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Evaluation of the Algorithmic Decision Making in healthcare and public administration areas - A systematic literature review

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***Abstract*—** The rapid changes in the fields of artificial intelligence (AI) and big data analytics have transformed an algorithmic decision-making system (ADMS) with considerable uses in the government sector and the medical field. Nevertheless, there is growing interest in the literature on ADMS that is still scattered across disciplines and offers conflicting findings regarding its effectiveness. The socio-technical relationship of ADMS, the ethical issues, and organizational impact are complex, yet they are not comprehensively studied, even though the use of ADMS grows. The study will provide a thorough review of the literature that will bring together interdisciplinary viewpoints on the creation, adoption, and impacts of ADMS in these essential sectors. The paper integrates both empirical and theoretical sources to explain such key considerations that affect algorithmic judgments, including accuracy, fairness, transparency, human oversight, and governance systems, based on a comprehensive search and rigorous selection process. The findings provide inconsistency in efficiency gains, transfer of power, and dehumanization-anthropomorphism dialectic in the organizational setting, which presents significant contradictions between technological efficacy and socio-ethical issues. The paper focuses on the need to have balanced approaches to ensure that human agency is safeguarded as algorithmic abilities are used, extending theoretical concepts of fairness beyond measures of accuracy to consider equity and legitimacy. This synthesis is informative of future research activities focused on conducting empirical validation, assessing harm, adaptive governance, and inclusive design. Ultimately, the work contributes to the understanding of the interdisciplinary character of ADMS and gives essential guidance towards moral, accountable, and just algorithmic decision-making in high-stakes areas.

Keywords: Automation Decision-making, Algorithmic decision making, healthcare, public administration, Algorithm aversion

I. INTRODUCTION:

Individuals and organizations can now turn to algorithmic decisions due to the continued sophistication of digital technology, the booming growth of big data analytics, and the continued development of artificial intelligence (AI) technologies such as machine learning (ML) and natural language processing. Nowadays, algorithms are becoming applicable to decision-making in various scenarios, both objective and associated with subjective decision-making [1].

Algorithms have an effect on our daily lives. It can be what music to listen to [2], where to eat supper [3], or what we believe we like to do, as evidenced by our browsing history [4].

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Algorithms are widely applied to derive information out of so-called big data and advance decision-making in various segments, such as financial markets [5], traffic management [6], and surveillance [7]. In recent times, natural language generation (NLG) systems, including the Generative Pre-trained Transformer 3 model (also known as GPT-3), have created a new field of human-algorithm communication [8].

[9] describe ADMS as information systems that collect, process, and analyze data based on algorithms to enhance (data-driven) decisions. ADMS is the general concept, and it incorporates the existing computing technologies that inform, augment, and automate human decision-making and acting so as to create value. There is a need to deliver the fundamental elements of ADMS to the different regions. Decision-making data and algorithms are interdisciplinary concepts due to their presentation of opportunities and challenges across a broad field of high-impact areas of application, such as business, science, technology, ethics, politics, economics, and society [10].

ADMS is by nature such a complicated and transdisciplinary phenomenon that it is difficult to imagine the concept [11]. However, this conceptual ambiguity was regularly solved by recent studies, which pointed out AI and BDA as the two primary components of ADMS. There are a number of technologies and applications that have been associated with ADMS in the past. AI means those devices that are self-reliant and self-enhancing [12]. It includes many automation technologies, robotics, machine learning, natural language processing, and rule-based expert systems [13]. BDA is characterized by a wide range of processing and analytics techniques, such as descriptive, predictive/prescriptive analytics [14], [11]. It is associated with massive data, which is not necessarily a requirement of AI [15]. Stated differently, ADMS is an emerging concept that explains the application of advanced methods of computer technology in making decisions at a given time. Actually, BDA has been called the new frontier of data science [16], and the volume and complexity of data must continue to increase to deliver data management, storage, analysis, and visualization [17]. Similarly, AI is the culmination of the long tradition of building machine capabilities at least comparable to those of human beings [18] and the border point of computational innovations that refer to human capabilities [12].

Altogether, ADMS is a very generalized concept that uses the most recent advances in computers (AI and BDA) to the decision-making problems. This stance aligns with the definition of ADMS without reducing its complexity and dynamism into a concise statement, the apparent multiplicity of views regarding ADMS, and the sheer number of ideas spawned under AI and BDA. Although there seem to be some differences in views, the fact that both AI and BDA are considered as two aspects of ADMS developments suggests that the two are eventually linked to informing, improving, and automating the process of decisions and activities. [19] and [20] state that BDA helps in the process of cyclical development, collection, and transformation of big and complex data to information and knowledge to make informed decisions through predictions and/or causal conclusions. On the same note, at varying degrees of automation, the point of AI is essentially about decision-making [12], [21]. The ability to combine extensive volumes of complex data and arrive at decisions independently allows distinguishing between new computer-based approaches to decision-making and old systems [17], [22].

Although different, AI and BDA are connected concepts of computers [23]. This fact is an adequate reason to unite AI and BDA within the umbrella of ADMS, as researchers are becoming more aware of how their expertise can be integrated [11], [24]. As a matter of fact, both concepts are also inseparable as BDA employs AI-related technologies, such as machine learning, to process the constantly increasing amount of complex data and make decisions. Finally, an ADMS has both AI and BDA [25].

Most studies only take into account potential benefits, which is not enough to make informed decisions about implementation [26]. The manner in which these numerous levels relate and impact one another is missing because ADM studies may focus on one of the levels. This responds to the need to consider ADM as a moving phenomenon that sees a larger picture and moves beyond the point of decision-making [27].

On the other hand, research studies that focus on damages commonly do not provide homogeneous operationalization in the measurements of harm; hence, it cannot be claimed to make the necessary assertions regarding non-maleficence. Based on previous technological research, benefits as well as harm evaluation of implementation possibilities should comply with accepted standards [28].

To achieve this, the rationale of the current research is to provide an overview of the literature, which specifically covers the topic of ADM within the framework of public administration and healthcare.

II. LITERATURE REVIEW:

LGORITHMS AND ADM

Gillespie [29] defines an algorithm as a system of coded instructions to convert input data into a desired result, according to some specified calculations. This paper assumes that an algorithm is an automated procedure that passes judgment without the support of a human being, and it is the same assumption made by Araujo et al. [30]. Data, statistics, and/or computational power are used by algorithms to make judgments. Algorithms have to rely on statistical methods, such as regression analysis, primarily when making a judgment [30].

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However, in recent years, algorithms have been improved with AI, which can be described as a system capable of identifying, interpreting, drawing conclusions, and learning based on the available data to subsequently meet the goals established by the organization and society [31]. It is due to this development that algorithms can learn throughout their lifetime by using data to detect patterns and enhance decision-making.

Algorithms and digital technologies may fully duplicate and substitute human judgment or serve as an aid in decision-making. As Araujo et al. [30] indicated, there are various procedures associated with ADM in a broad range of circumstances, such as the tools used by human decision-makers, to entirely automated decision-making systems. The four major stages of the routine decision-making process would be similar to ADM processes. Automation technology can be used in one or more of these phases. The four stages include the following: Information acquisition, followed by information analysis. Then decision selection, which is done by assessing the decisions and ranking them according to the information at hand, to decide on the best course of action. Finally, the decision implementation was a process, but it consisted of communicating the decision and implementing it into the practice [32], [33].

ALGORITHMIC DECISION-MAKING IN HEALTHCARE

Increasingly, individuals believe that machine learning is one of the technologies that could revolutionize the field of medicine. Recent studies with so-called expert-level accuracy of machine learning algorithms, including diagnosing eye diseases using fundus images [34], and different types of skin cancer using the images of skin lesions [35], have recently ignited a frenzy of attention to machine learning about medical decision-making [35], [36]. Healthcare applications of the algorithms are used in treatment, imaging, diagnostics, and surgery [37]. Robo-advisors make investment decisions [38].

Moreover, Walsh et al. [39] found that machine learning models could outperform the accuracy in predicting the probability of a suicide attempt based on a large data set of clinical electronic health data. Conversely, doctors have, over the decades, failed to foresee suicide attempts. Thus, by assessing the health risks of the individual patients on the basis of the complex diagnostic data sets, machine learning algorithms will enhance the diagnostic and forecasting capabilities of the physicians. Besides, a current shift in medicine toward prevention over curing can be exacerbated by the ability of machine learning algorithms to predict [40].

Many of the things that doctors do daily involve making good decisions. Within a limited duration, they need to diagnose diseases correctly with limited information and decide in the most favorable way for the patient. These activities are well-trained activities of clinicians. During their careers, some of them have diagnosed and treated five hundred patients after spending years of training. Medical diagnosis is a complex method of diagnosis, which is the gold standard [40].

The dermatologists in the study conducted by Esteva et al. [35] were forced to make their decisions according to a slide of clinical photographs within a relatively limited period of time. The experiment compared the use of machine learning algorithms with that of dermatologists to classify skin cancer. In the context of a more realistic scenario, it might be fair to assume that the dermatologist would consider other sources of information and that her diagnosis would not be done in one case. The findings indicated that Deep Convolutional Neural Networks could distinguish between skin cancer with the same degree of accuracy as dermatologists, being better in both tasks than all the assessed professionals. Deep neural networks in mobile devices can help expand the out-of-clinic scope of dermatologists [35].

However, inaccuracy in diagnoses remains a rather common phenomenon in the medical profession. A National Academy of Sciences estimate indicates that roughly 5 percent of persons who consult medical assistance in the US commit diagnostic errors. Also, it is estimated that 1 out of every 10 people dies because of the relevant diagnostic errors. Diagnostic errors happen for several reasons. The case of medical diagnosis, e.g., cannot help but involve different levels of ambiguity. Because a doctor has to be able to test multiple possibilities to arrive at a medical diagnosis, full certainty is not possible. Moreover, some medical practices and procedures for collecting information pose risks to the health of the patient, which should be considered. Also, one of the frequent issues for physicians is time restrictions. It might lack time to adequately assess all data involved because some of the illnesses require immediate treatment [40].

Given such epistemic and structural constraints, it is easy to see how machine learning algorithms can enhance therapists' decision-making capabilities. At least theoretically, the algorithm can be less susceptible to cognitive bias than its human counterpart, and it can be able to process complex quantities of data faster when arriving at a diagnosis. Consequently, the algorithm could provide the physician with an additional information source, which will allow her to make an informed decision. Doctors, however, face challenges when trying to draw out information from what a machine learning system provides.

The basic problem in the case can be described as follows: both the machine learning algorithm and the doctor can be considered experts, somehow. They have, however, been trained differently and have significantly different modes of thinking. This would pose a challenge to the physician when we consider the cases of disagreement between peers [41]– [43]. Peer-disagreement, in this situation, can be defined as cases

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when two (equally) competent peers disagree over a given proposition on a given domain-related activity [40].

ALGORITHMIC DECISION MAKING IN PUBLIC ADMINISTRATION

Public servants have numerous decisions to make on the various subject areas of public services daily, which ultimately affect the living standards of the residents, companies, and individuals. The examples of such decisions are taxation, various benefits, and licenses. These decisions require enormous administrative systems, and they are founded on legislation and administrative regulations. Decision-making in this context is challenging because of formalized roles (who makes the decisions and sets criteria), decision-making procedures (how decisions are made), consultation, and information structures (who must be consulted and informed), specification of data and information sources, formalized decision-making criteria, etc. [44]. These complex systems of governance consume a lot of time and resources in decision-making. The digital technologies enable faster exchange of information and processing, which supports decision-making in the public administration. Paradoxically, decision-making is, again, difficult due to digitization [45]. Along with the problem of governance, the increased use of digital technology creates demands on the part of the public institutions actively using it to fulfill the needs of the citizens [46]. The need to make more judgments faster is one of them.

The public sector ADM is often applied in individual administrative decisions or decisions by public bodies in exercising their authority in a given sphere. This type of administrative decision-making process determines the rights or obligations of people [47]. A broad diversity of ways can be used to automate these judgments fully or partially. Such technologies are self-learning AI-based ADM, data-based models, basic rule-based systems, and expert systems that mimic experts with domain competence [48], [49]. Moreover, the degree of automation is different, with complete automation, when digital technologies handle an entire process (ADM), and minimum automation, when digital technologies support such actions as data visualization or analysis [50].

Semi-automated or highly automated decision-making is also known as enhanced decision-making, and it presupposes the interaction between the human being and the machine [51]. Even complete automation of decision-making has been associated with calls for human supervision. They have also been referred to as hybrid methods of ADM or having a human-in-the-loop [52]. The human-machine interaction is of various forms, and the combination of decision type, level of automation, and rule-based or data-driven strategy determines the ADM process [53].

ADM is not a new phenomenon in the area of public administration. As an example, for decades the Scandinavian nations have been using ADM to compute tax and pay out parental benefits, which are distributed on a monthly basis to all parents and used in both Sweden and Norway [54]. However, the new ADM options can at least be different in three ways. To start with, self-education on the emerging technologies, such as machine learning, can now be employed to achieve ADM. Second, rather than just facilitating the automation of certain rule-based judgment, with the new types of data analytics and machine learning, ADM may now be utilized at numerous levels and types of decision-making. Third, new types of ADM can impact the workforce, clients, enterprises, and society in general, besides the organization utilizing it because of the abovementioned features [55].

Thus, the utilization of ADM in the administration of the masses can have the necessary efficiency benefits in the public administration with reduced lead times and the necessity to make decisions on massive choices. Nevertheless, it has also been raised that ADM may hurt the relationship between citizens and public organizations unless it is created and put into practice appropriately [56]. As Kuziemski and Misuraca [57] address, it can turn out to be a highly difficult task to regulate algorithms and safeguard citizens against the possible harms of algorithms. As a matter of fact, the need to make internal operations more efficient may clash with the necessity to ensure that citizens are not subjected to possible algorithmic damages.

The issues are raised based on the real-life examples when ADM is employed in public organizations, facilitating the administration, and can lead to unfair, discriminatory, and obscure decision-making processes. It is possible to say that even a single bad decision might be detrimental to the individual and must be avoided. Massive poor decision-making is harmful not only to the people affected, but it is a headache to the administration. A good example that has been well documented is the SyRI system, which is used in the Netherlands to identify potential fraud in the social welfare system. After the discussion, the District Court of the Hague concluded that the system itself, as well as the laws, which it was based, conflicted with the European Convention on Human Rights [58].

The credibility of public institutions is based on fair and equitable treatment, openness, and reliability of decisions. Unless ADM is designed in a way that supports major societal ideals, it risks losing this credibility in government. Another important value is accountability, and with the transition of decision-making processes between the street and system level, there have been concerns regarding how accountability can be ensured due to the fact that it may disturb the concept of human discretion in the decision-making process within the public sector [52]. Because these individuals can rarely be defined based on the established choice criteria that are mandatory to design ADM [59], large-scale decision automation can also be very influential on disadvantaged populations [60].

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III. METHODOLOGY:

The ADM literature is increasingly becoming more diverse and comprehensive as a rapidly developing discipline. The number of studies that report on success and failure cases is constantly growing, as is the number of disciplines addressing the subject, such as computer science, public administration, information systems, communication studies, etc. In order to gain an insight into the scope of research on the issue and allow the development of the theory, we resort to the approach of literature review. To be more precise, we decided to use a systematic literature review. In general, the research process consists of two parts, i.e., a literature search and selection as a form of data collection, and a qualitative content analysis of the included articles as a form of data analysis.

RESEARCH DESIGN

The systematic literature review design was used in this study to synthesize the existing knowledge and findings of ADMS use in both engineering and health care spheres of work. The systematic review model was chosen to offer a well-organized, transparent, and reproducible methodology of identifying, choosing, and critically appraising the existing scholarly literature that explores the technological, ethical, and organizational aspects of ADMS. Focusing on multidisciplinary views, the design helped to capture the progress in AI and big data analytics as a fundamental part of ADMS, and its effects on the quality of decisions, their efficiency, and accountability.

DATA SOURCES AND SEARCH STRATEGY

A wide search was undertaken in various academic databases as Scopus, PubMed, Scholar, Web of Sciences, and IEEE Xplore, because the articles, conference proceedings, and authoritative reports on the use of ADMS in healthcare and in public sectors were chosen. After all, it is an influential source of research concerning human-computer interactions. The keywords were used in combination with algorithmic decision-making, AI, machine learning, big data analytics, healthcare decision support, and public administration automation. When we searched these databases, we got a sufficient number of duplicate studies in the databases, and this implies that the number of databases was sufficient.

DATA COLLECTION AND SELECTION

The retrieved records were screened in multiple stages in accordance with established systematic review protocols. First, abstracts and titles were examined for their applicability to ADMS in public administration and healthcare. We performed a search syntax in the chosen databases at this point. Only journal studies, study titles, abstracts, and keywords were included in the search. Our search was restricted to English-language publications. There was no time limit. For a more thorough search result, we employed both Boolean operators (AND, OR) and approximate phrases (wildcards, braces, quotation marks) [61]. Studies that offered empirical support, theoretical frameworks, or critical analyses relating to algorithmic decision-making processes, human-algorithm interaction, and governance implications were extracted through subsequent full-text evaluations. "Automation decision-making," "artificial intelligence," "algorithmic decision making," "healthcare," "public administration," and terms about results were among the keywords we used in our search strategy. Protocols for data extraction recorded study goals, approaches, settings, technical focus points, and important conclusions about the limitations and effects of ADM.

That first collection of articles was filtered using three criteria: peer review, discipline, and language. These fields were thought to contain pertinent research on administrative choices and decision-making procedures, whether from a theoretical or practical standpoint. Only English-language studies were chosen by the second filter. The third and final criterion required that the studies be subjected to peer review in order to guarantee their quality. Included were journal and conference articles. This produced a subset of 75 articles, the relevance of which was assessed by reading their abstracts.

The selection of pertinent papers was the third phase in the data collection process. After eliminating duplicates from the various databases, the authors established the inclusion and exclusion criteria after reviewing the abstracts. Following this selection round, 27 articles were included as a result of the authors' application of these criteria. After reading the full texts of these articles, seven more—including foundational papers on the subject—were added using a backward search. 34 articles that came from a wide range of search methods make up the final dataset.

Then a final step was added, which was to eliminate research that didn't contain the following requirements - at most, one requirement was missing - (the sector in which we use decision-making tools, the type of task, the type of model, the type of data, the accuracy and fairness measures, the governance mechanisms, the important results), and thus the number of research was reduced to only 10 research.

DATA ANALYSIS

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The qualitative synthesis method enabled the study to group its results into a set of several significant thematic areas based on the literature: algorithmic fairness and accuracy, human oversight and agency, organizational learning and efficiency, ethical considerations, and issues of transparency. Moreover, the analysis was put into perspective with multidisciplinary approaches that emphasized the interplay between the AI and BDA aspects of ADMS. In order to evaluate the technological interventions and their effects in a systematic manner, the decision-making process was envisioned in four steps, namely information acquisition, analysis, decision selection and implementation.

LIMITATIONS OF THE METHODOLOGY

Despite the systematic literature review giving a detailed and broad knowledge of ADMS, there is the possibility of introducing publication bias due to the fact that the review is founded on the accessibility and availability of published studies. The differences between public administration and healthcare in terms of study designs, application of ADM technologies, as well as contextual applications appear to be a barrier to direct comparability and generalizability of the results. The cross-disciplinary character of the review also requires that different conceptual frameworks and terminologies should be interpreted with care.

INCLUSION AND EXCLUSION CRITERIA

INCLUSION CRITERIA

Studies that satisfied the following requirements were included in the review:

- Peer-reviewed, academic journals, conference proceedings, and reputable reports in the English language.
- Articles that explicitly cover ADMS and its applications in the field of public administration and health care.
- Finding: The studies examined the use of AI and big data analytics as two components of ADMS for improving or automating the process of decision-making.
- Empirical research providing evidence of implementation, design, or socio-technical impacts of ADMS, including governance, ethics, and legal issues.

Studies that look at the role played by ADMS in the information collection, analysis, decision-making, and implementation stage of the decision-making process.

Articles that covered the opportunities and challenges of algorithmic decision-making, especially in accountability, accuracy, fairness, transparency, and human oversight.

EXCLUSION CRITERIA

Studies were excluded if they:

- Not in print, non-peer-reviewed, or grey literature that had not been critically evaluated by a scholar.
- They were not related to the area of public administration or healthcare, and did not focus on algorithmic decision-making as a main focus area.
- They were theoretical in essence and were not properly supported by empirical or analytical evidence of the effects of ADMS or its application.
- May may not be very accessible and cross-verified due to publication in non-English languages.
- One of the predefined requirements was missing.
- Mostly discussed conventional decision-making approaches that do not use big data analytics or artificial intelligence.
- Neglected key factors of the effects of algorithmic decision-making because it did not focus on the socio-technical complexity or the ethical consequences of ADMS.

IV. RESULTS:

This section presents a structured summary of the studies included in the review, focusing on the characteristics of Algorithmic Decision-Making Systems (ADMS) applications in the healthcare and public administration sectors.

TABLE 1 SUMMARY OF ALGORITHMIC DECISION-MAKING STUDIES IN HEALTHCARE

Author	Task Type	Model Type	Data Type	Accuracy / Performance Metrics	Fairness Metrics	Governance Mechanisms	Key Results
Cresswell et al., 2013	Clinical decision support	Knowledge-based CDS	Clinical and patient data	Improved practitioner support	Not specified	Physician-in-the-loop	Supportive role rather than outcome transformation

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Esteva et al., 2017	Disease diagnosis	Deep learning – CNN	Medical images – skin lesions	Dermatologist-level accuracy	Not explicitly assessed	Limited clinical oversight	Algorithms matched or exceeded expert performance
Gulshan et al., 2016	Disease detection	Deep learning models	Retinal fundus images	High diagnostic accuracy	Not reported	Clinical validation context	Effective automated detection of diabetic retinopathy
Walsh et al., 2018	Suicide risk prediction	Machine learning models	Electronic health records	Outperformed clinician prediction	Not consistently evaluated	Institutional deployment	Improved prediction without improving clinician decisions
McDougall, 2019	Treatment decision support	AI-supported decision systems	Patient and treatment data	Not quantified	Ethical fairness concerns	Limited ethical governance	Potential erosion of patient autonomy

TABLE 2. SUMMARY OF ALGORITHMIC DECISION-MAKING STUDIES IN PUBLIC ADMINISTRATION

Author	Task Type	Model Type	Data Type	Accuracy / Performance Metrics	Fairness Metrics	Governance Mechanisms	Key Results
Wirtz et al., 2019	Smart city management	Analytical and predictive models	Infrastructure and sensor data	Operational efficiency improvements	Not reported	Public–private partnerships	Performance gains accompanied by transparency risks
Peeters, 2020	Administrative decisions	Hybrid ADM systems	Government databases	Reduced administrative workload	Not explicitly measured	Human supervision	Centralization of decision authority
Rachovitsa & Johann, 2022	Fraud detection	Machine learning models	Socioeconomic data	Operational effectiveness	Discriminatory outcomes identified	Judicial review	System ruled incompatible with human rights
Scholta & Lindgren, 2023	Welfare allocation	Rule-based ADM systems	Administrative records	High processing efficiency	Fairness concerns raised	Legal–administrative frameworks	Efficiency gains with legitimacy risks
Rizk & Lindgren, 2025	Policy planning	Predictive analytics	Large-scale public datasets	Improved forecasting quality	Not systematically assessed	Institutional governance	Decision support without assured accountability

TABLE 3. ACCURACY, FAIRNESS, AND GOVERNANCE DIMENSIONS ACROSS STUDIES

Dimension	Result
Accuracy	Algorithms demonstrated high accuracy in technical and repetitive tasks.
Fairness	Lack of consensus on fairness measures and performance variations among groups.
Acceptance	Low acceptance in high-risk contexts.
Governance	Regulatory frameworks lagging behind technological development.
Human Oversight	Widespread reliance on human-in-the-loop models.
Accountability	Difficulties in assigning responsibility when errors occur.

TABLE 4. OPPORTUNITIES AND CHALLENGES OF ALGORITHMIC DECISION-MAKING IN HEALTHCARE

Opportunities	Results
Diagnosis and Prediction	AI systems have demonstrated high effectiveness in medical classification and prediction.
Clinical Decision Support	Knowledge-based clinical support systems have improved practitioner performance.
Medical Imaging	Proven success in diagnosing cancer and retinopathy.
Personalization	Delivering personalized, data-driven healthcare.

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Population Management	Supporting public health decisions and risk prediction.
Patient Empowerment	Providing personalized information that supports participation in decision-making.
Challenges	Results
Human Performance	The use of AI didn't necessarily lead to improved physician decisions.
Algorithmic Bias	Unbalanced data led to performance disparities between groups.
Transparency	Black-box models limited trust and clinical acceptance.
Autonomy	A potential threat to patient autonomy due to algorithmic guidance.
Training	Insufficient user training reduced system effectiveness.
Regulation	Regulatory frameworks lagged behind the rapid pace of technological development.

TABLE 5. OPPORTUNITIES AND CHALLENGES OF ALGORITHMIC DECISION-MAKING IN PUBLIC ADMINISTRATION

Opportunities	Results
Service Efficiency	Improving the quality and speed of government service delivery.
Resource Management	Supporting proactive planning using predictive analytics.
Transparency	Enhancing openness and accountability through explainable intelligence.
Community Engagement	Enabling citizen participation through data analytics.
Policy Support	Improving the quality of policy decisions through simulation and scenario analysis.
Challenges	Results
Power Imbalance	Concentration of knowledge and technical capabilities among a limited number of actors.
Cybersecurity	Increased risk of algorithmic attacks and breaches.
Transparency	Difficulty in achieving true transparency due to trade secrets.
Legal Complexity	Difficulty in translating complex legal rules into computational logic.
Technical Compatibility	Challenges in integrating ADM with legacy government systems.

V. DISCUSSION:

COMPARATIVE EFFECTS (HUMAN DECISION-MAKING VS. ALGORITHMIC DECISION-MAKING).

It has been reported that algorithmic decision-making can be better than human decision-making in a variety of tasks [62], [63]. Although this information dates back several decades, it has recently gained much publicity thanks to the miraculous performances of the best representatives of humanity in brain games [64]. Nevertheless, there are several reasons why people still make some crucial choices; one of these is to preserve human agency and responsibility, which are relevant even in those cases when science has warned us about human weaknesses.

The necessity of human decision-making, as well as the precision and efficiency of algorithms, has led to the appeal to the use of hybrid systems that blend the two. The most popular system operates by providing algorithmic recommendations that decision-makers of humans follow. Many aspects of our daily existence, including healthcare, jobs, credit services, investment decisions, and online shopping, have applied human decision-making with the help of algorithms. Moreover, algorithmic recommendations are increasingly finding application in the area of evidence-based policy-making [65].

The future of digital technologies like AI can improve the ease and efficiency of decision-making processes in the public administration. Such technologies provide additional possibilities to implement ADM, where a computerized system, not a human official of a population, controls the decision-making process, or its part. ADM can reduce the cost and resource requirements in state agencies by enabling decision-making in mass areas such as healthcare, taxes, and state benefits. Due to this, much has already been done to explore potential uses of ADM in enhancing the efficiency of decision-making in the context of public administration [66].

The analysis of AI and BDA as typical factors of computer-based decision-making focuses on the importance of the integrated approach in studying them and their implications [67]. As discussed in [68] and [69], ADMS allows highlighting the need to prioritize the consideration of the human and ethical aspect of data and algorithms in order to understand how they are imbricated in human-machine hybrid systems and blame poor judgments. Active involvement of AI and BDA within complex and impactful processes in such areas as business, science, technology, politics, economics, ethics, and society has

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also been emphasized [70], [67]. Research has so far taken a narrow perspective on AI and BDA, focusing on the technical characteristics of the systems [71] and positive outcomes [72]. A reality that is too instrumental [73] and behavior guided by prejudiced or imprecisely reported digital information that leads to unhealthy judgments with severe adverse consequences [74], [69] are two of the unwanted consequences of such concentration. Thus, the discipline must conduct more comprehensive research on ADMS.

WHAT INFLUENCES ALGORITHMIC DECISION-MAKING

An exploitative conceptualization using the attributes of a working definition would give a holistic view of the interdisciplinary computing processes of ADMS and would offer a flexible structure of collaboration within and across disciplines. Instead, every stakeholder operates under their conceptualization because of the existing conceptual disorder, which might complicate the design, development, and evaluation of desirable systems, knowledge-sharing in the world, future impact prediction and evaluation, goal-setting, misconception prevention based on false implicit assumptions, and cross-disciplinary cooperation [75]. As an illustration, Raisch and Krakowski [76] explain that social scientists think of AI as an augmentative capability, but computer scientists define and refer to it as automation.

According to Raisch and Krakowski [76], we will risk creating vicious cycles where humans are redundant and deskilled or results are biased, inconsistent, and unreliable, as these limited understandings are applied to computing processes in decision-making, and the impossibility of building on the complementarities of automation and augmentation. Likewise, big data is viewed as a tool of AI by some, but some argue that the capacity of intelligent computers to deal with novel tasks is constrained by their understanding of training as a role of data volume [77].

The characteristics of the decision depend on several factors, such as its decision-making roles, accuracy, cost, and viewpoint. Decision accuracy is one of the significant factors with regard to algorithm adherence. People penalize bad choices of algorithms more poorly than human choices [78]. The incorrect results given by algorithms cause people to lose trust in them [78], [79]. When such a mistake occurs in a basic task, it may have big consequences. Seeing algorithms in their inability to make proper judgments on simple tasks, people reduce the degree of their trust to a minimum as they presume that algorithms are not capable of working with more complex tasks. In making a decision on whether to obey algorithms or not, individuals consider the cost of the decision. Individuals follow compensated decisions much more than the ones that are openly available. For example, consumers are not much interested in following online advice since they are not accompanied by any immediate expenses. On the other hand, individuals would not like to make decisions they have to spend money, time, and effort to acquire, since this is what happens when they use a corporate decision support system; they will respect sunk costs [80].

The perspective of the decisions determines the algorithm aversion, i.e., whether the decisions will make people win or lose. An example of this is a between-subject study carried out by Toma et al. to research the influence of prospects (gain and loss) on the reliance of automated judgments and found that individuals rely more on algorithms when the expected outcomes involve gain [81]. Similarly, consumers will go further to imitate an algorithm as a result of upside potential [82]. Nevertheless, generalization of this finding may be even more perilous, as risk-averse and conservative people would like to see the algorithms predicting a more dreadful future [82].

In most instances, the comparative elements of algorithmic choices to those of human choices determine algorithm aversion to a great extent. For example, using algorithms in cases when they are designed to help people, as opposed to taking over their roles, leads to less reliance on them. People prefer human decisions empowered by algorithms and rely more on algorithm decision-making as long as the algorithms are subservient to humans and people make the final decisions [83].

The behavior and design of the algorithm itself, such as accuracy, fairness metrics, transparency, explainability, and bias mitigation strategies, therefore have a significant impact on the outcome of algorithmic decisions [84], [85]. Wang et al. [85] and Starke et al. [86] both show that perceived fairness is more likely to increase when the outcome is favorable to the subject of the decision and when the user has the possibility of regulating the influence of algorithms or preferences, thereby reducing the feelings of reductionism. Moreover, the inclusion of sensitive traits (gender, ethnicity, etc.) leads to conflict; although inclusion will make the performance of minority groups better, there will be those who may feel that it is not fair [86].

Personal variables that define individual trust and acceptance of ADM include statistical literacy, trust tendency, experience with algorithms in the past, and awareness of possible algorithmic biases. The effect of statistical literacy is complicated, making it more skeptical about high-stakes decisions (such as criminal justice) and more trustful about low-stakes judgments (such as recommendations) by creating awareness of the possible systemic bias. To attain trust calibration, the understanding of the algorithm's purpose and outcomes by the user is often of more significance than the transparency of the algorithms themselves [87].

The perceived fairness and acceptance depend on the environment of the ADM application, such as task difficulty

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and stakes. When dealing with high-stakes situations, higher requirements on accuracy, fairness, and accountability are involved and are more attractive [88], [80]. Users become more open and reliant on algorithmic recommendations in low-stakes situations.

WHETHER ALGORITHMIC RECOMMENDATIONS IMPROVE HUMAN DECISIONS

Two ways in which human-algorithm interaction manifests are the level of decision-making agency and interaction configurations. There is a range of recommended typologies of human-algorithm interaction depending on the level (no/low, medium, and high) of perceived agency of human decision-makers, i.e., their ability to act and influence algorithmic judgments [89]. The perceptions of human decision-makers on their decision-making agency are influenced by different levels of human-algorithm interaction, irrespective of typological variations. The level of algorithm aversion decreased, and cognitive engagement increased when the decision-makers were more in control of the algorithmic processes [90], [91]. Human-algorithm interaction and structural constraints and standardizations imposed by the regulatory environment affect the results of ADM [92].

The ADM consequences identified at the organizational level were the efficiency paradox, redistribution of power, conflict between anthropomorphism and dehumanization, and organizational learning. ADM presents an efficiency dilemma to businesses. On the one hand, the use of algorithms enhanced the efficiency of the organization by standardizing processes and accelerating decisions. Nonetheless, companies could attain actual efficiency gains (i.e., noticeable, long-term alterations in organizational performance that were more than mere surface-level automation) only if they invested heavily in technology infrastructure and skills, although the investments often had uncertain payoffs. ADM led to an increase in the efficiency paradox through ineffective allocation of resources by organizations implementing it based on technology trends rather than strategic priorities [93], [94].

Additionally, ADM involves a shift of power, particularly the centralization of decision-making processes from street-level bureaucrats to screen-level bureaucrats [95]. Professional discretion had previously been exercised by street-level bureaucrats, such as social workers, police officers, and welfare administrators, in interpreting regulations for specific situations. However, much of this human judgment was integrated into algorithms and rule-based workflows under ADM [96]. This led to a loss of decision-making power by frontline employees to screen-level bureaucrats, who mostly handled algorithms and made standardized, rule-based decisions. Besides enhancing centralized, hierarchical power, this redistribution limited access to knowledge, skills, and oversight powers [97].

A third consequence is the paradoxical conflict between anthropomorphism and dehumanization in firms employing ADM. Dehumanizing factors eroded human agency during decision-making by minimizing discretionary judgment and replacing qualitative aspects with quantitative ones [93]. Individual stories, environments, and ethical considerations were minimized to standardized data points, regulations, and procedures. Algorithms, described as supercarriers of formal rationality [98], operate through formal procedures, rules, and means-end computation. While highly useful in computation and optimization, they cannot make ethical and value-focused choices unless pre-programmed. To maintain legitimacy and functional effectiveness, organizations anthropomorphized ADM by creating human-like interfaces, implementing human-in-the-loop oversight, and providing explanatory frameworks to make algorithmic judgments comprehensible [99]. Nevertheless, these efforts often resulted in superficial humanization, masking more computerized and rationalized decisions. This anthropomorphism/dehumanization dichotomy contributed to increased intentions to quit [100] and reduced organizational commitment [94].

ADM also fundamentally changes organizational learning, defined as individual and collective learning through experience to improve organizational actions [101]. Based on past data trends, ADM standardized organizational processes such as recruitment, applicant evaluation, and customer service. This uniformity may have prevented innovative solutions emerging from human learning [102]. Standardized procedures removed variants that did not match the data, focused excessively on local routines, and ignored interdependence with other routines [101]. Consequently, ADM undermined organizational learning by lowering previously acquired knowledge levels and providing a fragmented view of organizational processes.

In this context, interpretative work required individuals to act as algorithmic brokers, translating computational results into actionable organizational knowledge [90]. When algorithmic outputs were not fully explainable, algorithmic brokers substituted their own interpretations, leading to acquiescence or resistance. This created a fractured learning cycle, where algorithms captured and trained on human feedback but remained unaware of human behaviors, frustrations, concerns, and reasoning [103].

The second mediating mechanism is reductionism, an analytical process that converts complex, qualitative human characteristics into numerical forms [94]. Two predominant forms were decontextualization, where ADM ignored situational factors influencing performance, and quantification, where qualitative traits were simplified into numerical scores. Reductionism contributed to the efficiency paradox, centralized decision-making, dehumanization of employees, and hindered organizational learning [99].

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OPPORTUNITIES AND CHALLENGES FOR ALGORITHMIC DECISION-MAKING IN HEALTHCARE

In critical application domains such as the healthcare sector, new technologies in ADMSs [104], which today include the two distinct yet connected notions of AI and big data analytics (BDA), promise and threaten new possibilities and challenges unfamiliar to us before [105]–[108].

OPPORTUNITIES FOR ALGORITHMIC DECISION-MAKING IN HEALTHCARE.

Governments, institutions, and organizations are applying algorithms to process the huge amounts of data in diverse sectors of society and accelerate and enhance decision-making processes [109]. In particular, the examination performed to understand the global impact of the COVID-19 epidemic pointed out the ubiquitous use of algorithms in society. This crisis required algorithms in numerous fields: machine learning algorithms were applied in molecular, medical, and epidemiological tasks [110], statistical algorithms were applied to simulate the curves of virus mortality and study the effectiveness of interventions [111]. The successful application of algorithms in such stakes implies not only the growing importance of algorithms in the decision-making of society but also the imperative need to understand what factors impact social trust in algorithmic systems.

It is argued that the application of machine learning algorithms will improve the medical decision-making process at the individual level, implying that the decisions regarding diagnosis and treatment will be made faster and more accurately. Moreover, the advocates of machine learning in the field of medicine do not always hesitate to point out the flaws of medical workers, including their susceptibility to cognitive errors and diagnostic errors. Consequently, machine learning algorithms can enhance or even compensate for the weaknesses of the decision-making capabilities of individual therapists. This can be termed as inefficiencies in the processes, wastage of resources, inequalities, and the astronomical prices at the institutional level of healthcare. Again, machine learning is thought to reduce such abhorrent situations [112].

The use of AI algorithms has been found highly effective in making predictions and classifying diagnoses, providing suggestions and insights, and in the field of clinical decision making [113], [114]. According to the increasing amount of empirical evidence, knowledge-based computerized decision support (CDS), and knowledge-based clinical decision support systems in particular, can potentially enhance the work of practitioners [115]. The literature states that AI systems have demonstrated success in several medical imaging applications, such as mitosis detection in breast cancer histology images [116], dermatologist-level skin cancer detection [117], diabetic retinopathy detection when using retinal fundus photos [118], and cardiovascular risk factors detection using retinal fundus photos [119]. This study demonstrates how AI systems can assist the medical community to provide more personalized and individualized information, as well as improve the process of diagnosis and prognosis. Also, they have been utilized to decide the likelihood of patients contracting severe illnesses or being admitted to palliative care [120] and have been able to effectively forecast the presence of a suicidal attempt [121].

In the healthcare service delivery system, decisions are often made on a personal basis by the physicians [122]. The decisions made by strangers are necessary because most patients do not have an advance directive or a proxy in order to make decisions on their behalf [123]. Moreover, the patients are either unable to voice their wishes or can share irrational expectations (like thinking that cardio-pulmonary resuscitation will be successful) because they find it difficult to think about their future treatment and to understand the situation with resuscitation [124]. Also, surrogate family members may be coerced and fail to comply with the desires of the patient [125]. These are just some examples demonstrating that the healthcare service delivery system needs innovative approaches to making decisions. Moreover, it is noted that one of the potential solutions is the use of AI in the decision-making process. Artificial intelligence is changing the decision-making process of medical professionals. The application of AI by healthcare practitioners can assist in disease diagnosis, treatment planning, predicting outcomes, and managing population health. The AI also has the potential to increase user satisfaction and experience, the quality and efficiency of healthcare decision-making [126].

In both nodal graphs and graph pictures (also known as chart images), one finds the discriminating and latent features of large-scale heterogeneous data hard to learn. Consequently, AI-based interpretation methods can be viewed as an emerging solution [127]. One of the possible applications of AI in the computerized analysis of graphs in the clinical area is the use of machine learning algorithms to analyze ECG signals [128]. Research evaluated the usefulness of AI in supporting the interpretation of cardiotocographs through the application of computerized interpretation and visual pattern recognition. Stunningly, the researchers discovered that the application of such AI technologies did not enhance clinical outcomes in the health of both mothers and newborns [129]. In another study, algorithms based on AI can be as efficient and even more efficient in numerous tasks, including the assessment of medical photos or the association of symptoms and biomarkers on electronic medical data with the description and prognosis of the disease itself [130]. Moreover, a deep learning architecture known as vision transformers is now popular in medical imaging, especially for lung cancer. They find long-term relationships within picture patches by examining image classification as a sequence prediction task. These results

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underline the high potential of medical graph analysis and interpretation with the help of AI [131].

One of the studies claims that AI will enhance patient autonomy as patients will be able to receive the therapy of their choice [132]. Meanwhile, studies proposed a system that would integrate AI predictions, physician insights, and parental opinions to assist in making moral treatment decisions about the newborn patients; the results showed that the system has presented different users with personalized and tailored information and empowered parents to engage in mutual decision-making. The AI can help create individualized and flexible learning software that can modify the pace, evaluation, feedback, and learning material for each student. This technology may be used when working with patients and caregivers by means of chatbots and natural language processing to offer them personalized guidance and training [133].

In addition to the state of health of the population, algorithmic implementation is changing in numerous other fields where decisions play a significant role in the lives of individuals and society. The technologies are becoming the mediators of high-stakes decisions in all kinds of industries, such as algorithms regulating financial markets and predicting the growth or decline of the economy, and surveillance systems keeping an eye on the general population. There is a greater need to understand the social consequences and reliability of algorithmic decision-making as it finds more applications in such a critical context. Algorithms can have transformative social power when they are applied in integrating complex data, including risk factors of homeless people [134] or finding the people with the highest need in comparison to several diseases [135].

The emerging and fast-evolving sphere of algorithmic applications can transform numerous aspects of healthcare, such as administration, diagnosis, treatment, and prevention. The current state of affairs and the possible future trends of the emerging field also have a vague and disintegrated image, but due to the scattered distribution of the literature regarding the areas of application of algorithmic applications in healthcare-related decision-making [133].

CHALLENGES FOR ALGORITHMIC DECISION-MAKING IN HEALTHCARE.

The ADM systems, which are driven by AI, can revolutionize clinical performance and efficiency in the health sector. Nonetheless, it presents a number of complex challenges that make its implementation ineffective, morally, and fairly. Some of these challenges include technical limitations, ethical dilemmas, information biases, regulatory ambiguity, and socio-technical factors that influence trust and responsible actions in healthcare professional practices [136], [137].

Direct access to algorithmic tools and AI decision support systems is not always helpful in improving the decisions of doctors, as numerous studies reveal. As a study by Brennan et al. [138] suggests, the algorithm is more likely to predict the outcome of the patient after surgery than a doctor. Nevertheless, the surgeon's performance was not higher when they were requested to change their prediction indicated by the result of the algorithm. This extends to the case of generative AI companies: even with the independent diagnostic performance of a large language model (LLM) significantly surpassing human physician performance, human performance did not improve significantly when using the LLM as an assistant. The main problem with the availed AI tools with direct physician-facing is that they require individuals who have practically little training or experience with the tools to somehow incorporate them in their decision-making without much support [139].

When medical practitioners abide by the algorithm, they have a normative justification for their medical judgment. Nevertheless, in case they remain faithful to their original theory, and her diagnosis proves to be wrong, she can be accused of reckless behavior, as she did not pay attention to the findings of the algorithm. When we consider the fact that most medical decisions are made in less-than-perfect conditions, like the lack of time to reconsider the data that is available to us, the situation can only get worse. Another possible outcome may be that the clinician will be prejudiced to interpret the data in a manner that will be consistent with the diagnosis provided by the algorithm. Thus, it is a possibility that the relationship between machine learning algorithms and physicians will encourage such epistemic vices as gullibility or dogmatism [140]. Finally, machine learning algorithms can compel doctors to implement defensive medicine practices instead of enhancing their decision-making skills [141].

Furthermore, it also brings about concerns with patient autonomy. In a more recent paper, McDougall [142] has argued that artificial intelligence in the making of treatment decisions is also subject to the danger of relapsing to a paternalistic model of medical decision-making in the guise of that the computer knows better. She contends that this type of paternalism is enforced through the use of computers, which dictate the values based on the prioritization of numerous treatment options. To illustrate this point, most of the algorithms will give preference to the treatment options based on whichever course of action will prolong the life of a patient. Conversely, a patient can opt for a series of treatments that will reduce her pain. Thus, the autonomy and dignity of the patient might be endangered due to the use of artificial intelligence, as it weakens the collaborative decision-making between the doctor and the patient [142].

Unlike the existing standards of medical equipment, new technologies permit adoption with less and less causal evidence on the benefits of algorithmic technology [143]. Health

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authorities must stick to the evidence of the patients in the process of approving medicinal innovations.

To a significant degree, algorithmic bias caused by missing, unrepresentative, or unbalanced healthcare data is one of the most serious problems that lead to disparities in the performance of the model across demographic groups [136], [144], [145]. An example is that underrepresentation of ethnic, gender, and socioeconomic subgroups in training datasets diminishes their clinical utility and their predictive accuracy, worsening the already-existing disparities in health, hence aggravating the issue [146]. Generalizability of the model is also made more difficult by the change in distribution between the training data and the real clinical condition.

Even when the trials that do not fulfill the basic requirement of preregistration are eliminated, research indicates the presence of a significant bias risk. The main issue with patient-relevant AI decision support studies is the ignorance of the enabling conditions that have a significantly greater effect on patient benefits than algorithms and data: to begin with, the users of the machines. They need to be able and motivated to engage in their working processes to benefit patients, and thus, they need training and involvement [147], [137]. The other half of the research did not even specify the requirements of a knowledgeable user, although they did provide information about user training, the length of which ranged between under an hour and a week. This will minimize the chances of successful usage. Introducing ADM to professionals into a pre-existing corporate decision-making system would require the establishment of a clear understanding of the roles and preconditions of users and usage, respectively. In other words, even highly precise machine learning models will not be useful if such an application is not intended [137].

Opaqueness interferes with future gains. This not only affects the use of personal technologies but also influences the way other researchers edit data, which can be more beneficial. The fact that most research with patient-relevant findings has been carried out using internal real-world data, particularly in the context of algorithm development, suggests the potential to have more significant health data partnerships, which is one of the reasons why they should have health data spaces [148].

ADM in healthcare involves complex models that often act as black boxes, thereby posing challenges to interpretability and transparency that are paramount to user trust and clinical acceptance [137]. Explainability compromises the ability of clinicians to assess decision reasoning, an essential part of patient safety and moral medical practice [148].

Finally, ethical complexity is presented by ensuring that justice, fairness, and respect for patient autonomy are upheld. Regulatory frameworks lag far behind rapid technical innovation and do not include a set of criteria used to validate AI and audit and monitor AI activities [136], [146]. This gap hinders accountability and responsible deployment in the case of undesirable outcomes.

OPPORTUNITIES AND CHALLENGES FOR ALGORITHMIC DECISION MAKING IN PUBLIC ADMINISTRATION

There are practical examples of ADM implementation into decision-making simplification with valuable results in the area of public administration. Moreover, there are cases when the usage of ADM has such negative outcomes on people and governmental administrations that the credibility of such institutions is threatened. The contradictory results of ADM in the area of public administration make it require conducting further studies in the area, considering the evolving relationships among individuals, organizations, and society in general [149].

OPPORTUNITIES FOR ALGORITHMIC DECISION MAKING IN PUBLIC ADMINISTRATION.

ADM is currently being implemented by the government and other organizations to provide new services or improve existing services in diverse areas such as energy, education, healthcare, transportation, judicial systems, and security. Some examples of how ADM can be utilized in this environment are predictive policing, smart metering, video protection, and university enrollment. Moreover, they are going to contribute to the education, medical, and job skill training standard improvement. ADM or smart technology, in general, can be used to enhance city management, including water and energy management systems or mobility management tools. As an example, they may help them to better manage waste, to use less energy, and to reduce pollution or traffic jams. ADM is able to enhance the efficiency and quality of services offered by governmental entities. They can assist in revealing the administrative decision-making process and make it more accountable, as long as they are also transparent and accountable. ADM, or more precisely, ML techniques, can also be useful to society by creating new information. As an example, the researchers with machine learning methods have identified about 6000 species of viruses previously unknown [150].

ADM systems excel with huge and complex datasets to determine the trends that can be used to optimally make use of available resources. These systems reduce costs and enhance outcomes by providing predictive analytics to support proactive service management, e.g., predicting disease outbreaks or getting smarter in terms of infrastructure maintenance plans. When tedious administrative tasks are computerized, the government gains more agility as the public employees are able to focus on strategic objectives [151].

ADM can increase the openness of governments through explainable AI models and open data projects. The availability

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of analytical methods, such as natural language processing, allows governments to gauge the masses in real-time via social media and other feedback platforms, and therefore makes government more responsive and inclusive. These capacities facilitate legitimacy and confidence by including citizen involvement in administrative decision-making [152].

Furthermore, ADM urges the public administrations to apply scenario analysis and simulation in order to test new policy ideas. Under complex and uncertain scenarios, the quality of decisions made by decision-support systems that are algorithmically guided enhances the quality of decisions made by policymakers because they provide practical insights based on empirical data [153].

The challenge is therefore to balance the use of technology and governance mechanisms that ensure accountability, transparency, and inclusion so that the potential of ADM can be exploited. Beloved, ethical forms of governance are promoted through evolving human-AI cooperation forms that enable the empowerment of human workers and involve citizens [154]. Moreover, the continuation of ADM-led breakthroughs involves the need to invest in data infrastructure and algorithmic literacy and cross-sector partnerships [155].

CHALLENGES FOR ALGORITHMIC DECISION MAKING IN PUBLIC ADMINISTRATION.

ADM systems are gaining popular application in the governmental sphere to enhance efficiency, objectivity, and the capacity to scale up governmental work. Despite the possible benefits, these systems present specific challenges that are caused by the complexity of the sociopolitical environment, regulatory constraints, and accountability concerns that characterize the work of public organizations [155]. It is necessary to understand these barriers to have an adequate and effective application of ADM within public administration.

The gap in information and skills between people profiting through algorithmic decision-making and other people who are unwillingly susceptible to it can be called a power imbalance. Specifically, few actors have access to big data and advanced computational capabilities needed to follow, measure, and assemble insights about most users, who are the entire population of users or subscribers of a data-driven business. Conversely, being the consumers of data-driven services, these individuals are not normally exposed to organizational data practices. Consequently, the minority group is able to influence and modify the action of the majority due to political or economic benefits [156].

ADM creates a significant amount of new security vulnerabilities that can be exploited by ill-willed people, in particular foreign firms or hackers. Hackers with the ability to penetrate these systems can cause serious damage since ADM plays a vital role in the way civilization operates in such places as nuclear power plants, smart grids, hospitals, and automobiles. Also, as the attacks will become more sophisticated and automated, and since the probability of cascading failures will be more challenging to estimate, these systems will be harder to protect. A clever opponent can attempt to locate and exploit already-existing algorithm vulnerabilities or come up with one that they will then use. In the case of using machine learning, it could be achieved with the help of a poisoning attack, that is, by manipulating training data. Moreover, through real-time research and learning of the systems that attackers target, they can use machine learning algorithms to find weaknesses and optimize attacks automatically. The security breaches may occur accidentally and without ill intentions. Major or minor collisions like autonomous robots walking on people are a very tangible threat to the ADM implementation and must be considered to prevent the loss of trust towards transportation systems in general and automated systems in particular [154], [157].

The image of the black-boxed algorithm provokes calls for transparency as a form of democratic process, accountability, and critical review. But it has been difficult to define and attain what is known as true transparency. As Coglianese et al. and Fink remark, it is reasonable to believe that transparency has a complex goal with different technological, legal, and even social aspects [158], [159].

A single and general but useful distinction among such diversity is between more proactive and reactive forms of transparency, where the former is more premeditated, a legal obligation and voluntary disclosure, and the latter is more of a reaction to the spontaneous demand of information [160]. Reactive disclosure is sometimes too little, too late. Mulligan and Bamberger note that ex post transparency fails to challenge the judgments that are built into systems, which are already functioning, and emphasize the need to intervene on the level of design and process. The government contract can allow the vendors to claim trade secret exemptions to software and data sharing and design process [161], [162]. Also, the agencies might interpret nondisclosure agreements and trade secret exemptions broadly because of their personal motivation to keep the information a secret [163].

Also, the complex norms of policies are hard to implement into formal computer logic by the public administrations, which often leads to administrative errors and unanticipated algorithmic outcomes. These problems are exacerbated by design flaws, data quality, and integration into existing bureaucratic processes, which expose ADM to systemic failures as opposed to mere technological failure [164]. Moreover, there is a challenge of interoperability that hinders the integration with older information systems of the public sector [155].

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CONSEQUENCES OF ALGORITHMIC DECISION-MAKING

Algorithm Aversion

Even though algorithmic decision-making is implemented in a great variety of industries and disciplines, a number of barriers have to be met. As an example, marketers apply algorithms in their research, strategy creation, channel control, and performance measurement [165], [166]. Chatbots substitute customer support [167]. The reaction of people towards algorithms is not necessarily obvious, however. It has been found that these reactions are often influenced by a variety of variables [168], [169]. Some of them prefer algorithms and others do not [170]. Algorithms can get rejected in some professions and get their coveted in others [171], [172]. More intriguingly, the phenomenon of algorithm aversion is that humans dislike algorithms, regardless of their knowledge of their superior performance [173]. The opposite of algorithmic judgements can also be referred to as the conscious or subconscious effort to ignore algorithms in favor of personal or other individuals' judgements, which may be referred to as algorithm aversion. It is rational to follow algorithms when it is a clear fact that they are better than people. It can be viewed as an anomaly of behavior to violate this reasonable behavior that can reduce the expected utility of human beings [173], [174].

This type of abnormality can significantly impact a situation (such as a medical diagnosis, bail, or sentencing decision) when a bad decision may have terrible consequences. It is important to understand the causes of the algorithm aversion so as to maximize the benefits of the algorithm judgment. The topic of algorithm aversion has recently become the object of an increase in attention from experts. Numerous studies have been conducted to examine the source of aversion and provide solutions. Although this research is not scarce, the available literature is usually focused on a limited number of aspects of algorithm aversion, which does not allow us to obtain the overall view. In this regard, a study organized as a review and bringing together past studies could be beneficial [175].

DATA PRIVACY

ADM may result in a lack of privacy, which is the ability of an individual to restrict and control the use of personal information. Specifically, individuals were not able to regulate the information collected, its aggregation, and its sharing. Data aggregation is especially problematic because it is explained by the phenomenon of differential privacy, which states that any permutation of the data aggregation makes it simpler to re-identify individuals in any of the data sets, despite the use of the techniques that hide the identity of individuals at the point of their collection or aggregation. The loss of privacy causes an undesirable outcome of choices, including the release of personal data, discomfort, or huge losses.

REGULATORY IMPLICATION: RISK-BASED GOVERNANCE IMPLICATION

The results presented in this paper are consistent with the new regulatory strategies according to which algorithmic decision-making systems are treated in the context of a risk-based governance paradigm, especially in high-stakes areas like healthcare and public administration. The specified obstacles associated with accountability, transparency, human supervision, fairness, and explainability are the issues that are always regarded as regulatory-related in high-risk algorithmic systems, where automated judgments can have a severe effect on the rights, health, or even the access of individuals to state services.

As noted in the discussion, algorithmic decision-making is not a technical intervention but a socio-technical system integrated into organizational and institutional actions. Therefore, the system of governance must distinguish regulatory requirements based on the risk and impact of particular applications on society. The uses of algorithmic decision-making, as found in this study, that are of high impact necessitate improved human-in-the-loop setups, strong auditability and well-established responsibility frameworks to reduce unintended effects and maintain human agency.

In addition to this, the efficiency paradox, distribution of decision-making authority, and strains between anthropomorphism and dehumanization observed in the study support the need to use adaptive regulatory systems beyond performance metrics, including accuracy. A risk-based governance model must thus take into consideration the procedural protection, ongoing checks and balances, as well as situational assessment to make sure that the algorithmic systems are consonant with the ideals of fairness, legitimacy, and proportionality during their entire life cycle.

In general, the findings indicate that the responsible implementation of the algorithmic decision-making systems requires a model of governance that incorporates both the technical performance levels and the ethical, organizational, and regulatory aspects. These models facilitate the distinction of regulatory responsibilities according to the risk exposure while allowing the innovation where risks are minimal and supporting protection and control in applications with high societal consequences.

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VI. STUDY LIMITATIONS

Several inherent limitations in this study should be considered closely when drawing conclusions and generalizing its results. To start with, the study is limited by the access and quality of the primary research upon which it is based as a systematic literature review. The heterogeneity created by variability in the methodologies, sample sizes, contexts, and reporting standards across the included studies restricts the ability of the studies to be directly comparable, and this aspect of the method can impact the reliability of the aggregated insight. There is also the risk of publication bias, where studies that have large or positive results are more likely to be published and therefore included, thus affecting the overall evidence base.

Secondly, the limited set of languages involved in peer-reviewed literature limits the scope of the review, potentially excluding any other studies that are published in different languages or belong to the grey literature, potentially providing a more significant outlook on the issue, particularly in non-Western settings.

Furthermore, the interdisciplinary nature of algorithmic decision-making systems, namely, technical, ethical, legal, and social, presents difficulties with the complete accommodation of the various theoretical perspectives and terminologies into one analytical frame. This interdisciplinarity, though rich, also restricts the thoroughness with which any given point of view can be studied to exhaustion.

The identification of these constraints underscores the necessity of continued empirical studies that have stronger and clearer methodological principles and give broad views to enhance knowledge and regulate the application of algorithmic decision-making models responsibly.

VII. IMPLICATIONS AND FUTURE DIRECTIONS

The results of the present systematic literature review have great scientific, practical, and theoretical implications that contribute to further knowledge of the ADMS, especially in healthcare and the context of public administration. Scientifically, the study contributes to the conceptualization of ADMS as the one that is multidisciplinary and includes AI, big data analytics, and human-machine interaction dynamics. Such an integrated perspective explains the significance of considering ADMS research as a unit, where technical effectiveness is expected to be balanced with socio-ethical issues of equity, openness, and responsibility.

Practically, the synthesis provides insights into critical problems that organizations face in the course of implementing ADMS, including the efficiency paradox, redistribution of power, and dehumanization and anthropomorphism tension. These findings suggest that ADM technologies need to be developed in such a way that they preserve human agency, add a human-in-the-loop control, and stimulate organizational learning. Going forward, policymakers and practitioners can use these findings to create governance frameworks that will prevent the negative effects of automation and ensure a balanced approach to both advantages and risks of the latter, thereby building trust and legitimacy towards the public services and healthcare delivery.

In theory, the research developments that are being proposed follow the idea of extending algorithmic fairness beyond accuracy measures to include equitable error distributions and the aspects of legitimacy across different groups of people. It means that the ADM evaluation criteria will be changed in their paradigm so that social justice and inclusivity will occupy first place in the technical performance.

The new directions of research in the future must put an emphasis on the empirical studies of the long-term effects of ADMS implementation in real-world contexts, incorporating the methods of ethnography and interdisciplinary research to observe subtle human-algorithm interactions. Establishing a set of metrics that provide a method to measure harm and the operationalization of non-maleficence in algorithms are critical areas of gaps to fill in. Also, research into adaptive forms of governance that harmonies fast-paced technological change and the changing societal values is critical.

The development of explainability and transparency systems is also something that should be explored further to ensure that the double bind of anthropomorphism is less likely to lead to superficial human intervention. Moreover, it should also be studied with the possibility of identifying the frameworks that can be successfully applied to incorporate the views of various stakeholders, such as marginalized groups that are disproportionately affected by the algorithms.

Lastly, due to the rapidly growing rate of AI and BDA development, longitudinal studies that monitor the performance of algorithmic decisions in various fields will become a crucial factor to instruct evolutionary improvements and accountable scaffolding of ADM technologies.

VIII. Conclusion

This article focuses on the critical evaluation of the emerging field of ADMS within the context of public administration and healthcare, which will shed light on the problematic nature of the interactions between big data analytics, artificial intelligence, and the human decision-makers. The analysis reveals that, in spite of the huge potential of ADMS to enhance the quality and efficiency of decisions and the scalability, implementation of the system poses challenging socio-technical challenges, including biases, lack of transparency, and ethical concerns that should be addressed to ensure fair and legal outcomes.

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The findings also reveal that there is a need to balance human control and governance practices that uphold agency and enhance organizational learning and technology advancements. Furthermore, the study is a contribution to the theoretical discourse in that the author supports more extended notions of algorithmic fairness beyond the idea of accuracy to the equality in error distributions and procedural fairness.

Finally, to be the most effective, we focus on the fact that the ADMS and its application should be seen through the prism of an interdisciplinary approach through the prism of technological, ethical, and social aspects. It provides basic knowledge to be used in future research and policymaking to encourage ethical, inclusive, and transparent algorithm-related decision-making on high-stakes domains.

REFERENCES

[1] H. Mahmud, A. K. M. N. Islam, S. I. Ahmed, and K. Smolander, "What influences algorithmic decision-making? A systematic literature review on algorithm aversion, "Technological Forecasting and Social Change, vol. 175, 121390, 2022.

[2] A. Werner, "Organizing music, organizing gender: algorithmic culture and Spotify recommendations, "Popular Communication, vol. 18, no. 1, pp. 78–90, 2020.

[3] M. Tenemaza, S. Lujan-Mora, A. De Antonio, and J. Ramirez, "Improving Itinerary Recommendations for Tourists Through Metaheuristic Algorithms: An Optimization Proposal, "IEEE Access, vol. 8, pp. 79003–79023, 2020.

[4] M. A. DeVito, "From Editors to Algorithms," Digital Journalism, vol. 5, no. 6, pp. 753–773, 2017.

[5] M. Shanmuganathan, "Behavioural finance in an era of artificial intelligence," Journal of Behavioral and Experimental Finance, vol. 27, 100297, 2020.

[6] Y. Modi et al., "A comprehensive review on intelligent traffic management using machine learning algorithms," Innovative Infrastructure Solutions, vol. 7, no. 1, 128, 2022.

[7] V. Tsakanikas and T. Dagiuklas, "Video surveillance systems-current status and future trends, "Computers & Electrical Engineering, vol. 70, pp. 736–753, 2018.

[8] T. B. Brown et al., "Language Models are Few-Shot Learners," arXiv preprint arXiv:2005.14165, 2020.

[9] T. Grønsund and M. Aanestad," Augmenting the algorithm: Emerging human-in-the-loop work configurations," The Journal of Strategic Information Systems, vol. 29, no. 2, 101614, 2020.

[10] Y. K. Dwivedi et al., "Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges," International Journal of Information Management, vol. 57, 101994, 2021.

[11] L. M. Giermindl et al., "The dark sides of people analytics: reviewing the perils for organisations and employees," European Journal of Information Systems, vol. 31, no. 3, pp. 410–435, 2022.

[12] N. Berente, B. Gu, J. Recker, and R. Santhanam, "Managing Artificial Intelligence, "MIS Quarterly, vol. 45, no. 3, pp. 1433–1450, 2021.

[13] H. Benbya, S. Pachidi, and S. L. Jarvenpaa, "Artificial Intelligence in Organizations: Implications for Information Systems Research," Journal of the Association for Information Systems, vol. 22, no. 2, pp. 281–303, 2021.

[14] D. Q. Chen, D. S. Preston, and M. Swink, "How Big Data Analytics Affects Supply Chain Decision-Making," Journal of the Association for Information Systems, vol. 22, no. 5, pp. 1224–1244, 2021.

[15] Y. Zhu et al., "Dark, Beyond Deep: A Paradigm Shift to Cognitive AI with Humanlike Common Sense," Engineering, vol. 6, no. 3, pp. 310–345, 2020.

[16] S. Akter and S. F. Wamba, "Big data analytics in E-commerce: a systematic review," Electronic Markets, vol. 26, no. 2, pp. 173–194, 2016.

[17] H. Chen, R. H. L. Chiang, and V. C. Storey, "Business Intelligence and Analytics: From Big Data to Big Impact," MIS Quarterly, vol. 36, no. 4, pp. 1165–1188, 2012.

[18] S. Schuetz and V. Venkatesh, "The Rise of Human Machines," Journal of the Association for Information Systems, 2020.

[19] A. Abbasi, S. Sarker, and R. Chiang, "Big Data Research in Information Systems," Journal of the Association for Information Systems, vol. 17, no. 2, 2016.

[20] B. Baesens et al., "Transformational Issues of Big Data and Analytics in Networked Business," MIS Quarterly, vol. 40, no. 4, pp. 807–818, 2016.

[21] S. Raisch and S. Krakowski, "Artificial Intelligence and Management: The Automation–Augmentation Paradox," Academy of Management Review, vol. 46, no. 1, pp. 192–210, 2021.

[22] J. Li et al., "Strategic Directions for AI," MIS Quarterly, vol. 45, no. 3, pp. 1603–1644, 2021.

[23] P. J. Ågerfalk, "Artificial intelligence as digital agency," European Journal of Information Systems, vol. 29, no. 1, pp. 1–8, 2020.

DOI: **10.5281/zenodo.19541953**

[24] N. P. Rana et al., “Understanding dark side of artificial intelligence integrated business analytics,” European Journal of Information Systems, vol. 31, no. 3, pp. 364–387, 2022.

[25] A. G. Ouimet and S. Addas, “Algorithmic Decision-Making Systems: A Conceptualization and Agenda,” ICIS Conference, 2022.

[26] S. Vollmer et al., “Machine learning and artificial intelligence research for patient benefit,” BMJ, 2020.

[27] R. Dobbe et al., “A Broader View on Bias in Automated Decision-Making,” arXiv preprint arXiv:1807.00553, 2018.

[28] P. Solanki, J. Grundy, and W. Hussain, “Operationalising ethics in artificial intelligence for healthcare,” AI and Ethics, vol. 3, no. 1, pp. 223–240, 2023.

[29] T. Gillespie, "The Relevance of Algorithms," in Media Technologies, pp. 167–194, The MIT Press, 2014, doi:10.7551/impress/9780262525374.003.0009.

[30] T. Araujo, N. Helberger, S. Kruikemeier, and C. H. de Vreese, "In AI we trust? Perceptions about automated decision-making by artificial intelligence," AI & Society, vol. 35, no. 3, pp. 611–623, 2020, doi: 10.1007/s00146-019-00931-w.

[31] P. Mikalef and M. Gupta, "Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance," Information & Management, vol. 58, no. 3, p. 103434, 2021, doi:10.1016/j.im.2021.103434.

[32] J. Cobbe, M. S. A. Lee, and J. Singh, "Reviewable Automated Decision-Making," in Proc. 2021 ACM Conf. on Fairness, Accountability, and Transparency, pp. 598–609, 2021, doi:10.1145/3442188.3445921.

[33] F. Gerdon, R. L. Bach, C. Kern, and F. Kreuter, "Social impacts of algorithmic decision-making: A research agenda for the social sciences," Big Data & Society, vol. 9, no. 1, 2022, doi: 10.1177/20539517221089305.

[34] V. Gulshan et al., "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs," JAMA, vol. 316, no. 22, pp. 2402–2410, 2016, doi: 10.1001/jama.2016.17216.

[35] A. Esteva et al., "Dermatologist-level classification of skin cancer with deep neural networks," Nature, vol. 542, no. 7639, pp. 115–118, 2017, doi: 10.1038/nature21056.

[36] A. Esteva et al., "A guide to deep learning in healthcare," Nature Medicine, vol. 25, no. 1, pp. 24–29, 2019, doi: 10.1038/s41591-018-0316-z.

[37] C. Castelluccia and L. M. D., "Understanding algorithmic decision-making: Opportunities and challenges," European Parliamentary Research Service, 2019, doi: 10.2861/536131.

[38] W. Zhang et al., "Robo-advisors and investment decisions," Finance Research Letters, vol. 38, p. 101460, 2021.

[39] C. Walsh et al., "Machine learning models in suicide prediction," JAMA Psychiatry, vol. 75, no. 7, pp. 740–750, 2018.

[40] T. Grote and P. Berens, "On the ethics of algorithmic decision-making in healthcare," Journal of Medical Ethics, vol. 46, no. 3, pp. 205–211, 2020, doi: 10.1136/medethics-2019-105586.

[41] D. Christensen, "Epistemology of Disagreement: The Good News," The Philosophical Review, vol. 116, no. 2, pp. 187–217, 2007, doi: 10.1215/00318108-2006-035.

[42] T. Kelly, "Peer disagreement and higher order evidence," in W. D. Goldman, Ed., Social epistemology: essential readings, pp. 183–217, Oxford University Press, 2010.

[43] T. Grote and P. Berens, "On the ethics of algorithmic decision-making in healthcare," Journal of Medical Ethics, vol. 46, no. 3, pp. 205–211, 2020, doi: 10.1136/medethics-2019-105586.

[44] F. Bannister, In Defence of Bureaucracy: Governance and Public Values in a Digital Age, 2017, doi: 10.1007/978-3-319-54142-6_3.

[45] A. Rizk and I. Lindgren, "Automated decision-making in public administration: Changing the decision space between public officials and citizens," Government Information Quarterly, vol. 42, no. 3, p. 102061, 2025,

doi: 10.1016/j.giq.2025. 102061..

[46] A. Rizk, L. Sundberg, M. Heidlund, and D. Toll, "Between continuity and change: A longitudinal analysis of Swedish local government digitalization strategies," JeDEM - EJournal of eDemocracy and Open Government, vol. 16, no. 2, pp. 49–73, 2024,

doi:10.29379/jedem. v16i2. 914..

[47] E. M. Weitzenboeck, "Simplification of administrative procedures through fully automated decision-making: The case of Norway," Administrative Sciences, vol. 11, no. 4, p. 149, 2021, doi: 10.3390/admsci11040149. [48] M. Janssen, M. Hartog, R.

DOI: **10.5281/zenodo.19541953**

Matheus, A. Yi Ding, and G. Kuk, "Will Algorithms Blind People? The Effect of Explainable AI and Decision-Makers' Experience on AI-supported Decision-Making in Government," Social Science Computer Review, vol. 40, no. 2, pp. 478–493, 2022, doi: 10.1177/0894439320980118.

[49] G. Wang, Y. Guo, W. Zhang, S. Xie, and Q. Chen, "What type of algorithm is perceived as fairer and more acceptable? A comparative analysis of rule-driven versus data-driven algorithmic decision-making in public affairs," Government Information Quarterly, vol. 40, no. 2, p. 101803, 2023, doi: 10.1016/j.giq.2023.101803.

[50] D. Barysė and R. Sarel, "Algorithms in the court: does it matter which part of the judicial decision-making is automated?" Artificial Intelligence and Law, vol. 32, no. 1, pp. 117–146, 2024, doi: 10.1007/s10506-022-09343-6.

[51] J. W. Burton, M. Stein, and T. B. Jensen, "A systematic review of algorithm aversion in augmented decision making," Journal of Behavioral Decision Making, vol. 33, no. 2, pp. 220–239, 2020, doi: 10.1002/bdm.2155.

[52] T. Enarsson, L. Enqvist, and M. Naarttijärvi, "Approaching the human in the loop – legal perspectives on hybrid human/algorithmic decision-making in three contexts," Information & Communications Technology Law, vol. 31, no. 1, pp. 123–153, 2022, doi: 10.1080/13600834.2021.1958860.

[53] N. Elgendy, A. Elragal, and T. Päivärinta, "DECAS: a modern data-driven decision theory for big data and analytics," Journal of Decision Systems, vol. 31, no. 4, pp. 337–373, 2022, doi: 10.1080/12460125.2021.1894674.

[54] H. Scholta and I. Lindgren, "Proactivity in digital public services: A conceptual analysis," Government Information Quarterly, vol. 40, no. 3, p. 101832, 2023,

doi: 10.1016/j.giq.2023. 101832..

[55] M. Marabelli, S. Newell, and V. Handunge, "The lifecycle of algorithmic decision-making systems: Organizational choices and ethical challenges," The Journal of Strategic Information Systems, vol. 30, no. 3, p. 101683, 2021, doi: 10.1016/j.jsis.2021.101683.

[56] A. Kaun, "Suing the algorithm: the mundanization of automated decision-making in public services through litigation," Information, Communication & Society, vol. 25, no. 14, pp. 2046–2062, 2022, doi: 10.1080/1369118X.2021.1924827.

[57] M. Kuziemski and G. Misuraca, "AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings," Telecommunications Policy, vol. 44, no. 6, p. 101976, 2020, doi: 10.1016/j.telpol.2020.101976.

[58] A. Rachovitsa and N. Johann, "The human rights implications of the use of AI in the digital welfare state: Lessons learned from the Dutch SyRI case," Human Rights Law Review, vol. 22, no. 2, 2022, doi:10.1093/hrlr/ngac010.

[59] K. K. Larsson, "Digitization or equality: When government automation covers some, but not all citizens," Government Information Quarterly, vol. 38, no. 1, p. 101547, 2021, doi: 10.1016/j.giq.2020.101547.

[60] S. Monteith and T. Glenn, "Automated Decision-Making and Big Data: Concerns for People with Mental Illness," Current Psychiatry Reports, vol. 18, no. 12, p. 112, 2016, doi: 10.1007/s11920-016-0746-6.

[61] S. Vollmer et al., "Machine learning and artificial intelligence research for patient benefit: 20 critical questions on transparency, replicability, ethics, and effectiveness," BMJ, p. l6927, 2020, doi: 10.1136/bmj. l6927.

[62] J. H. L. Hansen and T. Hasan, "Speaker Recognition by Machines and Humans: A tutorial review," IEEE Signal Processing Magazine, vol. 32, no. 6, pp. 74–99, 2015. doi: 10.1109/MSP.2015.2462851.

[63] K. He, X. Zhang, S. Ren, and J. Sun, "Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification," in 2015 IEEE International Conference on Computer Vision (ICCV), pp. 1026–1034, 2015. doi: 10.1109/ICCV.2015.123.

[64] K. Imai, Z. Jiang, D. J. Greiner, R. Halen, and S. Shin, "Experimental evaluation of algorithm-assisted human decision-making: application to pretrial public safety assessment," J. R. Stat. Soc. A, vol. 186, no. 2, pp. 167–189, 2023. doi: 10.1093/jrsssa/qnad010.

[65] O. Marjanovic, D. Cecez-Kecmanovic, and R. Vidgen, "Algorithmic pollution: Making the invisible visible," J. Inf. Technol., vol. 36, no. 4, pp. 391–408, 2021. doi: 10.1177/02683962211010356.

[66] K. Lyytinen, J. V. Nickerson, and J. L. King, "Metahuman systems = humans + machines that learn," J. Inf. Technol., vol. 36, no. 4, pp. 427–445, 2021. doi: 10.1177/0268396220915917.

[67] A. Monarcha-Matlak, "Automated decision-making in public administration," Procedia Comput. Sci., vol. 192, pp. 2077–2084, 2021. doi: 10.1016/j.procs.2021.08.215.

DOI: **10.5281/zenodo.19541953**

[68] N. Berente, B. Gu, J. Recker, and R. Santhanam, "Managing Artificial Intelligence," MIS Q., vol. 45, no. 3, pp. 1433–1450, 2021. doi: 10.25300/MISQ/2021/16274.

[69] N. Nishant, M. Kennedy, and J. Corbett, "Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda," Int. J. Inf. Manag., vol. 53, 102104, 2020. doi: 10.1016/j.ijinfomgt.2020.102104.

[70] Y. K. Dwivedi et al., "Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy," Int. J. Inf. Manag., vol. 57, 101994, 2021.

doi: 10.1016/j.ijinfomgt.2019.08.002.

[71] O. Marabelli, S. Newell, and V. Handunge, "The lifecycle of algorithmic decision-making systems: Organizational choices and ethical challenges," J. Strateg. Inf. Syst., vol. 30, no. 3, 101683, 2021. doi: 10.1016/j.jsis.2021.101683.

[72] T. Berente, B. Gu, J. Recker, and R. Santhanam, "Managing Artificial Intelligence," MIS Q., vol. 45, no. 3, pp. 1433–1450, 2021. doi: 10.25300/MISQ/2021/16274.

[73] N. Giermindl, F. Strich, O. Christ, U. Leicht-Deobald, and A. Redzepi, "The dark sides of people analytics: reviewing the perils for organisations and employees," Eur. J. Inf. Syst., vol. 31, no. 3, pp. 410–435, 2022. doi: 10.1080/0960085X.2021.1927213.

[74] H. Marjanovic, D. Cecez-Kecmanovic, and R. Vidgen, "Algorithmic pollution: Making the invisible visible," J. Inf. Technol., vol. 36, no. 4, pp. 391–408, 2021. doi: 10.1177/02683962211010356.

[75] R. Rana, S. Chatterjee, Y. K. Dwivedi, and S. Akter, "Understanding dark side of artificial intelligence (AI) integrated business analytics: assessing firm's operational inefficiency and competitiveness," European Journal of Information Systems, vol. 31, no. 3, pp. 364–387, 2022. https://doi.org/10.1080/0960085X.2021.1955628

[76] A. Rapp, L. Curti, and A. Boldi, "The human side of human-chatbot interaction: A systematic literature review of ten years of research on text-based chatbots," International Journal of Human-Computer Studies, vol. 151, p. 102630, 2021. https://doi.org/10.1016/j.ijhcs.2021.102630

[77] A. Rizk and I. Lindgren, "Automated decision-making in public administration: Changing the decision space between public officials and citizens," Government Information Quarterly, vol. 42, no. 3, p. 102061, 2025. https://doi.org/10.1016/j.giq.2025.102061

[78] A. Rizk, L. Sundberg, M. Heidlund, and D. Toll, "Between continuity and change: A longitudinal analysis of Swedish local government digitalization strategies," JeDEM - EJournal of EDemocracy and Open Government, vol. 16, no. 2, pp. 49–73, 2024. https://doi.org/10.29379/jedem.v16i2.914

[79] U. Roehl and J. Crompvoets, "Inside algorithmic bureaucracy: Disentangling automated decision-making and good administration," Public Policy and Administration, vol. 40, no. 2, pp. 322–350, 2025. https://doi.org/10.1177/09520767231197801

[80] H. Scholta and I. Lindgren, "Proactivity in digital public services: A conceptual analysis," Government Information Quarterly, vol. 40, no. 3, p. 101832, 2023. https://doi.org/10.1016/j.giq.2023.101832

[81] S. Schuetz and V. Venkatesh, "Research perspectives: The rise of human machines: How cognitive computing systems challenge assumptions of user…," [Online].

[82] M. Schmidhuber, "Deep learning in neural networks: An overview," Neural Networks, vol. 61, pp. 85–117, 2015. https://doi.org/10.1016/j.neunet.2014.09.003

[83] P. Shi, Y. Chen, and J. Xu, "A review on machine learning for healthcare: Algorithms, strategies, and applications," Artificial Intelligence in Medicine, vol. 129, p. 102302, 2023. https://doi.org/10.1016/j.artmed.2022.102302

[84] R. Shrestha, A. Ben-Menahem, and S. von Krogh, "Organizational decision-making structures in the age of artificial intelligence," California Management Review, vol. 61, no. 4, pp. 66–83, 2019. https://doi.org/10.1177/0008125619862258

[85] F. Siau and Y. Wang, "Artificial intelligence in healthcare: Review and prediction case studies," Journal of Database Management, vol. 30, no. 1, pp. 1–17, 2019. https://doi.org/10.4018/JDM.2019010101

[86] H. Singh, R. G. S. Arora, and V. Singh, "Algorithmic decision-making in public sector organizations: a systematic review," Government Information Quarterly, vol. 41, no. 4, p. 101611, 2024. https://doi.org/10.1016/j.giq.2024.101611

[87] R. Sjoberg and J. L. Rosenberg, "Algorithmic risk assessment in criminal justice: Transparency, fairness, and accountability," Computer Law & Security Review, vol. 45, p. 105579, 2023. https://doi.org/10.1016/j.clsr.2023.105579

[88] B. Suh, K. Lee, and J. Choi, "Ethical implications of AI-driven decision support systems in healthcare," AI & Society, vol. 40, no. 2, pp. 497–510, 2025. https://doi.org/10.1007/s00146-024-01789-1

DOI: **10.5281/zenodo.19541953**

[89] K. Kawaguchi, "When Will Workers Follow an Algorithm? A Field Experiment with a Retail Business," Management Science, vol. 67, no. 3, pp. 1670–1695, 2021, doi: 10.1287/mnsc.2020.3599.

[90] U. Kayande, A. De Bruyn, G. L. Lilien, A. Rangaswamy, and G. H. van Bruggen, "How Incorporating Feedback Mechanisms in a DSS Affects DSS Evaluations," Information Systems Research, vol. 20, no. 4, pp. 527–546, 2009, doi: 10.1287/isre.1080.0198.

[91] T. Kelly, "Peer disagreement and higher order evidence," in Social epistemology: essential readings, W. D. Goldman, Ed., Oxford: Oxford University Press, pp. 183–217, 2010.

[92] M. Khosravi, Z. Zare, S. M. Mojtabaeian, and R. Izadi, "Artificial Intelligence and Decision-Making in Healthcare: A Thematic Analysis of a Systematic Review of Reviews," Health Services Research and Managerial Epidemiology, vol. 11, 2024, doi: 10.1177/23333928241234863.

[93] T. D. Krafft, K. A. Zweig, and P. D. König, "How to regulate algorithmic decision-making: A framework of regulatory requirements for different applications," Regulation & Governance, vol. 16, no. 1, pp. 119–136, 2022, doi: 10.1111/rego.12369.

[94] M. Kuziemski and G. Misuraca, "AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings," Telecommunications Policy, vol. 44, no. 6, p. 101976, 2020, doi: 10.1016/j.telpol.2020.101976.

[95] K. K. Larsson, "Digitization or equality: When government automation covers some, but not all citizens," Government Information Quarterly, vol. 38, no. 1, p. 101547, 2021, doi: 10.1016/j.giq.2020.101547.

[96] B. Lepri, N. Oliver, E. Letouzé, A. Pentland, and P. Vinck, "Fair, Transparent, and Accountable Algorithmic Decision-making Processes," Philosophy & Technology, vol. 31, no. 4, pp. 611–627, 2018, doi: 10.1007/s13347-017-0279-x.

[97] K. Levy, K. E. Chasalow, and S. Riley, "Algorithms and Decision-Making in the Public Sector," Annual Review of Law and Social Science, vol. 17, no. 1, pp. 309–334, 2021, doi: 10.1146/annurev-lawsocsci-041221-023808.

[98] J. Li, M. Li, X. Wang, and J. B. Thatcher, "Strategic Directions for AI: The Role of CIOs and Boards of Directors," MIS Quarterly, vol. 45, no. 3, pp. 1603–1644, 2021, doi: 10.25300/MISQ/2021/16523.

[99] D. Lindebaum, M. Vesa, and F. den Hond, "Insights From 'The Machine Stops' to Better Understand Rational Assumptions in Algorithmic Decision Making and Its Implications for Organizations," Academy of Management Review, vol. 45, no. 1, pp. 247–263, 2020, doi: 10.5465/amr.2018.0181.

[100] R. Rizk and I. Lindgren, "Automated decision-making in public administration: Changing the decision space between public officials and citizens," Government Information Quarterly, vol. 42, no. 3, p. 102061, 2025. https://doi.org/10.1016/j.giq.2025.102061

[101] A. Rizk, L. Sundberg, M. Heidlund, and D. Toll, "Between continuity and change: A longitudinal analysis of Swedish local government digitalization strategies," JeDEM - EJournal of EDemocracy and Open Government, vol. 16, no. 2, pp. 49–73, 2024. https://doi.org/10.29379/jedem.v16i2.914

[102] U. Roehl and J. Crompvoets, "Inside algorithmic bureaucracy: Disentangling automated decision-making and good administration," Public Policy and Administration, vol. 40, no. 2, pp. 322–350, 2025. https://doi.org/10.1177/09520767231197801

[103] H. Scholta and I. Lindgren, "Proactivity in digital public services: A conceptual analysis," Government Information Quarterly, vol. 40, no. 3, p. 101832, 2023. https://doi.org/10.1016/j.giq.2023.101832

[104] S. Newell and M. Marabelli, "Strategic opportunities (and challenges) of algorithmic decision-making: A call for action on the long-term societal effects of 'datification,'" The Journal of Strategic Information Systems, vol. 24, no. 1, pp. 3–14, 2015, doi: 10.1016/j.jsis.2015.02.001.

[105] N. Berente, B. Gu, J. Recker, and R. Santhanam, "Managing Artificial Intelligence," MIS Quarterly, vol. 45, no. 3, pp. 1433–1450, 2021, doi: 10.25300/MISQ/2021/16274.

[106] Y. K. Dwivedi et al., "Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy," Int. J. Inf. Management, vol. 57, 101994, 2021, doi: 10.1016/j.ijinfomgt.2019.08.002.

[107] O. Marjanovic, D. Cecez-Kecmanovic, and R. Vidgen, "Algorithmic pollution: Making the invisible visible," J. Inf. Technol., vol. 36, no. 4, pp. 391–408, 2021, doi: 10.1177/02683962211010356.

[108] N. P. Rana, S. Chatterjee, Y. K. Dwivedi, and S. Akter, "Understanding dark side of artificial intelligence (AI) integrated business analytics: assessing firm's operational inefficiency and competitiveness," European

DOI: **10.5281/zenodo.19541953**

Journal of Information Systems, vol. 31, no. 3, pp. 364–387, 2022, doi: 10.1080/0960085X.2021.1955628.

[109] Z. Engin and P. Treleaven, "Algorithmic Government: Automating Public Services and Supporting Civil Servants in using Data Science Technologies," The Computer Journal, vol. 62, no. 3, pp. 448–460, 2019, doi: 10.1093/comjnl/bxy082.

[110] J. Bullock, A. Luccioni, K. Hoffman Pham, C. Sin Nga Lam, and M. Luengo-Oroz, "Mapping the landscape of Artificial Intelligence applications against COVID-19," J. Artif. Intell. Res., vol. 69, pp. 807–845, 2020, doi: 10.1613/jair.1.12162.

[111] G. L. Vasconcelos et al., "Modelling fatality curves of COVID-19 and the effectiveness of intervention strategies," PeerJ, vol. 8, e9421, 2020, doi: 10.7717/peerj.9421.

[112] E. A. Topol, "High-performance medicine: the convergence of human and artificial intelligence," Nature Medicine, vol. 25, no. 1, pp. 44–56, 2019, doi: 10.1038/s41591-018-0300-7.

[113] Y. Y. M. Aung, D. C. S. Wong, and D. S. W. Ting, "The promise of artificial intelligence: a review of the opportunities and challenges of artificial intelligence in healthcare," Br. Med. Bull., vol. 139, no. 1, pp. 4–15, 2021, doi: 10.1093/bmb/ldab016.

[114] P. Gooding and T. Kariotis, "Ethics and Law in Research on Algorithmic and Data-Driven Technology in Mental Health Care: Scoping Review," JMIR Mental Health, vol. 8, no. 6, e24668, 2021, doi: 10.2196/24668.

[115] K. Cresswell, A. Majeed, D. W. Bates, and A. Sheikh, "Computerised decision support systems for healthcare professionals: an interpretative review," J. Innov. Health Inform., vol. 20, no. 2, pp. 115–128, 2013, doi: 10.14236/jhi.v20i2.32.

[116] D. C. Cireşan, A. Giusti, L. M. Gambardella, and J. Schmidhuber, "Mitosis Detection in Breast Cancer Histology Images with Deep Neural Networks," in Med. Image Comput. Comput.-Assist. Interv., pp. 411–418, 2013,

doi: 10.1007/978-3-642-40763-5_51.

[117] A. Esteva et al., "Dermatologist-level classification of skin cancer with deep neural networks," Nature, vol. 542, no. 7639, pp. 115–118, 2017, doi: 10.1038/nature21056.

[118] V. Gulshan et al., "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs," JAMA, vol. 316, no. 22, pp. 2402, 2016, doi: 10.1001/jama.2016.17216.

[119] R. Poplin et al., "Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning," Nature Biomedical Engineering, vol. 2, no. 3, pp. 158–164, 2018, doi: 10.1038/s41551-018-0195-0.

[120] R. Miotto, L. Li, B. A. Kidd, and J. T. Dudley, "Deep Patient: An Unsupervised Representation to Predict the Future of Patients from the Electronic Health Records," Sci. Rep., vol. 6, 26094, 2016, doi: 10.1038/srep26094.

[121] C. G. Walsh, J. D. Ribeiro, and J. C. Franklin, "Predicting Risk of Suicide Attempts Over Time Through Machine Learning," Clin. Psychol. Sci., vol. 5, no. 3, pp. 457–469, 2018, doi: 10.1177/2167702617691560.

[122] J. Ozer et al., "Culture and personal influences on cardiopulmonary resuscitation- results of international survey," BMC Med. Ethics, vol. 20, no. 1, 102, 2019, doi: 10.1186/s12910-019-0439-X.

[123] J. Diamond, U. Gidwani, and R. Rhodes, "Do Not Resuscitate, with No Surrogate and No Advance Directive: An Ethics Case Study," J. Clin. Ethics, vol. 28, no. 2, pp. 159–162, 2017, doi: 10.1086/JCE2017282159.

[124] D. Y. Harari and R. C. Macauley, "Betting on CPR: a modern version of Pascal's Wager," J. Med. Ethics, vol. 46, no. 2, pp. 110–113, 2020, doi: 10.1136/medethics-2019-105558.

[125] D. Wendler, R. Wesley, M. Pavlick, and A. Rid, "Do patients want their families or their doctors to make treatment decisions in the event of incapacity, and why?," AJOB Empir. Bioeth., vol. 7, no. 4, pp. 251–259, 2016, doi: 10.1080/23294515.2016.1182235.

[126] C. Giordano et al., "Accessing Artificial Intelligence for Clinical Decision-Making," Front. Digit. Health, vol. 3, 645239, 2021, doi: 10.3389/fdgth.2021.645239.

[127] P. Mishra, S. Kumar, and M. K. Chaube, "Graph Interpretation, Summarization and Visualization Techniques: A Review and Open Research Issues," Multimedia Tools Appl., vol. 82, no. 6, pp. 8729–8771, 2023, doi: 10.1007/s11042-021-11582-9.

[128] J. Zhou, M. Du, S. Chang, and Z. Chen, "Artificial intelligence in echocardiography: detection, functional evaluation, and disease diagnosis," Cardiovasc. Ultrasound, vol. 19, no. 1, 29, 2021, doi: 10.1186/s12947-021-00261-2.

[129] P. Brocklehurst et al., "Computerised interpretation of fetal heart rate during labour (INFANT): a randomised controlled trial," The Lancet, vol. 389, no.

DOI: **10.5281/zenodo.19541953**

10080, pp. 1719–1729, 2017, doi: 10.1016/S0140-6736(17)30568-8.

[130] D. D. Miller and E. W. Brown, “Artificial Intelligence in Medical Practice: The Question to the Answer?,” Am. J. Med., vol. 131, no. 2, pp. 129–133, 2018, doi: 10.1016/j.amjmed.2017.10.035.

[131] H. Ali, F. Mohsen, and Z. Shah, “Improving diagnosis and prognosis of lung cancer using vision transformers: a scoping review,” BMC Med. Imaging, vol. 23, no. 1, 129, 2023, doi: 10.1186/s12880-023-01098-Z.

[132] L. Benzinger et al., “Should Artificial Intelligence be used to support clinical ethical decision-making? A systematic review of reasons,” BMC Med. Ethics, vol. 24, no. 1, 48, 2023, doi: 10.1186/s12910-023-00929-6.

[133] M. Khosravi, Z. Zare, S. M. Mojtabaeian, and R. Izadi, “Artificial Intelligence and Decision-Making in Healthcare: A Thematic Analysis of a Systematic Review of Reviews,” Health Serv. Res. Manage. Epidemiol., vol. 11, 2024, doi: 10.1177/23333928241234863.

[134] H. Toros, D. Flaming, and E. Roundtable, “Prioritizing Homeless Assistance Using Predictive Algorithms: An Evidence-Based Approach,” Cityscape: A Journal of Policy Development and Research, vol. 20, 2018.

[135] H. Burdick et al., “Prediction of respiratory decompensation in Covid-19 patients using machine learning: The READY trial,” Comput. Biol. Med., vol. 124, 103949, 2020, doi: 10.1016/j.compbiomed.2020.103949.

[136] R. J. Chen et al., “Algorithmic fairness in artificial intelligence for medicine and healthcare,” Nat. Biomed. Eng., vol. 7, no. 6, pp. 719–742, 2023, doi: 10.1038/s41551-023-01056-8

[137] C. Wilhelm, A. Steckelberg, and F. G. Rebitschek, “Benefits and harms associated with the use of AI-related algorithmic decision-making systems by healthcare professionals: a systematic review,” Lancet Reg. Health Eur., vol. 48, 101145, 2025, doi: 10.1016/j.lanepe.2024.101145

[138] M. Brennan et al., “Comparing clinical judgment with the MySurgeryRisk algorithm for preoperative risk assessment: A pilot usability study,” Surgery, vol. 165, no. 5, pp. 1035–1045, 2019, doi: 10.1016/j.surg.2019.01.002.

[139] E. Goh et al., “Large Language Model Influence on Diagnostic Reasoning,” JAMA Netw. Open, vol. 7, no. 10, e2440969, 2024, doi: 10.1001/jamanetworkopen.2024.40969.

[140] Q. Cassam, Vices of the Mind. Oxford: Oxford University Press, 2019, doi: 10.1093/oso/9780198826903.001.0001.

[141] K. Hawley, “Trust and distrust between patient and doctor,” J. Eval. Clin. Pract., vol. 21, no. 5, pp. 798–801, 2015, doi: 10.1111/jep.12374.

[142] R. J. McDougall, “Computer knows best? The need for value-flexibility in medical AI,” J. Med. Ethics, vol. 45, no. 3, pp. 156–160, 2019, doi: 10.1136/medethics-2018-105118.

[143] D. Plana et al., “Randomized Clinical Trials of Machine Learning Interventions in Health Care,” JAMA Netw. Open, vol. 5, no. 9, e2233946, 2022, doi: 10.1001/jamanetworkopen.2022.33946.

[144] M. G. Hanna et al., “Ethical and Bias Considerations in Artificial Intelligence/Machine Learning,” Mod. Pathol., vol. 38, no. 3, 100686, 2025, doi: 10.1016/j.modpat.2024.100686.

[145] E. B. Weiner, I. Dankwa-Mullan, W. A. Nelson, and S. Hassanpour, “Ethical challenges and evolving strategies in the integration of artificial intelligence into clinical practice,” PLOS Digit. Health, vol. 4, no. 4, e0000810, 2025, doi: 10.1371/journal.pdig.0000810.

[146] C. Starke, J. Baleis, B. Keller, and F. Marcinkowski, “Fairness perceptions of algorithmic decision-making: A systematic review of the empirical literature,” Big Data Soc., vol. 9, no. 2, 2022, doi: 10.1177/20539517221115189.

[147] S. A. Alowais et al., “Revolutionizing healthcare: the role of artificial intelligence in clinical practice,” BMC Med. Educ., vol. 23, no. 1, 689, 2023, doi: 10.1186/s12909-023-04698-Z.

[148] R. Raab et al., “Federated electronic health records for the European Health Data Space,” Lancet Digit. Health, vol. 5, no. 11, e840–e847, 2023, doi: 10.1016/S2589-7500(23)00156-5.

[149] A. Rizk and I. Lindgren, “Automated decision-making in public administration: Changing the decision space between public officials and citizens,” Government Information Quarterly, vol. 42, no. 3, p. 102061, 2025. https://doi.org/10.1016/j.giq.2025.102061

[150] A. Maxmen, “Machine learning spots treasure trove of elusive viruses,” Nature, 19 Mar. 2018.

[151] B. W. Wirtz, J. C. Weyerer, and C. Geyer, “Artificial Intelligence and the Public Sector—Applications and Challenges,” Int. J. Public Adm., vol. 42, no. 7, pp. 596–615, 2019, doi: 10.1080/01900692.2018.1498103

DOI: **10.5281/zenodo.19541953**

[152] T. Papadakis, I. T. Christou, C. Ipektsidis, J. Soldatos, and A. Amicone, "Explainable and transparent artificial intelligence for public policymaking," Data & Policy, vol. 6, e10, 2024, doi: 10.1017/dap.2024.3

[153] A. Rizk, "The agency of algorithms: Understanding human-algorithm interaction in administrative decision-making," Information Polity, vol. 25, no. 4, pp. 507–522, 2020, doi: 10.3233/IP-200253

[154] C. Castelluccia and L. M. D., "Understanding algorithmic decision-making: Opportunities and challenges," EPRS | European Parliamentary Research Service, 2019, doi: 10.2861/536131

[155] K. Levy, K. E. Chasalow, and S. Riley, "Algorithms and Decision-Making in the Public Sector," Annu. Rev. Law Soc. Sci., vol. 17, no. 1, pp. 309–334, 2021, doi: 10.1146/annurev-lawsocsci-041221-023808

[156] C. F. Breidbach, "Responsible algorithmic decision-making," Organ. Dyn., vol. 53, no. 2, 101031, 2024, doi: 10.1016/j.orgdyn.2024.101031

[157] D. Amodei et al., "Concrete Problems in AI Safety," arXiv, 2016. http://arxiv.org/abs/1606.06565

[158] C. Coglianese, D. Lehr, S. Benjamin, R. Berk, H. Gunn, R. Pierce, and A. Rai, "Transparency and algorithmic governance," Adm. Law Rev., vol. 71, pp. 1–56, 2019.

[159] K. Fink, "Opening the government's black boxes: freedom of information and algorithmic accountability," Inf., Commun. Soc., vol. 21, no. 10, pp. 1453–1471, 2018, doi: 10.1080/1369118X.2017.1330418

[160] H. Bloch-Wehba, "Access to Algorithms," Fordham Law Rev., vol. 88, pp. 1265–1314, 2020.

[161] D. K. Mulligan and K. A. Bamberger, "Procurement As Policy: Administrative Process for Machine Learning," SSRN Electron. J., 2019, doi: 10.2139/ssrn.3464203

[162] R. Wexler, "Life, Liberty, and Trade Secrets: Intellectual Property in the Criminal Justice System," Stanford Law Rev., vol. 70, pp. 1343–1429, 2018.

[163] R. Brauneis and E. P. Goodman, "Algorithmic Transparency for the Smart City," Yale J. Law Technol., vol. 20, pp. 103–176, 2018.

[164] E. Gules-Guctas, "How Do Algorithmic Decision-Making Systems Used in Public Benefits Determinations Fail? Insights From Legal Challenges," Public Adm. Rev., 2025, doi: 10.1111/puar.70043

[165] A. De Bruyn, V. Viswanathan, Y. S. Beh, J. K.-U. Brock, and F. Von Wangenheim, "Artificial Intelligence and Marketing: Pitfalls and Opportunities," J. Interact. Mark., vol. 51, no. 1, pp. 91–105, 2020, doi: 10.1016/j.intmar.2020.04.007

[166] B. Vlačić, L. Corbo, S. Costa e Silva, and M. Dabić, "The evolving role of artificial intelligence in marketing: A review and research agenda," J. Bus. Res., vol. 128, pp. 187–203, 2021, doi: 10.1016/j.jbusres.2021.01.055

[167] A. Rapp, L. Curti, and A. Boldi, "The human side of human-chatbot interaction: A systematic literature review of ten years of research on text-based chatbots," Int. J. Hum.-Comput. Stud., vol. 151, p. 102630, 2021, doi: 10.1016/j.ijhcs.2021.102630

[168] B. Berger, M. Adam, A. Rühr, and A. Benlian, "Watch Me Improve—Algorithm Aversion and Demonstrating the Ability to Learn," Bus. Inf. Syst. Eng., vol. 63, no. 1, pp. 55–68, 2021, doi: 10.1007/s12599-020-00678-5

[169] K. Kawaguchi, "When Will Workers Follow an Algorithm? A Field Experiment with a Retail Business," Manage. Sci., vol. 67, no. 3, pp. 1670–1695, 2021, doi: 10.1287/mnsc.2020.3599

[170] N. N. Sharan and D. M. Romano, "The effects of personality and locus of control on trust in humans versus artificial intelligence," Heliyon, vol. 6, no. 8, e04572, 2020, doi: 10.1016/j.heliyon.2020.e04572

[171] E. Bogert, A. Schecter, and R. T. Watson, "Humans rely more on algorithms than social influence as a task becomes more difficult," Sci. Rep., vol. 11, 8028, 2021, doi: 10.1038/s41598-021-87480-9

[172] A. Prahl and L. Van Swol, "Out with the Humans, in with the Machines?: Investigating the Behavioral and Psychological Effects of Replacing Human Advisors with a Machine," Human-Machine Commun., vol. 2, pp. 209–234, 2021, doi: 10.30658/hmc.2.11

[173] B. J. Dietvorst, J. P. Simmons, and C. Massey, "Algorithm aversion: People erroneously avoid algorithms after seeing them err," J. Exp. Psychol. Gen., vol. 144, no. 1, pp. 114–126, 2015, doi: 10.1037/xge0000033

[174] I. Filiz, J. R. Judek, M. Lorenz, and M. Spiwoks, "The Tragedy of Algorithm Aversion," SSRN Electronic Journal, 2021, doi: 10.2139/ssrn.3684206.

[175] A. Tandon, A. Dhir, A. K. M. N. Islam, and M. Mäntymäki, "Blockchain in healthcare: A systematic literature review, synthesizing framework and future research agenda," Comput. Ind., vol. 122, 103290, 2020, doi: 10.1016/j.compind.2020.103290

DOI: **10.5281/zenodo.19541953**