/public data (Baesens et al. 2016). Together, these entry points communicate the digital traces of humans and machines interacting within connected networks and enable ADMS to capture and represent naturally occurring contextual events in real-time (Abbasi et al. 2016; Grover et al. 2020). While most ISs generate value by maintaining some form of relationship, the scope, speed, and intricacy of data points used by AI and BDA provide new potential alternatives for solving problems and set current ADMS advances apart from conventional systems (Božič and Dimovski 2019). These new data points and techniques also generate disruptions within their ecosystems, such as challenging organizations in their strategic approaches and pushing for their digital transformation (Constantiou and Kallinikos 2015; Koch et al. 2021), defining new industries (Martin 2015), changing the scope of digital products and services (Loebbecke and Picot 2015), creating new or extending existing discriminatory treatments of individuals (Newell and Marabelli 2015), and in some cases even replacing humans as machines become more skilled (Schuetz and Venkatesh 2020).

Computing advancements are not limited to receiving from their wider contexts without giving back: the relationships among ADMS processes and their contexts are reciprocal and mutually shaping. For instance, the evolution of data generation and data-related techniques, such as storage, management, analysis, and visualization, are intimately related and promote one another (Chen et al. 2012). Similarly, the cognitive capabilities of machines are driven by the growing availability of data and advances in software and hardware (Berente et al. 2021). Outside of the data, software, and hardware realm, the reciprocal exchanges take the form of socio-technical relationships where the cyclical process of converting data into augmented or automated actions generates additional data and leads to a self-referential loop within which computing processes influence and draw from their contexts continuously (Abbasi et al. 2016; Parmiggiani et al. 2022). This reciprocal evolutionary process is enhanced by recent advances in machines' cognitive abilities such as learning, perceiving, interacting, and decision-making that enable computing processes to perform functions formerly assigned to humans and to form metahuman systems where machines and humans complement and amplify one another (Lyytinen et al. 2021; Rai et al. 2019). These intelligent interactions with the world can occur without human awareness or knowledge, result in digital and material outcomes that further influence ADMS' surroundings, and happen in ways that were not possible before or even planned by designers (Aleksander 2004; Berente et al. 2021). However, ADMS' systemic nature also highlights that computing processes are ultimately governed by organizational, social, and institutional logics embedded into their core by designers and technological boundaries (Ågerfalk 2020; Sturm et al. 2021). In some cases, this human-related governance is blurry as computing processes can interact, adapt, learn, and increase their capabilities when interacting with other parts of their system (Lyytinen et al. 2021). In sum, ADMS' components are active agents within their broader contexts and the functional relationships they maintain are characterized by reciprocity and increased intensity and autonomy.

Key Aspect 2: Contingent Reality

Contingent reality states that computing processes are "not just representing an external reality; they are actively participating in and shaping reality" (Ågerfalk 2020, p. 6). In other words, human reality, and therefore their decisions and actions, depends on the (in)correct representation of data by computing processes. In some cases, human reality is entirely mediated by fully autonomous machines rather than partially mediated or augmented (Baskerville et al. 2020; Raisch and Krakowski 2021). As "the real world becomes a purposeful product of the digital world [and] [r]eality becomes a reflection of our models in the digital world" (Baskerville et al. 2020, p. 509), the omnipresence of (big) data generation and its continuous, invisible, and autonomous analysis increasingly manipulate our perceptions and behaviors (Zuboff 2015). To compute a representation of reality, ADMSs work inductively and their outcomes emerge from data (Asatiani et al. 2021; Berente et al. 2021; Rana et al. 2021). Hence, the quality of computing advancements' functioning and outputs and the accurate representation of our world are heavily dependent on the data generated by and collected through the many different parts of ADMS' ecosystem. In addition, algorithms can also lead to false or harmful representations of our world that may inform or automate actions with detrimental effects (Newell and Marabelli 2015). Considering the self-referential loop within which computing processes generate and draw from data continuously (Abbasi et al. 2016), errors and biases stemming from data and algorithms may generate ever-increasing and undetectable consequences (Kane et al. 2021). This can result in situations where the many stakeholders of decision-making processes operate in response to an inaccurate and unquestioned reality. This datafication process (Lycett 2013) of representing various phenomena through data may result in "unjustified, unfair, discriminatory, and other harmful effects of automated algorithmic decision-making for individuals, their families, groups of people, communities, organizations, sections of the population, and society at large" (Marjanovic et al. 2021, p. 404). Contingent reality also considers *how* we make decisions, as machine intelligence increasingly encourages instrumentally sound decisions rather than value-oriented ones (Berente et al. 2021).

Key Aspect 3: Ambivalent Regulation

Ambivalent regulation stipulates that computing processes evolve inductively through data and experience but only to a certain extent. Internally, intelligent ADMSs have the ability to learn and regulate themselves automatically (Berente et al. 2021). Intelligent machines possess the agency to change the rules under which they operate without any human involvement, but these modifications are governed by other rules created by humans operating within organizational, social, and institutional logics (Ågerfalk 2020). Hence, there exists a tension within intelligent computing processes between the notions of consciousness, directed at the machine's own internal functioning, and cognitive intelligence, determined and limited by predefined tasks (Aleksander 2004). On the outside, ambivalent regulation means that the evolution of both AI and BDA is shaped as much by their own computing processes as by the other parts of their ecosystem. Indeed, the systemic nature of ADMS states that its reciprocal exchanges with the broader context take the form of socio-technical relationships where the cyclical process of converting data into improved actions generates additional data and leads to a self-referential loop within which computing processes change and are changed by their contexts (Abbasi et al. 2016; Parmiggiani et al. 2022). Using existing data, algorithms inform, augment, and automate actions having an effect in the world (Jones 2019), which is captured back by AI and BDA's data points and continuously processed for self-improvement aligned with contextual conditions. However, as the automation of decision-making processes increases, computing processes become more (1) self-referential due to their reliance on historical data and the increasing absence of human intervention and (2) self-fulfilling as they shape their surroundings into self-affirming circles within which actions constantly align with predictions (Giermindl et al. 2021). To illustrate, predicting that a client isn't a good prospect may lead to neglecting them, and then to fewer purchases from them. As errors and biases can plague computing processes' self-referential loop and tarnish their value (Giermindl et al. 2021), recent work suggests that hybrid systems where humans and machines complement one another can regulate themselves better than those solely based on self-regulating technologies (Lyytinen et al. 2021).

Key Aspect 4: Inscrutability

The fourth key aspect is inscrutability, meaning that the complexity of ADMS advancements leads to difficulties in understanding, interpreting, and explaining (Asatiani et al. 2021). Inscrutability is an increasingly present aspect as ADMSs constantly grow in complexity. As explained by Berente et al. (2021), the inscrutability of AI is a product of the advances in autonomy and learning and is defined by four interdependent elements: opacity, transparency, explainability, and interpretability. What the four elements have in common is that the algorithm or the user is unable to make the process from data to action-taking clear and intelligible. As machines are gaining autonomy and changing in unexpected ways due to learning capabilities (Lyytinen et al. 2021), the mutual understanding of machines and humans is challenged by technological flux and is ever more elusive. In addition to intelligible challenges with algorithms, "[b]ig data now poses a challenge [...] in that it arises from wider configurations of information pools – past and present, structured and unstructured, formal and informal, social and economic, and which constantly evolve in their content and representation" (Bhimani 2015, p. 66). Due to the ever-increasing volume, velocity, and variety of big data sets, it becomes progressively more challenging for stakeholders dealing with emerging technologies to ascertain the reliability and validity of the computing processes' outputs (Müller et al. 2016). While there are ways to deal with unintelligibility, relying on inscrutable systems proves problematic as it can generate systematic and undetectable bias in decision-making (Kane et al. 2021; Marjanovic et al. 2021). In addition to these problems, humans face the explainability-accuracy tradeoff, where complex models are better at prediction but more difficult to interpret, which often results in relying on highly precise models despite not being able to identify and understand detrimental or faulty machine reasonings (Asatiani et al. 2021).

Key Aspect 5: Technology

Technology refers to two major blocks: data-related and algorithmic-related technologies. As explained by Grover et al. (2018), the data-related block is an infrastructure that "includes data sources (e.g., transactional, clickstream, social media, user-generated, external databases) and a platform needed for collecting, integrating, sharing, processing, storing, and managing big data" (p. 399). Hence, the data-related block includes advancements that emerged in response to novel "big" data generation technologies such as the ones falling under the SMACIT (i.e., social, mobile, analytics, cloud, and internet-of-things) acronym (Chen et al. 2012; Koch et al. 2021). However, analytical capabilities are truly what ties data to decisions (Goes 2014). The analytical capabilities, or the algorithmic-related block of ADMS, consist of advances focused on the "cognitive" aspects of computing processes and include technologies such as descriptive, predictive, prescriptive, and autonomous analytics (Giermindl et al. 2021). Autonomous systems relate to machine learning and its sub-classes, natural language processing, robots, automation technologies, and rule-based expert systems (Benbya et al. 2021). These technologies' core is the algorithmic performance of different functions relying on cognitive and behavioral human capabilities. Depending on their goals, these algorithms may learn through (un)supervised training and experience, identify patterns in data through processes that range from structured automation to mimicking the way the human brain functions, operate on data taking various formats, and result in physical and digital activities (Benbya et al. 2021). The relationship between the two technological blocks is shaped by ADMS' systemic nature, which stipulates that machines' cognitive capabilities are reciprocal to the advances in data, software, and hardware (Berente et al. 2021). Put differently, while each technology under the AI and BDA umbrellas is its own, it is their imbrication and interdependence that allow for the continuous growth of their scope and performance and the creation of specific competitive advantages.

Key Aspect 6: Human Agents

Despite their technological core, ADMS processes are part of a collaborative, mutually-shaping socio-technical practice within which humans and technologies interact (Parmiggiani et al. 2022). Therefore, the sixth key ADMS aspect is labeled "human agents." First, humans are seen as points of reference for intelligent computing. For instance, Lyytinen et al. (2021) explain that machines can learn in a manner similar to humans but with a different speed, scope, and scale. In addition, intelligent machines are also trained to act like humans (Rana et al. 2021). Hence, it seems that designers look at the human model and try replicating it within the artificial realm. However, some authors note that the human and machine models are, for now, two different concepts (Aleksander 2017). Second, similar to the idea of metahuman systems where humans and machines augment one another (Lyytinen et al. 2021), humans and ISs have been presented as complementary. From an organizational perspective, humans act as collaborators within the decision-making process considering the necessity of human knowledge and skills in creating value from data (Grover et al. 2018; Lebovitz et al. 2021). From a systemic viewpoint, the cyclical process through which computing processes create and capture changes in the world (Jones 2019) ultimately highlights the complementarity of the digital and physical in creating intended value for humans (Aleksander 2017). A simple representation of this is the generation of data by human activities, which is then fed into computing processes to benefit humans. Berente et al. (2021) also explain that cognitive computing can inform humans' decision-making processes, framing humans and machines as complementary actors.

Third, humans and machines can be controllers. To illustrate, this means that humans set up systems to address some specific problems with provided data and implemented algorithms (Sturm et al. 2021). This point is aligned with the conceptual element of ambivalent regulation: computing processes can auto-regulate, but "[t]he boundaries of such modifications are still managed by humans within technological, organisational and institutional frames" (Ågerfalk 2020, p. 5). Conversely, humans are controlled by intelligent computing as autonomous and intelligent machines slowly take over decisional processes and create their own self-affirming cycles (Giermindl et al. 2021). Fourth, humans and computing processes can be seen as competing, and humans may, in some cases, be superseded by them. Indeed, the "notions of emulating or outperforming humans remain presently at the center of discussions around AI" (Berente et al. 2021, p. 1435). In some cases, AI acts on behalf of humans and improves enough to take over tasks formally undertaken by them (Coombs et al. 2020). Lastly, humans are described as "in the dark" as per the key aspect of inscrutability defined above.

Key Aspect 7: Functions

The seventh key aspect is function, meaning the different activities computing processes undertake to inform, augment, and automate decision-making. For example, Benbya et al. (2021) present a typology of AI that includes conversational, biometric, algorithmic, and robotic functions. The conversational function refers to systems that understand and respond with natural human language under various formats. The biometric function captures physiological or behavioral data with identification, authentication, and security objectives. The algorithmic function is mostly based on machine learning algorithms with the intent to execute complex tasks such as classification, prediction, and recognition. Lastly, the robotic function takes physical shapes and performs tasks in the physical world. BDA has additional functions: descriptive, predictive, prescriptive, and autonomous (Giermindl et al. 2021). Descriptive functions examine past events and their influence on the present, predictive functions look for explanatory patterns to forecast the future, and prescriptive functions forecast future trends and make recommendations to decision-makers. Autonomous analytics, also called AI integrated business analytics (Rana et al. 2021), is distinguished from the other BDA functions as it can learn and act autonomously (Giermindl et al. 2021). Autonomous analytics is the combination of both AI and BDA within the same decision-making process. Similarly, conversational functions can be embedded into robotics to enable complex interactions between human and physical machine agents (Benbya et al. 2021). Hence, the unprecedented potential of ADMS processes comes from the emergence of new functions that build upon previously existing functions and the combination of functions to create new possibilities (Rana et al. 2021; Watson 2017).

Key Aspect 8: Decision-Making

The eighth key aspect is decision-making, stating that the ultimate objective of computing processes is to improve decisions and actions by informing, augmenting, or automating them. Decision-making is the key to understanding the role of computing processes within our organizations and societies (Berente et al. 2021). By supporting our decisions, data and algorithms demonstrate goal-oriented performance and fulfill their purpose of benefiting mankind (Aleksander 2017). The role of computing in decision-making is changing alongside its capabilities, as illustrated by the ongoing debates on replacing human labor with intelligent machines (Grønsund and Aanestad 2020). For instance, Giermindl et al. (2021) categorize descriptive and predictive functions under a "decision support" label, whereas they respectively frame prescriptive and autonomous analytical functions as "joint human-algorithm decision-making" and "automated decision-making." Similarly, Watson (2017) explains that the evolution of computing from decision support systems to cognitive systems changed its strategic importance, scope, focus, user base, management, complexity, governance, and value. Despite ADMS being an operational and strategic "capability that organizations could leverage to create cutting-edge knowledge in a dynamic environment" (Chen et al. 2015, p. 8), completely automating decision processes presents some risks and challenges. Indeed, human-led data and analytical strategies and interpretations are needed to transform data into valuable decision support (Grover et al. 2018; Lebovitz et al. 2021). As machines still need a defined purpose (Aleksander 2017), the strategic aspects of decision-making cannot be automated yet. Moreover, completely automating decisions can lead to a purely instrumental reality and create undetectable, self-reinforcing harmful effects (Berente et al. 2021; Marjanovic et al. 2021). Hence, despite AI and BDA besting humans for some tasks (Schuetz and Venkatesh 2020), the best decisions and actions may come from systems making the most of both human and computational capabilities (Lyytinen et al. 2021).

Key Aspect 9: Autonomy

The ninth key aspect is autonomy, meaning intelligent ADMS is a goal-oriented form of cognition where it displays flexibility by self-regulating and finding the optimal solution to the problem at hand (Berente et al. 2021). Autonomy relates to actions without human intervention. It explains with more precision how AI is restrained by some boundaries imposed by humans (Aleksander 2017) while retaining enough flexibility to drive decision-making and action-taking autonomously. As put by Sturm et al. (2021), autonomous ADMS "must be set up by humans: A specific real-world problem must be chosen, data need to be provided, and the learning algorithm must be implemented" (p. 1584). Hence, despite some form of autonomy, the possibility space of computing processes is ultimately governed by sets of rules set up by humans and their institutions (Ågerfalk 2020). These ideas are captured in concepts such as AI envelopment, which suggests "that, by controlling the training data carefully, appropriately choosing both input and output data, and specifying other boundary conditions mindfully, one may [...] erect a predictable envelope around the agent's virtual maneuvering space" (Asatiani et al. 2021, p. 327). Despite this potential for "enveloping" autonomous ADMS, the goals and tasks attributed to computing processes are increasingly similar to the ones humans pursue, which suggests that the boundaries of machines' autonomy are progressively blurred by new capabilities such as creativity and common sense (Rai et al. 2019; Schuetz and Venkatesh 2020; Zhu et al. 2020). This increasing autonomy can be associated with big data as we can now train machines to learn and act in new and innovative ways (Sturm et al. 2021). However, it has been suggested that the future of autonomy and learning lies with making technologies able to act autonomously without access to sufficient information (Zhu et al. 2020). Hence, despite being an aspect specific to AI, it is still unclear if and how autonomy relates to big data and analytics within the boundaries of ADMS processes.

Key Aspect 10: Intelligence

Intelligence is the tenth ADMS key aspect and is specific to AI. The intelligence of computing processes is often compared with human intelligence as machines can simulate human cognitive functions and their behaviors (Li et al. 2021). However, the debate about how close human and machine intelligence are is still ongoing and might influence the future of computing (Aleksander 2017). For instance, Wang's (2019) definition of intelligence emphasizes that to be intelligent, machines must be able to develop novel programs in response to changing contextual conditions and needs instead of effectively running predefined programs designed for specific goals and tasks (Thorisson 2020). This means that to be considered intelligent, machines must be conscious of their own internal mechanisms and capabilities to autonomously leverage them in accomplishing various and changing goals in contrast to cognitive or behavioral optimization in very specific conditions (Aleksander 2004). Zhu et al. (2020) further suggest that common sense, the capability of understanding how the physical and social worlds work that most human adults use to make rich inferences from limited information, would enable machines to evolve in a wide range of situations in spite of limited resources. Despite these debates about what intelligence means for machines, this aspect is central to defining ADMS and understanding its future. Thus, researchers developed ways to categorize or label machine intelligence. For instance, AI systems have been categorized into narrow intelligence, general intelligence, and superintelligence (Benbya et al. 2021). Other researchers explain that *human-like systems* (Schuetz and Venkatesh 2020) have cognitive capabilities usually associated with humans, such as "perceiving, reasoning, learning, interacting with the environment, problem-solving, decision-making, and even demonstrating creativity" (Rai et al. 2019, p. iii). Whether human imitation is a sign of machine intelligence is a hot debate. Nevertheless, despite not reaching a consensus about the nature of machine intelligence or its definition, researchers have identified different levels of capabilities helpful to categorizing and understanding "intelligent" ADMS systems.

Key Aspect 11: (Big) Data

Big data refers to "an all-encompassing term for collections of data sets with appreciable levels of size and complexity" (Chen et al. 2015, p. 8). Hence, big data is associated with characteristics like high volume, velocity, and variety (Goes 2014). The role of big data in ADMS is central and explicit: analytics is a data-centric approach encompassing data storage, management, analysis, and visualization, for which the evolution is intimately connected to that of increasingly large and complex data sets (Chen et al. 2012). The role of big data in AI is less straightforward. While data has been at the core of developing intelligent machines that learn and act autonomously (Sturm et al. 2021), the necessity to rely on "big" data was recently questioned. For instance, Zhu et al. (2020) explain that the reliance on big data sets to train AI for narrow tasks restrains its development to the availability of sufficient data. They therefore propose that the future of AI lies within the "small data for big tasks" paradigm, wherein AI uses common sense to deal with various tasks despite limited information. This view is important for the future of ADMS since the world machines evolve in "presents novelty at every turn that must be dealt with on-demand," which creates a constant lack of knowledge (Thorisson 2020, p. 8). In sum, AI and BDA are both technological and data-related processes as per the key aspect of "technology" that they share, but as the next advancements in machine intelligence take shape, "big" and "small" data might both become key to ADMS.

Summary: Conceptualization and Interdependence

ADMS, currently consisting of the two distinct but related concepts of AI and BDA, is characterized by a set of eleven key aspects expected to significantly affect the progress of research. Each aspect is relevant to fully grasping computing processes for decision-making and their impacts. To comprehensively study ADMS, researchers should understand it as increasingly complex, inscrutable, interrelated, and interdependent socio-technical arrangements of somewhat autonomous, intelligent technologically-enabled analytical functions and human capabilities that describe, predict, and shape (big) data to inform, augment, and automate decisions and actions with an impact on the world. The conceptualization is intended to support the development of a more inclusive field of study around ADMS. For example, researchers may use the eleven key aspects to identify poorly understood issues of various high-impact application areas, theorize the interactions among ADMS components and their contexts with a better awareness of their nomological network, and formulate recommendations addressing all the aspects affected by their subject of study.

The conceptualization highlights the importance of the inter-relations among the eleven key aspects, as per ADMS' systemic nature. Focusing on a specific key aspect, or relationship, without consideration for other important mechanisms could lead to limitations in explaining the emergence of ADMS outcomes. For instance, when studying machine learning performance, focusing on data, algorithms, and models without consideration for the faithfulness of the computed representation of the world and its subsequent shaping of reality (i.e., contingent reality) could lead to an overemphasis on standard AI accuracy measures that do not capture the ambiguity of many human decisions (Lebovitz et al. 2021). This focus on the technical aspects of ADMSs may lead to a narrow evaluation of their consequences and results in the faulty conclusion that algorithms perform better than humans and improve high-impact processes without any adverse effects. Another relevant example is the study of human-machine collaboration, where both parties complement and amplify one another (Lyytinen et al. 2021). While humans and machines possess complementary knowledge and capabilities, focusing on humans, technologies, their characteristics, and the resulting decisions without consideration for the continuous co-adaptation of ADMS components (i.e., systemic nature, contingent reality, and ambivalent regulation) may lead to overlooking important evolutionary traits such as dependency effects and loss of unique human knowledge (Berente et al. 2021). Overlooking these key aspects conceals critical questions like: "[a]s the frontier of machine autonomy expands, do humans lose their autonomy and their ability to effectively augment those machines?" (Berente et al. 2021, p. 1440). It is only by comprehensively studying ADMS components, logics, and dynamics that we may address such worrisome possibilities. Below, we use green IS as a case to more concretely illustrate the importance of comprehensively studying ADMSs and propose a research agenda for green ADMS.

Setting an ADMS Research Agenda: The Case of Green IS

This section focuses on green IS as a relevant area to showcase how the conceptualization can guide future research efforts. Environmental sustainability research in IS is concerned with addressing technologies' adverse environmental impacts and/or developing new sustainable solutions using them. What we know about ADMS for sustainability primarily concerns its technical aspects (Nishant et al. 2020). Extant research was thus effective in showing the potential for ADMS to (1) generate new sustainable solutions based on emerging patterns and advanced algorithmic models and (2) objectively and autonomously implement effective environmental governance (Nishant et al. 2020; Song et al. 2017). This technical focus also led to important insights into how ADMS may cause a decrease in environmental performance considering its resource-intensive nature (Vinuesa et al. 2020). Such research enabled significant efficiency improvements in storage, networking, infrastructure, virtualization, modeling, and so on (Kaack et al. 2022). In sum, most of what we know about ADMS for sustainability pertains to only three key aspects: function, (big) data, and technology. This narrow ADMS conceptualization undermines our ability to identify and explain the important dimensions of sustainable decision-making, their interactions, and the emergence of outcomes. We now build upon what we still do not know about ADMS for sustainability to propose two research questions and show how they can be addressed using the ADMS conceptualization.

Research question 1: What is the net environmental impact of ADMSs?

With the focus on ADMS functions, technologies, and data, extant research mostly conducted artificial evaluations of ADMS with few considerations for its natural effects. However, ADMS is inherently socio-technical, meaning that artificial and natural performances are required for the emergence of expected outcomes (Nishant et al. 2020). A great example of this is rebound effects, referring to increased algorithmic environmental performance paradoxically followed by lower systemic sustainability (Kaack et al. 2022). Rebound effects in green ADMS contexts can take three forms: (1) the carbon footprint of ADMSs, (2) greater ADMS resource efficiency encouraging greater use of ADMSs, and (3) unforeseen human behavioral responses. The first type is covered by extant research focusing on ADMS' technical efficiency. The second and third types, however, cannot be addressed using current conceptualizations of ADMS for sustainability. The second type highlights the emergence of outcomes at the system level where greater environmental efficiency encourages greater use, leading to greater total emissions (Kaack et al. 2022). By focusing on efficiency and marginal effects, research may inadvertently encourage greater pollution. To fully address the above question, researchers must consider ADMS' systemic nature, which emphasizes how new, disruptive computing processes transform industries, organizations, products, and services. By highlighting the broader impacts of ADMS efficiency gains, systemic nature encourages a greater focus on how rebound effects materialize through the transformation of consumer preferences, organizational processes, and institutions (Nishant et al. 2020). In sum, systemic nature addresses the above question by clarifying the paradox between greater ADMS efficiency and the expansion of a resource-intensive decision model. The third type of rebound effect also falls outside of artificial evaluation and concerns individual responses to ADMS. Even if highly accurate and efficient, ADMSs might not generate the intended behaviors within humans (Leonardi 2012). Two key aspects are particularly relevant in exploring the gap between the designed sustainable actions and the actual behaviors: inscrutability and humans. The first refers to a poor understanding between humans and machines responsible for lack of collaborative performance and the second highlights the importance of the social dimensions of human behaviors (Berente et al. 2021). As such, our conceptualization encourages researchers to leverage "environmental psychology and sociology perspectives, as understanding the psychological and sociological underpinnings of human response is necessary for effective long-term solutions" (Nishant et al. 2020, p. 9).

Research question 2: To what extent can we rely on ADMSs for sustainable decision-making?

One central assumption of current ADMS research can be summed up as "the more data, the better" (Zhu et al. 2020) as ADMS performance is intimately related to the availability of growing volumes and formats of continuously produced data sets (Berente et al. 2021). Thus, increased access to behavioral, economic, hydrogeological, meteorological, and environmental surveillance data is presumed to increase the benefits of augmented/automated environmental management (Song et al. 2017). However, these arguments omit the complex social and technical systemic nature of ADMS, meaning that the ADMS is itself part of a broader context that might be poorly captured because of partial or biased data. Put differently, unavailable data causing representational biases may lead to the computation of poor global environmental assessments (Marjanovic et al. 2021). A practical example of this is the management of e-waste, where domestic data in rich countries enable informed policies showing increases in e-waste recycling, but limit our understanding of the transboundary movements of e-waste from rich to low-income countries and the consequences of hardware exportation and recycling in low-income countries due to a lack of data coverage (Forti et al. 2020). By operating using a partial picture of e-waste management, ADMSs rely on an incomprehensible representation of global pollution, and the decisions taken omit the inferior conditions and severe health issues that toxic e-waste recycling creates within low-income communities. Researchers and decision-makers need to take into account the contingent reality key aspect of ADMS, meaning carefully consider (1) how the ADMS broader environment is represented by data and algorithms and (2) the consequences of the gaps existing between the real world and its digitized representation. In the case of e-waste management, contingent reality indicates that these representational limitations are associated with data coverage and agency problems as algorithmic logics benefit some actors by omitting others. These representational gaps shape a reality where some parts of the world better manage their localized environmental performance, and other regions become environmental catastrophes. Green IS researchers must explore ways to improve the representational capabilities of ADMSs and explore with more care the resulting shaping of our world. For instance, future efforts could study how the direct contacts that humans cultivate with the world can be better integrated within ADMSs, the consequences of increased automation of environmental management based on partial empirical representations, and how inscrutability may lead to decision-makers being unable to understand the states of the world and their decisions' impacts.

Concluding Remarks

This literature review is motivated by the lack of conceptual clarity around the algorithmic decision-making system (ADMS) concept. It follows a grounded theory approach to analyze the IS literature and propose a conceptualization of ADMS. The resulting eleven key aspects are then used to propose a green IS research agenda, aimed at demonstrating the usefulness of the conceptualization and providing avenues for future research. Hence, this review contributes to the capacity of the IS community to (1) identify the key aspects of computing processes for decision-making, (2) understand the relationships among ADMS' key aspects and their contexts and the resulting positive (/adverse) consequences, (3) comprehensively research relevant aspects of ADMS, and (4) build a cumulative tradition of knowledge under a more inclusive umbrella. By inductively generating eleven key aspects of most current computing advancements for decision-making, this review relates to the common usage of the ADMS concepts, clarifies its boundaries, encourages and guides future inclusive research efforts, and represents the intricate nature of current computing advancements. Furthermore, the present work can be used as a starting point for conceptualizing future advancements in computing.

In spite of these contributions, the present work presents some limitations. First, because the search focused on the major IS journals, the literature was not covered comprehensively. Other aspects of ADMS may exist in other literature streams. As the paper proposes a flexible conceptualization rather than a penultimate one, future research could improve our work as more research streams are considered or as computing continues to evolve. Second, the coding of the sample was conducted by the leading author of this paper only. While the conceptualization resulted from both authors' efforts and was debated with colleagues during seminar presentations, the review could benefit from additional coders' perspectives.

It is hoped that this research will motivate a more thorough and balanced exploration of the evolving computing advancements. As indicated by recent green IS research, technologies have the potential to create solutions as well as issues, and this must inform our reflections (Nishant et al. 2020).

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*: Used to identify papers included in the reviewed sample.