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KNOWLEDGE IN ACTION

Faculty of Business Economics

Master of Management

Master's thesis

The influence of organizational structure on Automated Decision-Making Systems.

Muhammad Junaid

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Business Process Management

SUPERVISOR :
Prof. dr. Koenraad VANHOOF

MENTOR :
Mevrouw Elisavet KOUTSOVITI-KOUMERI

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Acknowledgments

Through the composition of this thesis, I am poised to conclude my academic pursuit of acquiring a master's degree in management, specializing in Business Process Management at Hasselt University Belgium. The university gave me a research topic to investigate "The Influence of Organizational Structure on Automated Decision-Making Systems". In executing this dissertation, I hope to emphasize the critical aspects of the research topic and contribute to the knowledge around it.

First, I extend my utmost appreciation to Prof. Dr. Koen Vanhoof, my supervisor whose guidance and assistance were instrumental in the successful completion of this dissertation. Furthermore, I express profound gratitude to Miss Lisa Koutsoviti Koumeri, who was my thesis mentor for her unwavering encouragement and support throughout this research endeavor. I am gratefully indebted for her valuable comments, and suggestions and for sharing her knowledge.

Furthermore, I would like to convey my profound gratitude towards my family and friends, especially Imad Khalid for his unwavering support during the course of attaining my master's degree.

Lastly, I wish to express my sincerest appreciation to my parents for their valuable assistance, encouragement, and endorsement during moments of triumph and difficulty. My heartfelt love is with you always.

Thank you!

Muhammad Junaid

Managerial Summary

Research Purpose

Organizational decision-making processes are increasingly using algorithmic decision support systems (ADSS). Although these systems are predicted to increase decision-making effectiveness and efficiency, there are questions concerning their fairness and moral implications. Recent studies have covered many of the possibilities for algorithmic bias and prejudice in decision-making. Research has shown that managerial practices can influence fairness in ADSS. For instance, the absence of inclusivity, diversity, and equity during algorithmic development. Neglecting to take into account the perspectives and knowledge of a range of stakeholders, in addition to having an insufficient organizational culture that does not promote collaboration between departments or transparency, may result in unfavorable consequences.

Although, several studies have been carried out to explore the elements that impact impartiality in algorithmic decision-making and provide guidance on enhancing fairness from a managerial standpoint. Yet, there is no comprehensive literature review nor a framework for examining how managerial practices can safeguard and enhance fairness in ADSS.

Thus, I perform a Narrative Literature Review (NLR) to scrutinize the intricate relationship between ADSS and organizational structure while evaluating various factors that affect fair decision-making.

My NLR is guided by the following sub-questions:

R1: How can organizations promote fairness in ADSS through their management structure?

R2: What factors influence fairness in ADSS through their management structure?

R3: How can firms be motivated to improve fairness in ADSS from a managerial standpoint?

Methodology

A Narrative Approach is used in this research that integrates methods used in prior scholarly works to proactively promote transparency, impartiality, and ethical deliberation when implementing Algorithmic Decision support systems.

The initial phase to carry on this research involves the identification of articles that held potential relevance. I took into account eleven academic databases comprised of papers from 2015 onwards as ADSS emerged a lot in the past couple of years. I refined the dataset by excluding papers that are outside the scope of my study and ended up with a final dataset of relevant 30 papers.

Findings

Based on the research papers that were examined during the literature review, a framework is suggested that is illustrated through the histogram provided in Figure 1. The percentages presented in the histogram are computed without normalization due to certain papers being applicable to numerous concepts.

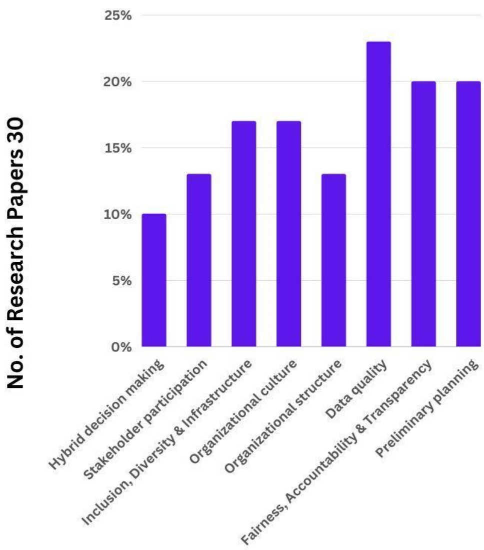

Figure1: ADM Framework: Key Concepts

The figure explains eight concepts gathered by analyzing the literature review. The height of each bin of a histogram represents the number of papers that are relevant to the respective concept that influences ADSS. In the following subsections, I shortly present and critically discuss the concepts.

Hybrid-Decision Making

Differentiating between Human Decision-Making (HDM) and Algorithm Decision-Making (ADM) alone proves insufficient in comprehending the intricacies of the real-world (Veale et al., 2018). Algorithmic decision-making cannot work in every situation for instance, in high stake decision-making processes, there will be ambiguity and algorithms will not ensure equity and transparency (Veale et al., 2018)

In certain situations, the involvement of human supervision is essential in making decisions. This is called the Human-in-the-loop approach. Conversely, when data becomes intricate and time-consuming to analyze by humans, algorithmic decision-making may be more practical. The author identified a combination of ADM and HDM, depending on the context or circumstance involved, would yield an efficient process that upholds fairness and responsibility in making decisions.

Stakeholder Participation

It implies the interpretation and communication of stakeholders in the decision-making process. The authors claim that if numerous stakeholders with diverse backgrounds, expertise, and experiences are included in the problem formulation process and various points of view are taken into account, algorithmic bias can be mitigated (Passi & Barocas, 2019). The authors argue that managers should make sure to incorporate stakeholder consultation procedures throughout the decision-making process.

Inclusion & Diversity and Infrastructure

Algorithmic design is a crucial aspect of the process that needs to be addressed with utmost care. In order to reduce the risk of algorithmic bias, it is imperative for designers to prioritize inclusion, diversity, and equity while developing algorithms (Seo & Gebru, 2020). This can be done by hiring organizational ethicists who will supervise the decision-making process. The absence of diversity in development teams may result in unnoticed blind spots and biases during the development process (Starke et al., 2022). To stay relevant in an increasingly competitive marketplace with global impact, organizations need to embrace new perspectives and attitudes by incorporating diversity at an early stage (Springer et al., 2018).

Organizational Culture

Springer et al. (2018) argue that the culture of an organization plays a crucial role in mitigating algorithmic bias and ensuring fairness throughout all stages of developing and deploying algorithms. If the company culture is based on collaboration, and openness as well as creates a secure environment for individuals to voice their worries, it will surely bring fairness in algorithmic decision-making.

Organizational Structure

In public sector organizations, the hierarchical structure may lead to a concentration of power in a few individuals or departments, leading to algorithmic bias and hindering decision-making diversity. Biased outcomes that unfairly target particular groups may result from narrow-minded group perspectives when designing and deploying algorithms (Wang et al., 2020). Organizational structures play an important role in addressing algorithmic bias as interdisciplinary teams combining experts from various fields such as data science, ethics, and law are recommended for combating this issue (Holstein et al., 2019; Köchling & Wehner, 2020). Participation equality among all departments through cross-functional teams ensures fair decision-making practices.

Data Quality

Biased user inputs, biased algorithms, and biased training data, can lead to algorithmic bias (Kordzadeh & Ghasemaghaei, 2022). Holstein et al. (2019) stress the significance of data quality and impartiality in algorithm development as biased data can generate unrealistic outcomes. To prevent partiality, two key values namely accountability and openness should be adopted by companies while handling information. Veale et al. (2018) prioritize both these values underlining that algorithms constructed without adequate consideration towards impartial representation could worsen existing societal challenges instead of resolving them.

Fairness, Accountability & Transparency

A crucial component of guaranteeing the fairness of machine learning algorithms is accountability (Veale et al., 2018). Transparency, on the other hand, increases the perception of accountability because it helps users understand the requirements for accountability and clarifies the oversight and mitigation procedures (Vedder & Naudts, 2017; Zouave & Marquenie, 2017).

According to Kordzadeh & Ghasemaghaei (2022) promoting clarity in machine learning algorithms can aid stakeholders' understanding. To achieve this objective, the authors recommend employing open-source algorithms alongside comprehensive documentation and unbiased evaluations. Accountability needs to be incorporated into the planning and execution of algorithms right away. This necessitates bias detection and correction tools in addition to openness (Meng & Berger, 2019). Algorithmic decision-making can also pose accountability challenges. Determining who is responsible for issues that arise may be difficult (Kordzadeh & Ghasemaghaei, 2022; Holstein et al.; Mahmud et al., 2022; Springer et al., 2018; Wang et al., 2020; Chiao et al.,2019). To simplify, it's recommended that each party involved – for instance, developers, users, and regulators should share accountability in their respective contexts.

Concerns about transparency have an impact on how ADM systems are perceived in terms of their fairness, accountability, and privacy, all of which are essential for the general public to adopt these systems (Jobin et al., 2019). Madaio et al. (2020) suggested approach is a co-designed checklist that includes contributions from multiple departments with the intention of identifying possible biases. Felzmann et al. (2019) suggest a holistic approach to transparency that considers both verifiability and performativity.

Preliminary Planning

Putting it in a simple way IT projects in the public sector can face challenges due to insufficient initial planning. That leads to problems with maintaining and performing well because their information systems often cross different hierarchies and areas of responsibility. Cross-functional collaboration and setting up a structured system for regular reviews can reduce algorithmic bias.

After analyzing the existing literature to overcome partiality from algorithmic decision-making, more recommendations are presented in Table 1. The first column shortly presents the recommendations, and the second lists the papers where each recommendation was introduced.

Table 1: Mitigating Bias in ADSS: Recommendations for Fairness

Recommendations	References
Being transparent can make resource allocation seem equal, but it can also highlight differences which decreases the perception of fairness. While transparency may not guarantee fairness in processes, it does help people detect biases in algorithmic results. This might dissuade companies from adopting such practices. To address this problem, researchers and governments have proposed various guidelines. Companies can work with relevant authorities like the European Center for Algorithmic Transparency to manage these issues more easily.	[38]
Education and communication can encourage individuals to consider the fairness of algorithmic processes beyond their personal interests.	[17]
There is no one solution for an effective explanation of algorithms being fair as it depends on specific fairness issues and user profiles. It may be necessary to provide hybrid explanations by giving an overview of the model while allowing scrutiny of individual cases for accurate fairness judgment.	[31]
A balanced involvement of humans and ADSS to avoid deferred decisions. Management practices that guarantee such involvement should be put in place. For instance, stakeholder consultation sessions can be organized.	[60]
A multidisciplinary approach to overcoming algorithmic bias and ensuring fairness and transparency in algorithms’ decision-making process is needed. It is suggested that managers encourage interdepartmental collaboration for this purpose.	[6]
Hybrid decision-making: This approach leverages algorithms to provide insights, recommendations, and objective data analysis, while humans retain the final decision-making authority. This ensures the utilization of algorithms as useful tools without completely replacing human judgment.	[38]
Auditors can acquire essential information for conducting audits only through effective teamwork and coordination with management and developers within a company. By establishing close collaboration among these three parties, organizations can reduce bias in ADSS and ultimately enhance their decision-making capabilities	[59]

Value of Study

This literature review offers guidance on establishing management processes that can safeguard equity and promote responsible algorithmic decision-making that considers the complexities of today's society. It could serve as a resource for individuals in various industries who seek to understand how organizational structure impacts algorithm decision-making.

Research limitations and recommendation

I have encountered a few limitations while performing this research that future research may take up. Initially, I pursued this investigation independently resulting in a narrow examination of the literature. My focus was confined to particular ideas that were explored solely by myself. Perhaps if conducted as part of a collective effort involving several individuals, a more comprehensive analysis could have been achieved. Secondly, I solely relied on existing literature and did not perform any empirical research. Third, I limit my search to specific academic databases, which may result in the omission of some important studies from this research. Fourth, I did not include technical research papers as they were beyond the scope of my study.

This literature has identified some gaps in the existing literature and provided a set of directions, with a special emphasis on algorithmic decision-making, to advance the research in the intersection of fairness, algorithmic decision-making, and relevant managerial practices. Further research is necessary to understand the legal and regulatory frameworks that govern algorithmic decision-making processes, including how these frameworks can be adapted to address emerging challenges related to these systems. Additionally, it is crucial to investigate different approaches for designing ADSS with stakeholder engagement and participatory design methods. To ensure the ethical use of ADSS in public sector organizations, more research must be conducted on social implications surrounding aspects like transparency, accountability, and fairness. Furthermore, research needs to be done in terms of fair datasets to be used to avoid ambiguity in the decision-making processes. Finally, research needs to be done on algorithmic aversion as there is no unified scale to measure Algorithmic aversion in a real-world setting.

Abstract

Algorithms are increasingly being utilized in decision-making processes, powered by the advancements in Artificial Intelligence. As a result of this development, algorithmic decision-making is proving to be highly effective and sometimes superior to human judgments. Despite that, there are questions concerning their fairness and moral implications. Algorithmic decision-making and its impartiality have been the subjects of various studies. These studies aimed to identify the factors that affect fairness in algorithmic decision-making and offer recommendations from a managerial perspective. I took the Narrative literature approach, with a view to synthesizing the findings of existing literature, I review 30 research papers identified through searching in eleven academic databases. I contribute to algorithm decision support systems (ADSS) literature by proposing a framework, highlighting the factors influencing fair algorithmic decision-making in existing studies, followed by recommendations to enhance fairness through management practices. Finally, potential future research directions are mentioned. This literature review offers guidance on establishing management processes that can safeguard equity and promote responsible algorithmic decision-making that considers the complexities of today's society. It could serve as a resource for individuals in various industries who seek to understand how organizational structure impacts algorithm decision-making.

Keywords: Fairness, Ethics, Management Practices, Organizational Culture, and Algorithmic Decision Support Systems

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1. Introduction

Organizational decision-making processes are increasingly using algorithmic decision support systems (ADSS). Although these systems are predicted to increase decision-making effectiveness and efficiency, there are questions concerning their fairness and moral implications. Recent studies have covered many of the possibilities for algorithmic bias and prejudice in decision-making (Webster & Watson, 2002). Research has shown that managerial practices can influence fairness in ADSS. For instance, the absence of inclusivity, diversity, and equity during algorithmic development. Neglecting to take into account the expertise and knowledge of a range of stakeholders, in addition to having an insufficient organizational culture that does not promote collaboration between departments or transparency, may result in unfavorable consequences.

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R3: How can firms be motivated to improve fairness in ADSS from a managerial standpoint?

To answer these research questions, the current literature review reviewed 30 academic studies found by searching eleven scholarly databases and conducting subjective citation analysis. I report the current state of the research through descriptive analysis. My analysis reflects on factors responsible for algorithm bias and how these biases can be addressed through managerial practices. Eight concepts that influence fairness in ADSS from a managerial perspective are identified and presented. In addition, the related challenges are summed up and listed along with recommendations for safeguarding and improving fairness through corporate management.

To comprehensively understand ADSS, it is imperative to familiarize oneself with the principles that correspond to organizational fairness. In this literature review, I have identified the concepts which have been utilized to gain a fair understanding of ADSS within a corporate setting. The structure, culture, and management of an organization are critical factors that contribute towards fairness in ADSS. It emphasizes that good business culture and structure are crucial for effective decision-making. Moreover, it examines the utilization of computational models and automated decision-making systems in data-rich environments. These incorporate predictive analytics that requires advanced technical skills. Data scientists use regression analysis and machine learning techniques, among others, to create prediction models using historical data as input. It is important to account for fairness in algorithmic decision-making because these models can then be employed in a variety of application domains for improved results. For instance, predictive analytics can be used by businesses to reduce costs by better forecasting future demand and altering output and inventory (Kawaguchi, 2021), by banks and other financial institutions to lower fraud and risks by anticipating suspicious activity (Zhang et al., 2021), by medical specialists to make wise decisions by anticipating patients who are at risk of diseases, (DG, E., 2019. Understanding algorithmic decision-making: Opportunities and challenges, EPRS: European Parliamentary Research Service. Belgium). Algorithms are utilized by marketers to conduct research, devise strategies, oversee channels, and assess performance. (De Bruyn et al., 2020; Huang and Rust, 2020; Vlačić et al., 2021). However, considering data scientists use historical data to forecast the upcoming outcomes if the data possess biases, it may affect these projections, producing unreliable results (Schmude et al., 2023). Also, where the use of algorithmic decision-making brings cost savings and efficiency it also has some negative impacts like bias, discrimination, and perceived unfairness (Köchling et al. 2020). To overcome impartiality and to succeed today, businesses must prioritize accountability, inclusivity, privacy, and openness as highlighted by current literature. The aforementioned values and principles are fundamental to management practices when it comes to building AI systems that incorporate ethical and social values, that ultimately lead to fair decision-making.

The rest of the research is structured in a subsequent manner. Chapter 2 provides a brief description of the concepts of organizational fairness and algorithmic decision-making. Chapter 3 explicates the research method. Chapter 4 explains the findings of the current study. Chapter 5 outlines a general discussion and results that incorporates a comprehensive framework and recommendation table. Chapter 6 concludes the study with insights into limitations and research gaps.

2. Concepts Of Organizational Fairness & Algorithmic Decision-Making

Fairness: Fairness is a complex concept that can be defined in different ways depending on the context. (Veale et al., 2018) defined fairness as "The lack of unjustified discrimination or treating similar cases equally". Nonetheless, achieving fairness in practice can be challenging due to diverse understandings of what constitutes unjustified discrimination and equal treatment among comparable cases.

Perceived fairness: (Starke et al., 2022) in their studies refer to perceived fairness as ''how individuals subjectively perceive the equity of ADSS". It considers factors like the system's context and technical design and can affect public trust in ADM systems. Literature underscores that assessing perceived fairness is crucial for evaluating ADM effectiveness.

Algorithms: The Oxford Living Dictionary defines algorithms as "Algorithms refer to a defined set of rules that guide the calculations or problem-solving procedures, primarily performed by computers."

Computational Models: By using the term algorithmic decision-making Lee, (2018) describes "computational models as a computational mechanism that autonomously makes decisions, based on rules and statistical models without explicit human interference".

Computational Models and Algorithms: Both serve distinct purposes, with the former being more versatile than the latter. Algorithms are often used as building blocks for computational models. Algorithms are specifically designed to achieve particular goals or address specific issues, whereas computational models can be utilized in various contexts to investigate complex systems' behavior. Assessment of algorithm efficiency and accuracy is possible; on the other hand, computational modeling involves abstract representations that capture fundamental attributes while excluding many details present in real-life processes or structures. Due to this limitation, validating these models necessitates comparing them accurately against actual observations before guaranteeing their precision and dependability (Mittelstadt et al., 2016)

Algorithmic Decision-Making: algorithmic decision-making is defined as automated decision-making and remote control, as well as standardization of routinized workplace decisions (Ko ¨chling & Wehner, 2020; Möhlmann & Zalmanson, 2017)

Algorithmic Bias: Bias, as defined by (Ko ¨chling & Wehner, 2020) is a ''Deviation between anticipated and actual values of a random variable''. In algorithmic decision-making, cognitive biases are systematic errors that arise from human judgments during uncertain situations which may affect the accuracy of automated assessments or predictions.

Training Data: (Mitchell et al., 2021) described training data as "The information used to teach a machine learning algorithm or another predictive system". The accuracy and fairness of the resulting model depend heavily on the quality and representativeness of this data. However, in decision-making systems that involve people, such as those used for hiring or lending decisions, using certain training data may lead to biased outcomes. Addressing these biases requires careful consideration of how decision-making systems are developed and what assumptions they make about individuals involved in them.

Organizational Culture: (Meng & Berger, 2018) defined organizational culture as "a set of beliefs, values, and assumptions that are shared by members of an organization." Organizational members rely on shared values to guide their decisions and behaviors, ultimately impacting an organization's effectiveness.

Organizational Structure: The paper (Organizational Structure, Environment and Performance: The Role of Strategic Choice - John Child, 1972) discusses the relationship between organizational structure, environment, and performance. The paper defines organizational structure as "the formal pattern of interactions and coordination designed by management to link the tasks of individuals and groups in achieving organizational goals".

Management Practices: The article by Marabelli et al. (2021) explores the significance of management practices in ADSS. The authors define management practices as "the strategies that managers use to plan, organize, lead, and control organizational activities." In relation to ADMS, effective management practices are crucial for determining their design, implementation, and utilization within an organization. For instance, efficient project and change management may be necessary for the timely development of ADMS within budget limits while ensuring seamless integration into existing processes. Ultimately responsible managerial approaches become indispensable for guaranteeing the ethical usage of these systems with optimal outcomes.

Stakeholders: Lee et al. (2017) define "a stakeholder as anyone with an interest or concern in the design and implementation of an algorithmic service, such as users, developers, managers, and other parties who may get affected by it."

Algorithmic Transparency: Lee et al. (2019) Algorithmic transparency means "An algorithm's capacity to clarify its decisions or results." The writers recommend a technique for achieving this called quantitative input influence, which gauges each input's impact on the machine learning model's output, which increases trust and accountability in the system.

Accountability: (Holstein et al., 2019; Veale et al., 2018) Accountability refers to "The obligation of professionals and institutions in ensuring that ADSS is created and executed equitably and on fairgrounds."

Inclusivity: (Holstein et al., 2019) Inclusivity refers to "guaranteeing that ADSS are unbiased and fair for all applicable subpopulations or groups".

Diversity: Passi & Barocas (2019) define diversity as "the presence of various groups in a population or dataset". Groups represent unique populations or subpopulations with differing demographic, socioeconomic, and geographic traits. These may comprise individuals from various racial or ethnic backgrounds, genders, ages, income levels, education levels, or locations. They suggest that data science projects should prioritize diversity to reduce biases in algorithms, data, and decision-making processes.

Cross-Functional Teams: According to Veale et al. (2018) Cross-functional teams refer to "groups composed of experts and professionals with diverse knowledge and perspectives." Such as domain specialists, data analysts, ethicists, and legal advisers. The objective is to guarantee that ADSS are developed equitably and responsibly through the involvement of individuals with different backgrounds and expertise.

Privacy: Aysolmaz et al. (2023) Privacy refers to "safeguarding personal information and data against unauthorized access or use by algorithmic decision-making (ADM) systems." The writers suggest that organizations should address privacy concerns to boost public trust in using ADM systems.

Data Ethics: Seo & Gebru, (2020) Data ethics refers to "ethical considerations surrounding the collection, annotation, and utilization of data in machine learning systems." Fairness, accountability, transparency, and ethical issues within these systems often stem from decisions made during the data collection process. Therefore, it is essential to contemplate potential biases and implications when selecting training data for ML models. This involves ensuring diversity while representing users transparently throughout the entire process of collecting/using said information.

Co-designing: (Madaio et al., 2020) "The practice of co-designing pertains to a cooperative approach in the design process, wherein practitioners and other stakeholders engage in active involvement towards developing checklists that ensure fairness". It is an iterative process where practitioners give feedback and based on that tools are made to improve fairness.

Simulatability: "Simulatability is the capacity to reproduce or recreate the behavior of an ML model" (Ko ¨chling & Wehner, 2020).

Decomposability: "Decomposability is the capacity to dissect an ML model into its constituent parts to understand how each part affects the performance of the model as a whole" (Ko ¨chling & Wehner, 2020).

3. Methodology

As organizational decision-making processes become increasingly complex, the use of ADSS has emerged as a promising solution. While ADSS promises to streamline and improve decision-making effectiveness, concerns have been raised regarding their fairness and moral implications. Recent studies have highlighted numerous possibilities for algorithmic bias and prejudice in decision-making that are cause for further investigation (Webster & Watson, 2002)

A narrative approach is used in this research that integrates methods used in prior scholarly works to proactively promote transparency, impartiality, and ethical deliberation when implementing such advanced technologies.

The initial phase to carry on this research involves the identification of articles that held potential relevance. In order to achieve comprehensive coverage, databases such as Elsevier's Scopus, IEEE Xplore Digital Library, Web of Science, ACM, ABI/INFORM, EBSCO, JSTOR, and ScienceDirect, University of Hasselt Library were used in the search process. This study mostly comprises papers from the year 2015 onwards as the algorithms and concept of ADSS emerged a lot in the past couple of years. The reason for excluding pre-2015 publications is due to the fact that the more recent papers contain and integrate numerous discoveries from their predecessors. The research has integrated scholarly works presented in the proceedings of (ICIS)(CHI) 2020. As ADSS is a rapidly expanding field, unreviewed papers from arXiv were also included due to their potential to provide both theoretical and practical perspectives.

The nature of fairness is complex and varied, thus leading to the inclusion of papers exploring technical, social, behavioral, organizational, and ethical factors influencing ADSS in decision-making within organizations in the research. A dataset comprising 90 articles was generated as a result. The next step was to screen the articles' titles, keywords, and abstracts in order to exclude publications that were not relevant conceptually or contextually. An article was considered relevant if it primarily addressed algorithmic bias, fairness, and ADDS while adhering to the ethical definition which emphasizes social biases integrated into algorithms potentially leading to discriminatory outcomes within businesses and society (J. Domanski, 2019).

To refine the dataset, those articles that lacked significant insights were excluded and 45 articles remained to analyze. To further streamline the analysis, technical papers that focused on developing mathematical solutions for detecting and mitigating bias in AI models were also excluded. Because these papers provided computational proof and demonstrated the efficacy of their proposed techniques using hypothetical or real-world datasets, such topics fell outside the scope of this study. Consequently, a relevant set of 30 papers were included in the final dataset.

Subsequently, I conducted an in-depth analysis of the aforementioned 30 papers to identify their common underlying themes. Although variations in wording were apparent, the contents of these articles remained largely homogeneous with regard to legal and ethical considerations. Notably, some scholars employed phrases such as "cross-functional" or "moral," while others opted for terms like "interdisciplinary" or "ethical." Nevertheless, all these works maintained semantic consistency by emphasizing core tenets such as accountability, inclusivity, diversity, and privacy preservation within ADSS at organizations. Based on my examination of available literature using relevant datasets concerning this topic area thus far; socio-technical design aspects featured prominently alongside how people perceive fairness and assess potential impacts arising from machine-generated advice towards decisions taken.

Additionally, this research also delves into computational models' role when used in conjunction with predictive analytics & automated decision-making processes aimed at supporting complex data-rich environments throughout the decision-making stages thereof.

3. Literature review

Overview:

The literature review covers important aspects that incorporate fairness in algorithmic decision-making. It consists of several chapters.

Chapter 4.1 explores how fairness is assessed and achieved. Chapter 4.2 Insights on the factors that influence Fairness in Algorithmic Decision-making. Chapter 4.3 explains Governance which includes the role of an organization's culture, structure, and management in fostering fairness in algorithmic decision-making. In Chapter 4.4 the main area of interest is centered around the examination of fairness in relation to computational models and ADSS. The aim is to determine both their potential benefits as well as challenges. Following in line with the significance of accountability, inclusivity, privacy, and transparency as key elements ensuring fair outcomes is discussed in chapter 4.5. Finally, Chapter 4.6 discusses practices that businesses can adopt to promote fairness in their algorithmic decision-making processes, providing recommendations for creating more equitable and transparent systems.

4.1 Algorithmic Decision-Making Fairness

Kordzadeh & Ghasemaghaei (2022), proposed an approach called fairness assessment with algorithms to tackle algorithmic bias. This method examines how algorithms make decisions that affect specific groups of people. The present essay delves into various approaches employed for this type of assessment and highlights its crucial role in ensuring just algorithmic decision-making.

One such approach is Fairness, Accountability, and Transparency (FAT) (Veale et al., 2018). It seeks to identify and mitigate undesirable biases or discrimination embedded within data, methods, or algorithm representations through statistical or mathematical techniques. FAT controls known factors contributing towards bias while addressing queries related to equity and prejudice simultaneously.

In their recent study, Kordzadeh & Ghasemaghaei (2022) suggest that the management's involvement is essential in reducing algorithmic bias. They recommend several measures to enhance fairness and transparency in decision-making through algorithms such as advocating diversity, performing audits, ensuring clarity of operation methods while allowing users for feedback and investing resources into training initiatives. These strategies can substantially address issues related to algorithmic bias like a lack of data variety, non-transparency, ambiguity concerning computation rationale, and ethical implications.

Kordzadeh & Ghasemaghaei (2022) emphasize the importance of taking a multidisciplinary approach to address algorithmic biases. They argue that impartiality and transparency in decision-making by algorithms necessitate collaboration among diverse stakeholders such as scholars, policymakers, industry leaders, and managers. Through this, equal utilization of these systems without discriminatory effects may be achieved.

The suggested human-in-the-loop methodology be incorporated into corporate management. For instance, interdepartmental meetings and communication channels could be established when different departments are involved within organizations namely Legal and IT.

The perception of fairness is reliant on the context, and each algorithm must undergo a comprehensive examination before being extensively employed. Nonetheless, differentiating between Human Decision-Making (HDM) and Algorithm Decision-Making (ADM) alone proves insufficient in comprehending the intricacies of the real world (Veale et al., 2018). In numerous practical scenarios, decision-making involving ADM systems does not occur solely through automated means; human intervention also plays a role. Furthermore, the hybrid decision-making approach, as described by (Starke et al., 2022) presents an opportunity for further refinement that warrants careful consideration in empirical research. According to HLEG, A. (2019). A definition of AI: main capabilities and disciplines. Brussels. https://ec. Europa. EU/digital-single. Seven fundamental prerequisites must be met by AI technologies to validate their reliability and impartiality. The original edition of this text was issued on December 18th, 2018, and underwent an open review process that assembled responses from over 500 commentators.

These preconditions are categorized as,

- Human supervision
- Technical stability and security
- Data management and confidentiality adherence
- Transparency in operation
- The inclusion of different perspectives while minimizing bias towards one group over another
- Contribution to societal welfare as well as environmental preservation of accountability.

Starke et al., (2022) in their research paper mentioned HLEG, A. (2019). A definition of AI: main capabilities and disciplines. Brussels. https://ec. Europa. eu/digital-single. It explains three distinct human oversight approaches and provides a relevant example. Firstly, the "human-in-the-loop" model involves humans at every stage of the ADM system's decision cycle with the ability to intervene whenever necessary. Secondly, in the "human-on-the-loop" model, individuals are involved during the design phase and subsequently monitor its functioning thereafter. Lastly, under "human-in-command," humans have ultimate responsibility over an ADM system's usage while overseeing economic, social legal, and ethical impacts on society overall.

These tools scrutinize outputs from machine learning models, with a specific emphasis on indicators for inherent discrimination, to identify any unfair outcomes. Starke et al., (2022) assert that utilizing such instruments is essential in identifying and remedying issues related to bias and fairness in algorithmic decision-making. Additionally, they suggest that research should concentrate on heterogeneity by investigating variances across multiple points along a decision boundary as it has shown promise concerning determinants linked to AI equity. The authors emphasize the significance of examining various elements, such as the domain in which a particular algorithm is being applied, task specifications, and technical configuration when assessing fairness perceptions. Hence it is crucial to conduct a comprehensive investigation before implementing an algorithm on a large scale. By analyzing differences among diverse groups and contexts, researchers can gain better insights into how algorithms affect different populations and develop more effective methods of promoting equity and impartiality within AI systems. For instance, one research study mentioned within this paper reveals that compared to White participants' Black counterparts perceived greater unfairness rendered by risk assessment algorithms implying that there may be differences in how different groups perceive algorithmic fairness.

Starke et al., (2022) propose that group fairness cannot be universally standardized, and diverse methods may be more suitable varying from case to case according to the particular context and goals of the ADSS. A feasible strategy to mitigate such biases entails focusing on the problem formulation stage where issues are defined, and data collection methods determined. Mindful consideration of these aspects during this phase could potentially alleviate or eliminate potential sources of bias in subsequent algorithms (Sarker, 2021).

The act of outlining the matter that the algorithm aims to tackle is recognized as problem formulation (Chiao, 2019). Passi and Barocas (2019) posit that problem formulation is critical in developing an effective ADSS as it establishes the scope of the issue at hand and identifies relevant data sources for decision-making. Veale et al. (2018) recommend employing unambiguous algorithms that can be thoroughly scrutinized for bias or discrimination while also promoting stakeholders' participation during the design process to reflect their values within the system. It is also important to acknowledge potential impacts on various groups of individuals when implementing algorithms within complex systems. By taking these measures, organizations can enhance their capacity for ethical decision-making while remaining mindful of any potential consequences related to algorithmic bias or discrimination towards certain demographics. To advance ethically and sustainably while promoting inclusive growth, organizations must collaborate thoroughly during problem formulation. They need to consider diverse perspectives and examine possible outcomes from various angles before implementing ADSS technology practices that align with academic rigor. This approach will help in the development of socially responsible technologies leading to long-term societal well-being and prosperity for all stakeholders involved.

Veale et al. (2018) contend that designers of ADSS must consider fairness and accountability. The authors propose prioritizing the algorithm's architecture, taking into account its potential impact on various demographic groups, such as minorities or individuals with disabilities. To ensure equity and transparency in ADSS design. As a whole, Veale et al. (2018) argument underscores designing ADSS through an equitable lens will avoid upholding existing biases or contributing toward discriminatory public-sector decisions.

4.2 Factors that Influence Fairness in Algorithmic Decision-Making

Algorithmic decision-making could be a complex and multifaceted process that can be affected by a number of factors. This includes algorithmic design, the organizational culture within which it operates, and the quality of data used in decision-making processes. Each variable has its own unique role to play in determining fairness in algorithmic decision-making. For Instance, creating an algorithm that has thorough measures to counter partiality is imperative in order to achieve just outcomes. In addition, instituting policies within the organization that endorse diversity and inclusivity can establish a work atmosphere that supports equitable decision-making processes (Holstein et al., 2019). Additionally, relying on relevant data sources rather than biased or incomplete ones can significantly enhance objectivity when making crucial choices. Therefore, ensuring fairness requires deep comprehension of these multiple facets involved in creating effective algorithms capable of generating unbiased results. Moreover, this group strives towards improving human comprehension levels when it comes to machine learning model results. Many factors, such as biased user inputs, biased algorithms, and biased training data, can lead to algorithmic bias (Kordzadeh & Ghasemaghaei, 2022). The authors propose an approach to assessing fairness in algorithmic decision-making that involves the utilization of various tools. It is recommended that a comprehensive strategy be adopted to evaluate equity in algorithmic decision-making procedures. Researchers and practitioners can achieve a deeper insight into how algorithms make decisions, as well as take measures to address any potential partiality or unfairness, by incorporating statistical tests, fairness metrics, explainability tools, and multidisciplinary, human-in-the-loop methodologies.

According to Holstein et al. (2019), data representativeness and quality are essential for algorithmic decision-making to be fair. Algorithms can be biased or incomplete if the training data has quality issues such as biases (Passi & Barocas, 2019; Starke et al., 2022).

The presence of biases and disparities in the structure, implementation, and outcomes of these systems defines what is known as structural inequality. If fairness and equity considerations with the involvement of the broader social context in which algorithms operate are not prioritized during the design and implementation phases, ADSS can unintentionally perpetuate or worsen existing structural inequalities (Mitchell et al., 2021; Veale et al., 2018; Holstein et al., 2019)

Holstein et al. (2019) acknowledge the significant impact of structural inequalities, namely those pertaining to race, gender, and socioeconomic status as a prominent source of bias and unjust treatment in ADSS. They posit that it is imperative to rectify these disparities for ensuring fairness in ADSS thus, suggesting that solely relying on technical remedies would be insufficient. Additionally, Holstein et al. (2019) argue that data quality and representativeness should be evaluated and enhanced as part of the decision-making process. Furthermore, Holstein et al. (2019) note that fairness in algorithmic decision-making is crucial for maintaining good relationships with humans. In the realm of data usage, Holstein et al. (2019) urge enterprises to place paramount importance on two key values: accountability and openness. The former demands that entities take responsibility for their actions, while the latter calls upon them to be transparent in how handling information. Moreover, Veale et al. (2018) research suggests that a factor often overlooked when analyzing decision-making fairness is the underlying architecture of algorithms themselves an element with potentially significant implications for outcomes generated by such systems. If constructed without adequate consideration for unbiased representation and treatment of all parties involved, these algorithms may even perpetuate existing biases and instances of discrimination, thus exacerbating pre-existing societal issues rather than contributing towards solutions. Therefore, to ensure a fair and just use of data, enterprises must prioritize accountability and openness while also considering the architecture.

Veale et al. (2018) suggest that to ensure fairness algorithms must possess a transparent and comprehensible structure to ensure fairness and accountability. The authors assert that algorithms should possess adaptable nature so that they can easily be tailored to the availability of new data accordingly. This approach facilitates continuous learning from incoming data inputs, enabling better-informed decisions in real-time. In real-time decision-making, organizational culture plays a critical role in determining whether algorithmic decision-making processes are fair or biased against certain groups. The values and beliefs embedded within an organization's culture may affect how people interpret data patterns leading to biased outcomes if those biases align with existing prejudices held by members of said organization's hierarchy toward certain demographics' characteristics specific age, gender ethnicity etcetera. In essence, a strong ethical foundation and a value-driven organizational ethos are imperative to ensure the fairness and accountability of algorithmic decision-making, ultimately resulting in increased trust among stakeholders. In the scholarly article authored by Madaio et al. (2020), it is asserted that a crucial step for organizations to promote fairness in decision-making processes with respect to ADSS involves instilling a culture of transparency and justice within their operations. In order to achieve this goal, Madaio et al. (2020) suggest utilizing co-design methodologies where different parties are invited into the decision-making fold - from employees at every level, customers, and clients served by ADSSs alike - giving them an equal voice in identifying issues related to fairness in automated systems' outputs or inputs such as biased data sources among others. Through active participation from each stakeholder group involved, more robust solutions could be designed leading towards enhanced accountability overall when implementing such technologies.

The way individuals perceive fairness in algorithms can be impacted by their personal attributes, such as educational background and demographic information (Wang et al., 2020). To enhance comprehension of how individuals, evaluate the impartiality of algorithms in various settings, the authors conducted an online experiment. The participants were grouped randomly and exposed to distinct scenarios featuring algorithmic decision-making. The researchers subsequently assessed how individual attributes influenced their perception of equity. According to the authors, individuals with greater educational attainment tend to perceive an algorithm as equitable when it is created via a transparent methodology that incorporates human perspectives. Additionally, demographic factors such as age and gender can impact one's sense of what constitutes fairness in this context (Wang et al., 2020). The authors recommended that Education and training can encourage individuals to consider the fairness of algorithmic processes beyond their personal interests. Offering education programs on algorithms could unite people with distinct backgrounds and enhance their comprehension for adopting such decision-making processes (Wang et al., 2020)

An overview and formal description of fairness in decision-making is given by Mitchell et al. (2021). According to them bias and fairness are closely related, and there are various factors that influence or undermine fairness. Some important factors include

- Sensitive variables, such as race and gender may influence decision-making.
- The quality and representativeness of training data play a critical role in algorithmic development.
- Assumptions about the correlation between sensitive variables and outcomes may impact decision accuracy.
- Model choice along with parameter configuration are important factors affecting algorithm performance.

- Effective interpretation and communication of results to all stakeholders is crucial for informed decision-making processes.

It is imperative to thoughtfully evaluate these variables during the development and execution of decision-making mechanisms in order to guarantee impartiality for every individual. The perceptions of fairness in algorithmic systems are significantly influenced by social and technical factors. Technical elements, including internal processes and outcomes, have been identified as key contributors to such judgments (Grgic-Hlaca et al., 2018; Lee et al., 2017; Saxena et al., 2019). Moreover, cultural norms and values also shape people's views on the issue of fairness. Designing equitable algorithms that promote motivation among users requires a human-centric approach that involves stakeholders' input. This process results in transparent and interpretable procedures being established. Furthermore, attributes such as individual characteristics and the way in which people respond to various types of explanations regarding algorithmic fairness are influenced by a variety of factors, such as previous roles and criteria used for making judgments. The assessment of fairness is not solely dependent on the design of an explanation but also relies on one's preexisting stance towards machine learning systems as decision-making tools and personal views pertaining to certain features. This underscores the need for both developers and users to be cognizant of their own predispositions when evaluating the impartiality exhibited by machine learning systems (Dodge et al., 2019; Lee et al., 2017). These determine whether an algorithm is deemed fair or not.

Furthermore, Research finds that there is no one solution for an effective explanation of algorithms being fair as it depends on specific fairness issues and user profiles. It may be necessary to provide hybrid explanations by giving an overview of the model while allowing scrutiny of individual cases for accurate fairness judgment (Dodge et al., 2019)

4.3 Organizational Culture, Structure, and Management Practices

An organization's conduct is shaped by its common beliefs, perspectives, and behaviors, which are referred to as its organizational culture. Machine learning system development and use may be significantly impacted. According to Springer et al. (2018), corporate culture has a substantial impact on how well businesses are able to address algorithmic bias. To lessen the possibility of algorithmic prejudice, they advise firms to foster a culture that places a high emphasis on inclusion, diversity, and equity (Seo & Gebru, 2020). Springer et al. (2018) argue that in a company's early development, limited resources and data may lead to technical debt. This can result in models being trained on internal data or ad-hoc evaluations, leading to biased results that reflect the developers' demographics or preferences. As the user base expands, these models may be overly tailored to current users instead of optimizing performance for global markets. As a company expands globally, it is crucial to adopt new perspectives and attitudes. Seeking diverse candidates and improving engineering culture can mitigate prejudice in the early stages. Therefore, according to Springer et al. (2018) recommendation, adapting organizational culture towards addressing algorithmic bias and promoting fairness throughout the development and deployment of algorithms is vital. This necessitates promoting moral decision-making, cooperation, and transparency, as well as providing people with a safe environment in which to express their concerns. Moreover, Passi &

Barocas (2019) stress the importance of company culture in overcoming algorithmic prejudice. They contend that organizations should follow a "justice-first" mindset, in which fairness is given precedence over objectives such as accuracy or efficiency. Organizations should create ethical guidelines, and train on data science ethics, in decision-making for transparency and accountability. They should also promote a culture of feedback where individuals can express ethical concerns without fear of retaliation. This requires a cultural shift towards valuing justice above other goals. If we talk about the relationship of organizational culture with job satisfaction, a supportive organizational culture is important for public relations professionals as it enhances their work engagement, trust, and job satisfaction. Such a culture values public relations and encourages two-way communication and diversity in decision-making. When PR professionals perceive such support from their organization, they believe that engaging with the workplace positively contributes to its development. The study found that when both excellent leader performance and supportive organizational culture were present together, engagement and trust played a crucial role in enhancing job satisfaction for PR professionals. Thus, indirectly supporting relationships between work engagement and trust can lead to better overall job satisfaction among these professionals (Meng et al, 2019).

The layout and arrangement of a company's numerous components is referred to as its organizational structure. The development and utilization of machine learning systems could be considerably influenced by biased datasets and algorithms, which may lead to discriminatory practices towards specific communities and impact their perception of fairness. According to Veale et al. (2018), IT initiatives in the public sector are vulnerable to shortcomings arising from inadequate preliminary planning. Additionally, information systems employed by such organizations have a reputation for transgressing boundaries across different hierarchies and spheres of responsibility, thereby posing numerous real-world issues related to upkeep and effectiveness. The hierarchical structure of public sector organizations may result in the concentration of power in a small number of people or departments this may increase the likelihood of algorithmic bias and reduce the diversity of decision-making (Wang et al., 2020). For example, if a narrow group with similar backgrounds or perspectives develops and deploys an algorithm, it may result in biased outcomes that unfairly affect certain groups. Also, lacking diverse stakeholder reviews or oversight of algorithmic decisions reduces accountability and increases the possibility of unfair results. They contend that organizations ought to embrace a more collaborative stance in which decision-making is dispersed among different stakeholders and divisions and ensure that data used to train algorithms is diverse. Further, Holstein et al. (2019) highlight the significance of organizational structure in combating algorithmic bias. Holstein et al. (2019) suggest that businesses need to address algorithmic bias using interdisciplinary approaches by bringing together experts from various fields like data science, ethics, and law (Köchling & Wehner, 2020). Establishing cross-functional teams and ensuring that representatives from all departments have an equal part in decision-making need structural changes on the part of organizations.

"Management practices" explain how a company allocates its resources and workers. The creation and use of machine learning systems could be dramatically impacted. According to Kordzadeh & Ghasemaghaei (2022), managerial tactics can have a variety of effects on the algorithmic bias. They might have an impact on things like the algorithms used, how data is collected, and how the results are interpreted. According to Kordzadeh & Ghasemaghaei (2022), businesses must adopt a more open and accountable approach if they are to lessen the possibility of algorithmic bias. This necessitates the development of a governance framework that guarantees accountability for results, transparency in decision-making, user training, and routine audits to detect and eliminate bias. Moreover, Madaio et al. (2020) emphasizes the significance of managerial tactics for combating algorithmic bias. Madaio et al. (2020) suggests businesses use the co-design method, in which representatives from various departments collaborate to create checklists that could spot any biases. Adding to it, efforts to ensure fairness in AI often lack formal processes and rely on individual advocates, leading to potential inefficiencies. Organizational culture can hinder these efforts, but checklists could help by providing a structure that aligns with existing workflows and is supported by the organization's values (Madaio et al. 2020). Researchers discovered that checklists alone were insufficient to address the issue. The effectiveness of checklists was influenced by organizational processes and culture (Burian, 2006; Degani & Wiener, 1991, 1993). For example, airplane manufacturers typically designed the checklists; however, they were rarely tailored for specific airline operations or culture when handed over to fleet or operations managers (Degani & Wiener, 1991). Pilots and co-pilots often skipped redundant items on the checklist which resulted in missing critical actions (Degani & Wiener, 1991, 1993). To tackle this problem researcher suggested human-centered design guidelines: Ensure the checklist is compatible with organizational processes and culture, and consistent internally and externally with other required processes/resources. Develop implementation protocols (the co-pilot reads each item, pilot confirms completion) and allow for customization after implementation (Burian, 2006; Degani & Wiener, 1993). This calls for a management strategy that prioritizes teamwork, communication, and consensus building.

More research shows Lee, (2018) discovered that individuals often perceive human decisions to be fairer than algorithmic ones in tasks requiring human skills, like hiring and work evaluation. This is because people may believe algorithms lack the intuition and experience necessary for impartial judgments. In contrast, Barlas et al., (2019) revealed that the type of task influence perceived fairness, considering dating apps as an example in their studies they proposed that perceptions made by algorithms are more acceptable to the audience if the task is mechanically based as compared to tasks that require human-like skills such as hiring and work evaluation. The subjectivity and contextual dependency of tags generated by humans may surpass those created algorithmically. Nonetheless, human-generated tags could offer higher precision and lower partiality when depicting complex, abstract, or culture-related traits. For example, human-generated tags are preferable for describing emotions, personality traits, and social status. These aspects may not be easily inferred from visual cues alone. Additionally, human-generated tags can account for cultural nuances and individual differences that may not be recognized by an image tagging API. In scenarios where properties can be physically perceived, like shape or color, machine-generated labels could outperform those produced by humans due to their better efficiency and precision.

The study indicates that users on a dating app generally favor human-generated tags over API-created ones to ensure fairness.

Bader & Kaiser (2019), propose that in specific scenarios, such as decisions involving extensive data and routine tasks, algorithmic decision-making may demonstrate greater efficiency compared to human-based decision-making. Mahmud et al. (2022) enlighten on managerial implications for the use and implementation of algorithmic decision systems. The authors assert that managers should bear in mind when selecting or executing algorithms. These involve task-related elements that determine which areas of operation are amenable to algorithmic decision-making and which require caution. Furthermore, personal traits can impact people's willingness to accept or reject algorithms (Mahmud et al., 2022). Thereby enabling leaders to tackle these concerns within their establishments. Taking these considerations into account trust can be built among people to adopt ADSS.

The authors emphasized on term "Algorithm Aversion". It refers to the reluctance of individuals to rely on algorithmic decision-making, even when it has been shown to be more accurate and efficient than human decision-making (Mahmud et al., 2022). The authors note that this phenomenon is not limited to laypeople but is also observed among experts and professionals in various fields.

The thematic map of algorithm aversion identifies key factors that contribute to this phenomenon and is presented in Figure 1 below.

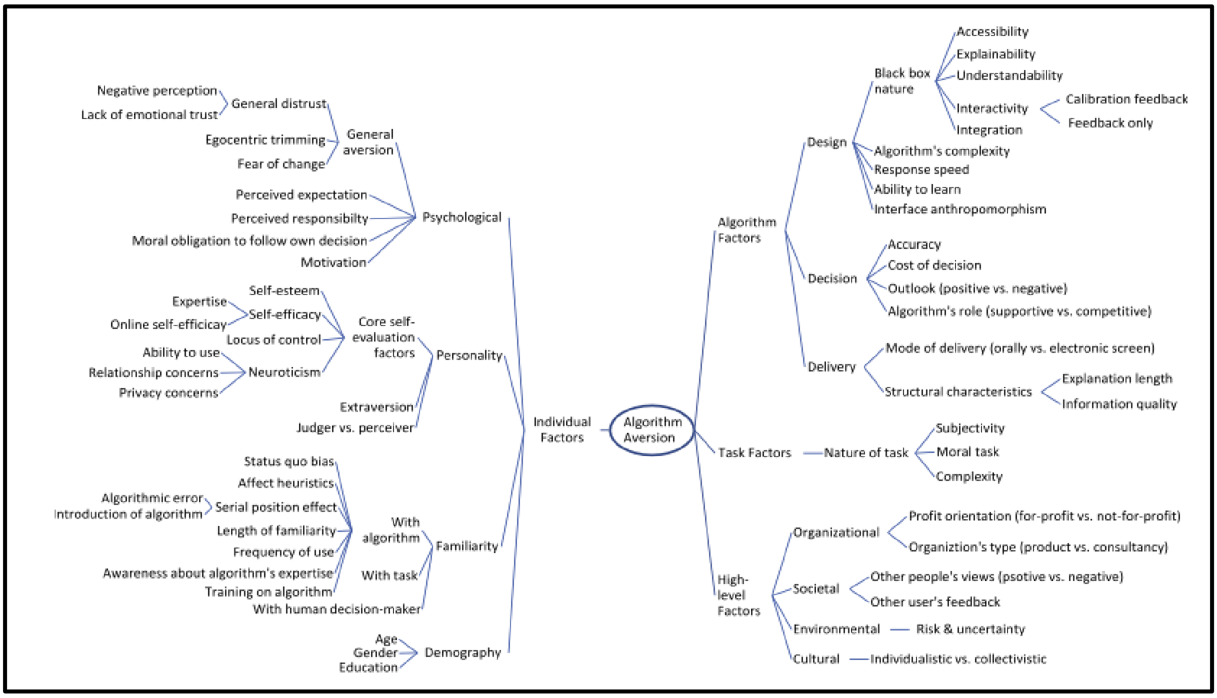

Figure 1: Thematic Map of Algorithm Aversion (Mahmud et al., 2022)

The Map provides a comprehensive understanding of the multitude of factors that impact organizational decision-making. The individual factors encompass demographic information, personality traits, familiarity levels with various scenarios, and psychological predispositions. On the other hand, task-related aspects include evaluating complexities within tasks at hand as well as assessing subjective viewpoints while factoring morality too. In addition to these critical elements affecting judgment calls made by organizations are high-level issues like societal expectations associated with making judgments about others' welfare (or harms). Further still are environmental considerations surrounding resource scarcity or abundance linked directly back towards culture— all shaping how decisions get handled within an organization setting. Finally, yet importantly comes algorithmic insights that characterize design quality concerning decisions made during delivery phases themselves - both preceded & followed through from the start.

The authors emphasized the importance of addressing algorithm aversion to realize the full potential of AI technologies in decision-making contexts. This requires designing algorithms that are transparent, trustworthy, and accountable and not based on black box design, while also educating people about the benefits and limitations of these technologies (Mahmud et al., 2022).

Bader & Kaiser (2019), It has been observed that the integration of algorithms and AI in decision-making may result in humans being detached from the process. This is attributed to their limited comprehension of crucial aspects such as data sources, collection procedures, analysis techniques, and information processing which are fundamental components for acquiring knowledge and making sound decisions. The authors performed a case study that investigated the utilization of IBM Interact, an AI-based system that utilizes cognitive abilities. The research delved into how human decision-makers interacted with algorithmic decisions via the platform's user interface. Their observations reveal that AI technology engenders both detachment and attachment among workplace decision-making entities to its results through a dualistic mechanism derived from low or high levels of human involvement during interactions with the software’s user interface.

The human interface creates a sense of detachment from decision-making through spatial and temporal separation, cognitive displacement, and rational distancing. Spatial separation is the distance between decision-makers and data sources. This can impact understanding of the decision context. Temporal separation refers to the time delay between data collection and decision-making, which may result in utilizing outdated information. On the other hand, rational distancing involves replacing human tasks with algorithms that restrict control over decisions. Cognitive displacement happens when algorithmic decision-making replaces human-based processes resulting in a loss of expertise among humans involved in making decisions. Therefore, the significance of the human decision-maker is reduced, resulting in less participation in the process of making decisions.

In contrast, the interface occasionally results in a substantial level of human participation in AI-generated conclusions. The authors classify three categories of human association with such decisions. Accidental and infrastructural proximity, imposed engagement, and affective adhesion. Accidental and infrastructural proximity pertains to the physical or material closeness between humans and the decisions made by AI systems. Imposed engagement happens when people make decisions in response to organizational conditions, they have no control over. Affective adhesion depends on emotions rather than logical thinking. The authors argue that contextual factors such as social norms, ethical considerations, and values cannot be fully taken into account by artificial intelligence alone but require human involvement alongside AI decision-making processes for more accurate results based.

Most importantly, Bader & Kaiser (2019) suggest a balanced involvement of humans in decisions to avoid deferred decisions, (when people can't make up their minds or postpone them because they don't know enough or have no power to decide) workarounds, (alternative solutions humans use to fix issues caused by AI systems that aren't what people want or expect) and manipulations (when someone changes data or a decision process on purpose to get the outcome they want). These actions may cause problems, mistakes, and ethical worries in businesses relying on AI-supported choices

4.4 Computational Models to Aid the Decision-making Process, Predictive Analytics, and Automated Decision-making Systems

The use of models to support decision-making is one of the most important technological challenges that predictive analytics, computational models, and automated decision-making systems face. These models have the ability to examine enormous volumes of data and predict future events using patterns found in the data. The quality of the data used to train the models, however, determines how accurate these projections will be, and skewed forecasts may be the result of biased data. Springer et al. (2018) address this issue by suggesting the use of a fairness evaluation technique to spot and fix the algorithmic bias in computational models. The problem of algorithmic and data bias has become a significant concern in the media, which is justified. Nevertheless, evaluating and mitigating unfair algorithmic and data biases present considerable challenges to practitioners due to insufficient established procedures or tools for this purpose. For example, Lack of lightweight tools, harmonizing with engineering practice, and delays in addressing bias early in long-term projects. Furthermore, because various communities are working on possible solutions with different perspectives from diverse disciplines, information about addressing these issues remains scattered across the literature. Springer et al. (2018) describe an early approach that aims to convert literature into production processes for teams seeking evaluation of both intended characteristics and unintended prejudiced biases arising from algorithms or data analysis.

According to Springer et al. (2018), this paradigm might aid designers in identifying and minimizing algorithmic bias in their models. In Passi and Barocas (2019) study, a similar discussion addressing the significance of issue design in overcoming algorithmic bias is found. They contend that the issue needs to be presented in a manner that takes into account potential data biases and potential negative effects on particular groups of individuals. The authors claim that if numerous stakeholders are included in the problem formulation process and various points of view are taken into account, this is conceivable. Predictive analytics are used to spot data trends and project upcoming outcomes (Schmude et al., 2023). Since the data scientists use historical data to forecast the upcoming outcomes, if the data possess biases, it may affect these projections, producing unreliable results. Veale et al. (2018) discuss the requirement for justice and accountability in the design of algorithmic assistance systems employed in high-stakes decision-making for example those used in taxation, or child protection. Veale et al. (2018) contend that programmers must consider the potential effects of their systems on various social groups and make sure the systems are open and accountable. Also, the degree of transparency in decision-making affects perceived procedural fairness.

Lee et al. (2018) examines decision fairness and how it is judged by individuals based on the procedures regulating the process, interpersonal interactions with decision-makers, and outcomes. The authors incorporate comparing algorithmic managers and human managers in influencing workers' perceptions of decisions made for tasks requiring human or mechanical skills. The study showed that people perceive algorithmic and human-made decisions equally when it comes to mechanical tasks. Both types of decision-making evoke similar emotions and are considered fair and trustworthy from an academic perspective. Nevertheless, the fairness and trustworthiness attributed to human managers stem from their authority, while algorithms' fairness is attributed more to their efficiency and objectivity in performing tasks. Therefore, procedural fairness perception among individuals can be affected by management (algorithmic vs human).

Lee et al. (2018) describe that People generally favor human decision-making over algorithms when it involves subjective judgment or intuition. This is because they associate fairness, trust, and positive emotions with the authority of managers and their social recognition. In contrast, algorithmic decisions are considered useful tools but may raise privacy concerns if used for tracking purposes and perceived as less fair and trustworthy than human ones. Hence, organizations should offer explanations about algorithmic decisions to enhance trust and fairness perception (Wang et al., 2020). According to Veale et al. (2018), this can be accomplished by putting in place procedures for system monitoring and auditing.

Automated systems that make decisions can also be complex and contribute to algorithmic bias. Without human input, these systems are built to make decisions based on algorithms. However biased data can affect the algorithms that are utilized, producing discriminating results. A further elaboration regarding HRM i.e., Human Resource Management is explained by (Cheng et al., 2021). Roscher et al. (2020) highlight those three fundamental aspects - including transparency, interpretability, and explainability should be considered with distinction in this perspective. While interpretability is concerned with the ML model when combined with the data, or making sense of the obtained ML model, transparency is concerned with the ML approach. The model, the data, and human interaction all contribute to explainability (Roscher et al., 2020). Regarding the former, there are three distinct levels of transparency that can be distinguished: at the level of the entire model (simulatability), at the level of individual components, such as parameters (decomposability), and at the level of the training (algorithmic transparency)" (Roscher et al., 2020). The qualities of an ML model that a person must be able to comprehend are referred to as interpretability (Roscher et al., 2020). Finally, the importance of explainability in HRM cannot be overstated. To understand the findings of the algorithms in various ways and come to conclusions about them, it is required to have human context information and HRM-related knowledge. Furthermore, we have to keep in mind that where the use of algorithmic decision-making in HR recruitment brings cost savings and efficiency it also has some negative impacts like bias, discrimination, and perceived unfairness (Köchling et al., 2020). Holstein et al. (2019) discuss the significance of including business professionals in the construction of fair machine-learning systems. They contend that practitioners can help detect potential bias sources and also offer insightful information about the practical difficulties involved in putting these systems into use (Starke et al., 2022). The authors propose that by incorporating checklists into company goals and priorities, integrating them into teams' existing workflows, supporting them with additional resources, not portraying them as a straightforward compliance process, and aligning them with organizational culture, practitioners can aid in identifying organizational issues and chances related to fairness in AI (Madaio et al., 2020).

Finally, Kordzadeh and Ghasemaghaei (2022) provide a comprehensive examination of algorithmic bias from various viewpoints, namely technical, organizational, and societal. They consolidate current literature on the subject matter and delineate two primary approaches employed in studying this phenomenon: an objective perspective utilizing statistical metrics to assess biases and a subjective outlook that emphasizes human judgments on perceived fairness.

The authors propose a theoretical model that addresses algorithmic bias in organizational decision-making processes, taking into account technical and organizational factors. These include a lack of interpretability, ethical concerns arising from the use of biased data due to a lack of diversity or transparency, and management practices. The model includes seven statements that explain how biases in algorithms can impact user behavior through perceived fairness. Different contextual factors play a role in moderating these relationships. These include individual, task-related, and organizational/environmental aspects.

The propositions include Biases in algorithms that can affect perceptions of fairness. Perceived fairness influences users' acceptance of machine-generated recommendations. Perceived fairness affects users' appreciation of the algorithm itself. Fairness perception is linked to system adoption by the user. Various factors may moderate the relationship between algorithmic bias and perceived fairness depending on whether they relate to individuals (i.e., personal characteristics), tasks (e.g., complexity or urgency involved), or broader contexts like organizations and environmental factors. The authors argue for a multidisciplinary approach to overcoming these challenges and ensuring fairness and transparency in algorithms' decision-making process. The authors emphasize the necessity for additional investigation into the underlying causes of bias in machine learning algorithms and the creation of corrective measures to lessen this bias.

4.5 Inclusion of Accountability, Inclusivity, Privacy, and Transparency

Concerns about transparency have an impact on how ADM systems are perceived in terms of their fairness, accountability, and privacy, all of which are essential for the general public to adopt these systems (Jobin et al., 2019). System adoption has been shown to be influenced by perceived transparency (Zhao and Benbasat, 2019). The impact of perceived fairness, accountability, and privacy on views toward ADM systems has also been noted by (Bitzer et al., 2021; Shin, 2022; Shin et al., 2020; Shin & Park, 2019). People may find it difficult to accurately assess an ADM system's fairness, accountability, and privacy if they do not understand how it works. Users must have access to information in order to evaluate an ADM system's fairness, accountability, and privacy, as their perceptions of these aspects affect their perception of the system's utility, trustworthiness, and likelihood to be adopted (Shin et al., 2019). Transparency increases the perception of accountability because it helps users understand the requirements for accountability and clarifies the oversight and mitigation procedures (Vedder & Naudts, 2017; Zouave & Marquenie, 2017).

A crucial component of guaranteeing the fairness of machine learning algorithms is accountability. Increased views of fairness, accountability, and privacy in ADM systems may result from improved transparency (Aysolmaz et al., 2023). When the users get to know how decisions are made it will create trust among them and eventually, that will lead to adopting the ADMs. According to Springer et al. (2018), accountability needs to be incorporated into the planning and execution of algorithms right away. This necessitates tools for both bias detection and correction in addition to openness (Meng & Berger, 2019). The performance of various algorithms can be compared and evaluated using fairness criteria. In algorithmic decision-making, two fairness criteria are often used: disparate impact and equal opportunity. Disparate impact occurs when an algorithm produces varying results for different groups without explicit bias. For instance, if a hiring algorithm favors

XYZ graduates, it may have a negative effect on candidates from lower-income backgrounds who lack access to such schools. Equal opportunity mandates algorithms to yield comparable false positive and negative rates for diverse groups. This implies that no particular group should be wrongly classified more than another. For instance, if an algorithm predicts recidivism rates in the criminal justice system, it ought to generate equivalent error rates across all racial or ethnic backgrounds. And there is also one called counterfactual fairness where you see whether by changing the race or other correlated characteristics of already assessed individuals would yield distinct results.

Algorithmic decision-making also poses challenges regarding accountability. When issues arise, it can be difficult to determine who should take responsibility (Kordzadeh & Ghasemaghaei, 2022; Holstein et al., (2019); Mahmud et al., 2022; Springer et al., 2018; Wang et al., 2020; Chiao et al., 2019). The authors suggest that accountability ought to be shared by different parties such as developers, users, and regulators. Developers must ensure fairness in algorithm design and increase transparency in their use; users need to use algorithms prudently while being mindful of their limitations; regulations should establish legal frameworks for oversight, transparency, and accountability when using algorithmic decision-making processes. Chiao, V. (2019) proposes simplifying accountability by implementing "algorithmic impact assessments." These assess whether algorithms will negatively affect different groups, and developers are required to take action to mitigate such effects. Legal liability may also be necessary for any unfair or discriminatory decisions made through these algorithms. Seo and Gebru (2020) propose establishing a culture of transparency and openness in corporations. Encouraging workers to speak freely about matters concerning impartiality and justice can promote accountability within ADSS. Additionally, the authors recommend reaching out to external stakeholders such as community groups or advocacy organizations for better comprehension of users' views and requirements. Wang et al. (2020) Organizations should acknowledge their responsibility for any unfair or biased decisions made by algorithms and take necessary measures to rectify them. The authors also highlight the significance of accountability in human involvement related to algorithmic decision-making. Human intervention can be advantageous as it enables individuals to be accountable for any prejudiced or partial verdicts made by such systems. Nonetheless, this can lead to further constraints due to personal bias and limitations. The authors propose that conducting frequent audits is crucial to resolving these concerns efficiently. Mahmud et al. (2022) discovered that individuals perceive the decision-maker as accountable for algorithmic decisions leading to greater acceptance of their use. Moreover, this implies if the result produced by an algorithm is unfair or incorrect, those affected are more likely to hold responsible entities such as people or organizations involved in creating or implementing the system instead of attributing fault exclusively to the algorithm itself. Kordzadeh & Ghasemaghaei (2022) suggest training employees on how to recognize and mitigate bias in their work will promote accountability and trust within ADSS. Furthermore, algorithmic audits, which can be used to evaluate how different groups are affected by algorithms. Akula & Garibay (2021) discussed the seven stages involved in performing an algorithmic audit and these are illustrated below in Figure 2.

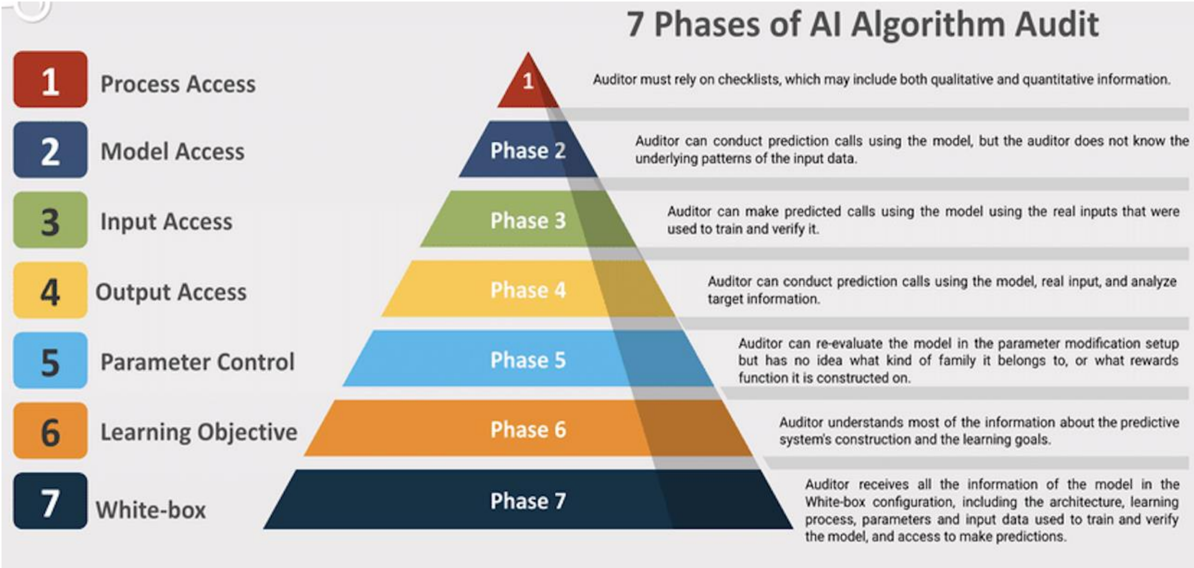

Figure 2: 7 Phases of AI Algorithm Audit

Upon examining phase 7 in the provided diagram, it becomes apparent that an auditor can acquire essential information for conducting audits only through effective teamwork and coordination with management and developers within a company. By establishing close collaboration among these three parties, organizations can reduce bias in ADSS and ultimately enhance their decision-making capabilities.

Tools such as explainability techniques could improve the transparency and understandability of an algorithm's decision-making. According to Passi & Barocas (2019), these measurements can be used to locate and eliminate bias-causing factors in data, algorithms, or decision-making processes. Designing inclusive ML algorithms requires several factors that include collecting data: making sure that data are gathered in a manner that is representative of the population and does not confirm preexisting prejudices.

Veale et al. (2018) use the term "social context" to refer to social, cultural, and political factors that affect algorithmic decision-support systems. The authors argue that algorithmic systems cannot be designed without considering their broader social context for ensuring fairness, accountability, and transparency. The authors highlight historical and cultural biases, power imbalances, institutional structures, and legal frameworks as significant contributors to this social context which can influence how these algorithmic systems are developed in practice. For instance, societal bias or flawed algorithms may impact training data leading to biased results. Similarly, the social implications of algorithmic decision-making might not be adequately taken care of by existing legal frameworks.

Veale et al. (2018) also suggests prioritizing the algorithmic architecture by taking into account several demographic groups to make these systems more vigilant. They also proposed employing algorithms that are fair and can be scrutinized fully to eliminate any prejudice that will make them accountable and transparent in the decision-making process but there is an argument on that. The authors argued that in high stake decision-making processes, there will be ambiguity and algorithms will not ensure equity and transparency. Holstein et al. (2019) contend that ML algorithms have the potential to preserve existing power inequities, particularly if they are applied to decisions that have a significant impact on people's lives. Holstein et al. (2019) suggest that, in order to decrease this, privacy precautions must be incorporated into the creation and application of algorithms. For this, the algorithmic pipeline must incorporate privacy-by-design concepts, such as data reduction. Making sure these problems are adequately handled requires transparency in crucial areas. Kordzadeh & Ghasemaghaei (2022) assert that transparency is essential for accountability, inclusivity, and privacy because it enables stakeholders to understand how an algorithm works and identify potential sources of bias. Kordzadeh & Ghasemaghaei (2022) advocate using open-source algorithms, making thorough documentation available, and publishing the findings of fairness assessments in order to achieve transparency.

4.6 Promoting Fairness in Algorithmic Decision-Making in Businesses

Inspiring fairness and cultivating a culture of transparency around ADSS can help assure the fairness of algorithmic decision-making. According to Kordzadeh and Ghasemaghaei (2022), it is very important to push firms and businesses to put these ideas into practice. The implication of ethical standards as mentioned in HLEG, A. (2019). A definition of AI: main capabilities and disciplines. Brussels. https://ec. europa. eu/digital-single. poses difficulties in the context of machine learning as there is no incentive mechanism for those involved. Although a foolproof approach has not been identified, the archival ecosystem provides pressure on archivists to adhere to ethical guidelines through various measures. For instance, most archivists are professional data collectors who may face consequences such as losing their membership if they violate the code of conduct within organizations that operate under a membership system (A Range of Resources for the Record Keeping Sector, 2018). Additionally, some sub-organizations have established ethics panels or committees to evaluate each alleged violation case-by-case (A Range of Resources for the Record Keeping Sector, 2018; ICRM Code of Conduct | Institute of Certified Records Managers, 2016). In the field of ML, incentivizing full-time employment for ethical data collection can enhance compliance with ethics codes. By making the selection and evaluation of data under such codes a primary task for data collectors, who must adhere to these standards in order to maintain their professional membership, enforcement may become simpler. This approach aligns with that used by archivists who rely on ethics guidelines to steer their work since collecting data is an open-ended job (Jo and Gebru, 2019).

However, Jo and Gebru (2019) have identified various factors that may impact ethical data collection, so while collecting data these factors need to be considered to avoid data impartiality.

This includes:

- Institutional frameworks and procedures are necessary to ensure ethical data collection. Clear guidelines should be developed, and mechanisms for monitoring compliance established.
- Diversity in data sources is crucial to avoid bias or unfair machine learning models.
- Obtaining informed consent from individuals whose data is collected plays a key role in ethics by providing clear information on usage with the option of opting out of said collection.

- Transparency is crucial for ethical data collection. Organizations must disclose their data collection practices, involving the gathering, storage, and usage of information.

Companies are more likely to prioritize fairness in algorithmic decision-making if it results in favorable outcomes, including enhanced consumer trust and brand reputation while minimizing legal risk. Thus, companies may encourage a digital organizational culture that promotes the ethical use of technology (Martínez-Caro et al., 2020). Furthermore, Kordzadeh and Ghasemaghaei (2022) also stress the importance of addressing the financial incentives that encourage the use of ADSS in organizations. Taking in account Digital technologies like AI and machine learning greatly affect how organizations perform. However, these systems are dependent on algorithms, and if partial data is utilized in constructing these algorithms, it will generate inequitable outcomes. Thus, companies should assess the ethical considerations of utilizing such technologies by prioritizing fair decision-making through transparent, explainable, and auditable algorithms with input from diverse stakeholders in system design/testing. This way digital strategies can be effective while remaining ethically sound and socially responsible (Martinez-Caro et al., 2020). Martinez-Caro et al. (2020), explained the research model in their study with the ultimate goal of improving organizational performance. Since digital technologies rely heavily on fair and ethical algorithms, the proposed model suggests that digital organizational culture is made up of three dimensions: digital leadership, digital mindset, and digital capabilities. Digital leadership involves leaders creating a shared vision for the company's technological future and encouraging experimentation and learning. Digital mindset refers to employee attitudes towards technology and their openness to change and innovation. Finally, digital capabilities are the skills, knowledge, and resources necessary for effectively utilizing technological tools. A strong implementation of this model can result in enhanced business digitization by transforming traditional models into e-business models through the use of technology, this practice is called techno-solutionism. This has several benefits such as improved efficiency, reduced costs, and better customer experience along with new revenue streams.

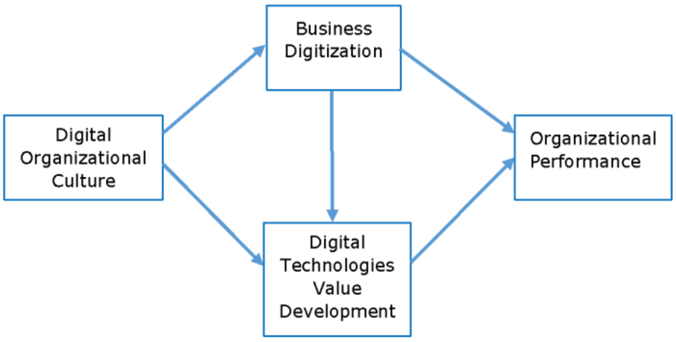

Figure 3: Proposed Research Model, (E. Martínez-Caro, et al.,2020)

Transparency makes it possible for individuals to accurately assess process aspects that would otherwise be hidden from them (Lee, Jain et al., 2019). Transparency enhanced perceived fairness by enabling people to grasp equalities in resource allocation, but transparency decreased perceived fairness by enabling people to recognize unequal distributions and differences. As a result, while openness may not ensure fairness in processes, it does make it possible for people to spot biases in algorithmic results. Another critical point here is that this might dissuade companies from adopting such practices.

According to Lee (2018), it is advisable for humans to be the ones making final decisions regarding employee potential and career development in order to maintain fairness perceptions. While automated evaluation may seem more valid, inconsistencies and insufficient evidence can arise with human raters (Woods et al., 2020). Human tasks such as hiring, and work evaluation should be left to humans instead of relying solely on algorithmic systems which are better suited for mechanical tasks like scheduling (Lee 2018). The lower acceptance of algorithms in assessing human potential is due to factors such as insufficient transparency regarding their operation. This results in greater emotional discomfort, decreased interpersonal treatment, and reduced social interaction (Lee 2018; Langer et al., 2018, 2019).

Fairness perceptions and performance opportunities are impacted by algorithmic decision-making in HRM (Kaibel et al., 2019). Companies should increase the usage of algorithms while ensuring transparency in how humans utilize them for decision-making processes to create valid and fair recruitment and career development HR systems (Tambe et al., 2019; van Esch et al., 2019). Future research could explore effective ways for companies to communicate or promote their use of algorithms. Adding to it some research has already been done in that context. According to Felzmann et al. (2019), there are two approaches related to transparency. Verifiability and Performativity. Verifiability involves providing more information to verify the accuracy of decisions made by AI systems, whereas performativity recognizes that transparency practices may influence behavior and decision-making, potentially creating unintended consequences such as new power dynamics or reinforced biases. To ensure positive outcomes while avoiding unintended effects, it is essential to balance both verifiability and performativity when implementing transparency practices.

Transparency has a dual nature (Felzmann et al., 2019). The authors use Google as an example to explain how transparency can have both clear and unclear aspects (dual nature) when discussing the subject. The details provided in Google's privacy policy about data collection are numerous, but its purpose is stated vaguely and generically, which leads to a mixed sense of transparency. While users gain some insight into certain elements of how Google collects data, it could give rise to accountability issues as well as build trust among consumers; however selective disclosure around data usage seems intended to hide problematic practices that might arise from what information has been collected.

Felzmann et al. (2019) suggest that in order to fully understand the advantages and disadvantages of transparency, we need a 'Holistic Approach'. By taking into account both verifiability and performativity aspects together, we can come up with better ways to encourage transparent practices that bring more benefits than risks. This would lead us towards increased use of algorithms for decision-making and promoting ADSS.

While some research suggests that candidates may react negatively to algorithmic decision-making (Kaibel et al., 2019; Lee, 2018), further investigation is necessary regarding individuals' acceptance of algorithms when they support human decisions. Additionally, it is crucial to explore whether transparency and providing more information about the algorithmic decision-making process can enhance fairness perception (Hiemstra et al., 2019). Although many studies have examined applicants' perspectives on fairness perception, HRM research has yet to adequately address current employees' views on algorithmic decision-making despite concerns over job loss due to digitalization and automation. The question of how algorithms can aid in assessing, promoting, and retaining qualified employees remains vital both currently and moving into the next decade. The perception of biases and fairness among current employees is a promising area for HR development research. HR managers have an important responsibility in implementing algorithmic decision-making, ensuring privacy and fairness, monitoring algorithms used, and informing employees about data usage and potential consequences such as career opportunities. Algorithmic decision-making in HRM involves a social process, and employees should participate actively (Leicht-Deobald et al., 2022; Tambe et al., 2019). To ensure fairness, applicants, and employees must have the option to disagree with these processes (Simbeck, 2019). Clear guidelines for algorithm execution and data usage transparency can help achieve this goal (Cheng & Hackett, 2021; Simbeck, 2019).

5. Discussion and Results

Based on the research papers examined during the literature review, a suggested framework is illustrated through the histogram provided in Figure 4. The percentages presented in the histogram are computed without normalization because certain papers apply to numerous concepts.

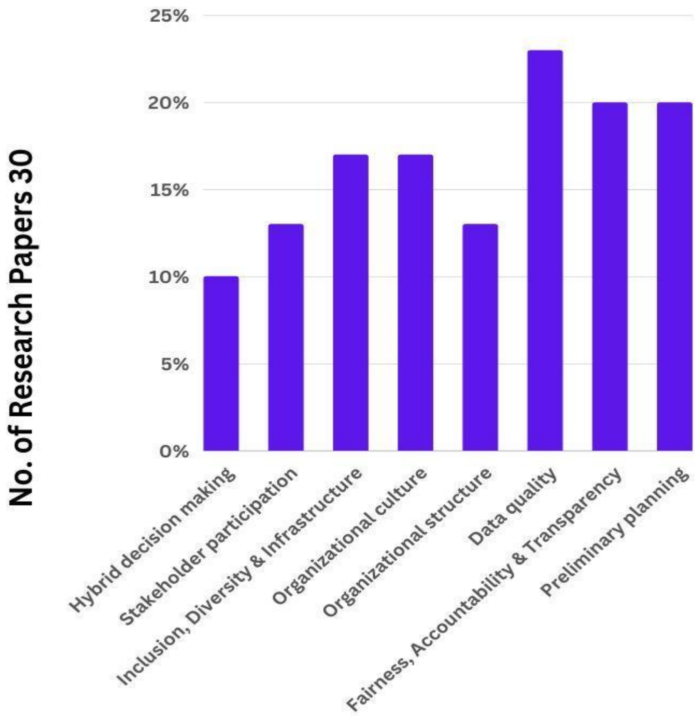

Figure 4: ADM Framework: Key Concepts

The figure explains eight concepts gathered by analyzing the literature review. The height of each bin of a histogram represents the number of papers that are relevant to the respective concept that influences ADSS. In the following subsections, I shortly present and critically discuss the concepts.

Hybrid-Decision Making

Differentiating between Human Decision-Making (HDM) and Algorithm Decision-Making (ADM) alone proves insufficient in comprehending the intricacies of the real world (Veale et al., 2018). In numerous practical scenarios, decision-making involving ADM systems does not occur solely through automated means; human intervention also plays a role. Algorithmic decision-making cannot work in every situation for instance, in high stake decision-making processes, there will be ambiguity and algorithms will not ensure equity and transparency (Veale et al., 2018)

In certain situations, the involvement of human supervision is essential in making decisions. This is called the Human-in-the-loop approach. Conversely, when data becomes intricate and time-consuming to analyze by humans, algorithmic decision-making may be more practical. The author identified, a combination of ADM and HDM depending on the context or circumstance involved, would yield an efficient process that upholds fairness and responsibility in making decisions. The suggested human-in-the-loop methodology be incorporated into corporate management. For instance, interdepartmental meetings and communication channels could be established when different departments are involved within organizations namely Legal and IT.

Stakeholder Participation

It implies the interpretation and communication of stakeholders in the decision-making process. The authors claim that if numerous stakeholders with diverse backgrounds, expertise, and experiences are included in the problem formulation process and various points of view are taken into account, algorithmic bias can be mitigated (Passi & Barocas, 2019).

Furthermore, robust solutions could be designed leading toward overall enhanced accountability when implementing ADSS (Madaio et al., 2020). The authors argue that managers should make sure to incorporate stakeholder consultation procedures throughout the decision-making process.

Inclusion & Diversity and Infrastructure

Algorithmic design is a crucial aspect of the process that needs to be addressed with utmost care. In order to reduce the risk of algorithmic bias, it is imperative for designers to prioritize inclusion, diversity, and equity while developing algorithms (Seo & Gebru, 2020). This can be done by hiring organizational ethicists who will supervise the decision-making process. The absence of diversity in development teams may result in unnoticed blind spots and biases during the development process (Starke et al., 2022). To stay relevant in an increasingly competitive marketplace with global impact, organizations need to embrace new perspectives and attitudes by incorporating diversity at an early stage (Springer et al., 2018).

Organizational Culture

Springer et al. (2018) argue that the culture of an organization plays a crucial role in mitigating algorithmic bias and ensuring fairness throughout all stages of developing and deploying algorithms. If the company culture is based on collaboration, and openness as well as creates a secure environment for individuals to voice their worries, it will surely bring fairness in algorithmic decision-making.

In addition, Passi and Barocas, (2019) propose that organizations should prioritize "justice first" with emphasis on devising moral standards, offering learning opportunities while engaging diverse parties involved in making decisions towards fostering transparency and responsibility.

Organizational Structure

In public sector organizations, the hierarchical structure may lead to a concentration of power in few individuals or departments, increasing algorithmic bias and hindering decision-making diversity. Biased outcomes that unfairly target particular groups may result from narrow-minded group perspectives when designing and deploying algorithms (Wang et al., 2020). Organizational structures play an important role in addressing algorithmic bias as interdisciplinary teams combining experts from various fields such as data science, ethics, and law are recommended for combating this issue (Holstein et al., 2019; Köchling & Wehner, 2020). Participation equality among all departments through cross-functional teams ensures fair decision-making practices.

Data Quality

Biased user inputs, biased algorithms, and biased training data can lead to algorithmic bias (Kordzadeh & Ghasemaghaei, 2022). Holstein et al. (2019) stress the significance of data quality and impartiality in algorithm development as biased data can generate unrealistic outcomes. To prevent partiality, two key values namely accountability and openness should be adopted by companies while handling information. Accountability refers to entities taking responsibility for their actions whereas openness emphasizes transparency in information management practices. Veale et al. (2018) also prioritize both these values underlining that algorithms constructed without adequate consideration towards impartial representation could worsen existing societal challenges instead of resolving them.

Fairness, Accountability & Transparency

A crucial component of guaranteeing the fairness of machine learning algorithms is accountability (Veale et al., 2018). Transparency, on the other hand, increases the perception of accountability because it helps users understand the requirements for accountability and clarifies the oversight and mitigation procedures (Vedder & Naudts, 2017; Zouave & Marquenie, 2017). The authors contend that designers of ADSS must consider fairness and accountability for better decision-making. To guarantee transparency and accountability in ADSS, it is necessary to create guidelines for documenting, examining, and affirming algorithms. According to Kordzadeh & Ghasemaghaei (2022) promoting clarity in machine learning algorithms can aid stakeholders' understanding. To achieve this objective, the authors recommend employing open-source algorithms alongside comprehensive documentation and unbiased evaluations. Accountability needs to be incorporated into the planning and execution of algorithms right away. This necessitates bias detection and correction tools in addition to openness (Meng & Berger, 2019). Algorithmic decision-making can also pose accountability challenges. Determining who is responsible for issues that arise may be difficult (Kordzadeh & Ghasemaghaei, 2022; Holstein et al.; Mahmud et al., 2022; Springer et al., 2018; Wang et al., 2020; Chiao et al.,2019). To simplify, it's recommended that each party involved – for instance, developers, users, and regulators should share accountability in their respective contexts.

Concerns about transparency have an impact on how ADM systems are perceived in terms of their fairness, accountability, and privacy, all of which are essential for the general public to adopt these systems (Jobin et al., 2019). Madaio et al. (2020) suggested approach is a co-designed checklist that includes contributions from multiple departments with the intention of identifying possible biases. Felzmann et al. (2019) suggest a holistic approach to transparency that considers both verifiability and performativity. This, they argue, will lead to improved transparent practices with greater benefits than risks, ultimately promoting ADSS. Finally, regulations should establish legal frameworks for oversight transparency, and accountability when using algorithmic decision-making processes.

Preliminary Planning

Putting it in a simple way IT projects in the public sector can face challenges due to insufficient initial planning. That leads to problems with maintaining and performing well because their information systems often cross different hierarchies and areas of responsibility. The way that public organizations are structured could lead to power being held by a few individuals or departments, which could result in unfair decision-making patterns; this is referred to as "algorithmic bias". Cross-functional collaboration and setting up a structured system for regular reviews can reduce algorithmic bias.

Challenges

Holstein et al. (2019) in their research found that when trying to improve fairness in ADSS, practitioners from a range of industries encounter a number of challenges, such as a lack of clarity regarding fairness metrics, a lack of resources to put fairness measures into practice, and a lack of tools to recognize and address bias. Holstein et al. (2019) offered a series of design recommendations for fairness tools in response to these difficulties. These recommendations include making tools simple to use, by thoroughly defining fairness criteria and allowing practitioners to customize fairness metrics to their own needs. The European AI Act is an attempt to define the fairness criteria (Wachter et al., 2021). Also, Canada's government has issued the Algorithmic Impact Assessment with a section on procedural fairness (McKelvey & MacDonald, 2019). According to Holstein et al. (2019), making tools easy to use is vital because it can lower the learning curve and motivate practitioners to use fairness tools more frequently. Some fairness tools are Aequitas, AI Fairness 360, and Fairlearn.

Holstein et al. (2019) concur that detailing fairness metrics can aid practitioners in understanding which metrics are pertinent to their context and how to measure them successfully. Additionally, Holstein et al. (2019) contend that allowing practitioners to customize fairness metrics to their unique needs can assist in ensuring that the measurements are tailored to the organization's particular environment and objectives. The absence of a unanimous definition for fairness within machine learning systems creates ambiguity as stakeholders possess distinct values and priorities which shape their understanding of what constitutes fairness (Passi & Barocas, 2019; Schmude et al, 2023; Starke et al., 2022; Jo & Gebru, 2019).

Along with Holstein et al. (2019), various other authors discussed in their studies different challenges in improving fairness in ADSS on common grounds. Creating a fair and responsible organizational culture can be difficult, especially when faced with competing priorities or resistance to change. The continually evolving legal and regulatory frameworks surrounding data science also present challenges in establishing ethical guidelines (Passi & Barocas, 2019). In the context of managing dynamic data, the authors acknowledge the possibility of evolving input data used for algorithm training, causing potential biases or inaccuracies in system outputs (Veale et al., 2018). AI ethics principles can be challenging for practitioners to implement due to their abstract nature (Madaio et al., 2020). Practitioners have not been actively involved in the development of AI ethics checklists, resulting in limited adoption (Kordzadeh & Ghasemaghaei, 2022; Madaio et al., 2020). Presenting AI fairness as a checklist may create false confidence and encourage problematic behavior or reinforce techno-solutionism (Madaio et al., 2020). It is crucial that AI fairness checklists stimulate team discussion and reflection instead of being relied upon as a guarantee of fairness (Madaio et al., 2020). Generalizability should be approached carefully because the research was carried out in different production centers with varying perspectives from diverse disciplines, that adhere to their respective company guidelines (Wang et al, 2020; Martínez-Caro et al., 2020). Additionally, resistance from employees toward digitalization may impede the integration and execution of new technologies (Martínez-Caro et al., 2020).

Machine learning models require diverse data to make accurate predictions. Unfortunately, many datasets do not capture the full range of human experiences and perspectives, limiting availability (Kordzadeh & Ghasemaghaei, 2022; Wang et al., 2020; Jo & Gebru, 2019; Schmude et al, 2023). Additionally, the lack of transparency in machine learning models makes it challenging to identify and address fairness issues (Starke et al., 2022; Jo & Gebru, 2019; Wang et al., 2020; Kordzadeh & Ghasemaghaei, 2022). Achieving fairness and accuracy may involve trade-offs. Certain methods to increase fairness can potentially decrease accuracy, while some methods that enhance accuracy might compromise fairness (Passi & Barocas, 2019; Schmude et al, 2023; Starke et al., 2022; Wang et al., 2020).

Teams require lightweight tools to personalize their processes instead of relying on external requests. Regrettably, such tools are currently unavailable (Springer et al., 2018). The literature concerning algorithmic and data bias is scattered, and diverse communities with varying expertise are tackling this interdisciplinary issue (Springer et al., 2018).

Some more recommendations after analyzing the existing literature to overcome partiality from algorithmic decision-making are presented in Table 1. The first column shortly presents the recommendations, and the second lists the papers where each recommendation was introduced.

Table 1: Mitigating Bias in ADSS: Recommendations for Fairness

Recommendations	References
Being transparent can make resource allocation seem equal, but it can also highlight differences which decreases the perception of fairness. While transparency may not guarantee fairness in processes, it does help people detect biases in algorithmic results. This might dissuade companies from adopting such practices. To address this problem, researchers and governments have proposed various guidelines. Companies can work with relevant authorities like the European Center for Algorithmic Transparency to manage these issues more easily.	[38]
Education and communication among individuals can encourage individuals to consider the fairness of algorithmic processes beyond their personal interests. Offering education programs on algorithms could unite people with distinct backgrounds and enhance their comprehension for adopting such decision-making processes.	[17]
There is no one solution for an effective explanation of algorithms being fair as it depends on specific fairness issues and user profiles. It may be necessary to provide hybrid explanations by giving an overview of the model while allowing scrutiny of individual cases for accurate fairness judgment.	[31]
A balanced involvement of humans and ADSS to avoid deferred decisions. Management practices that guarantee such involvement should be put in place. For instance, stakeholder consultation sessions can be organized.	[60]
A multidisciplinary approach to overcome algorithmic bias and ensuring fairness and transparency in algorithms' decision-making process is needed. It is suggested that managers encourage interdepartmental collaboration for this purpose. One possible strategy could be creating teams consisting of individuals from various departments such as developers, lawyers, ethicists, and marketers who can provide diverse perspectives on this matter.	[6]
Hybrid decision-making: This approach leverages algorithms to provide insights, recommendations, and objective data analysis, while humans retain the final decision-making authority. This ensures the utilization of algorithms as useful tools without completely replacing human judgment.	[38]
Auditor can acquire essential information for conducting audits only through effective teamwork and coordination with management and developers within a company. By establishing close collaboration among these three parties, organizations can reduce bias in ADSS and ultimately enhance their decision-making capabilities	[59]

Future research directions

The study has identified some gaps in the existing literature and provided a set of directions, with a special emphasis on algorithmic decision-making. Further research is necessary to understand the legal and regulatory frameworks that govern algorithmic decision-making processes. including how these frameworks can be adapted to address emerging challenges related to these systems.

Additionally, it is crucial to investigate different approaches for designing ADSS with stakeholder engagement and participatory design methods. To ensure the ethical use of ADSS in public sector organizations, more research must be conducted on social implications surrounding aspects like transparency, accountability, and fairness. Furthermore, research needs to be done in terms of fair datasets to be used to avoid ambiguity in the decision-making processes. Finally, research needs to be done on algorithmic aversion as there is no unified scale to measure Algorithmic aversion in a real-world setting.

6. Conclusion

The use of ADSS in organizations is increasing every passing day because of its effectiveness and efficiency, but on the other hand, there are concerns related to its fairness and moral implications. That leads to mixed responses from the individuals. Some individuals favor algorithmic approaches and some hold negative views concerning the same issue. Several studies have been carried out to explore the elements that impact bias in algorithmic decision-making and provide guidance on enhancing fairness from a managerial perspective. Therefore, a literature review has been conducted to examine the links between fairness in ADSS and managerial practices. As such, in this work, 30 research papers have been reviewed. I attempt to answer the research question following descriptive analysis and the narrative literature method. The analysis shows that there are a number of factors that influence algorithmic decision-making. A framework delineating the factors that affect algorithmic decision-making is presented, followed by the recommendation table that leads to fair designing, development, and deployment of algorithmic support systems and ultimately ends up with fair decision-making.

This literature has identified some gaps in the existing literature and provided a set of directions, with a special emphasis on algorithmic decision-making, to advance the research in the intersection of fairness, algorithmic decision-making, and relevant managerial practices. Further research is necessary to understand the legal and regulatory frameworks that govern algorithmic decision-making processes, including how these frameworks can be adapted to address emerging challenges related to these systems. Additionally, it is crucial to investigate different approaches for designing ADSS with stakeholder engagement and participatory design methods. To ensure the ethical use of ADSS in public sector organizations, more research must be conducted on social implications surrounding aspects like transparency, accountability, and fairness. Furthermore, research needs to be done in terms of fair datasets to be used to avoid ambiguity in the decision-making processes. Finally, research needs to be done on algorithmic aversion as there is no unified scale to measure Algorithmic aversion in a real-world setting.

Finally, I have encountered a few limitations while performing this research that future research may take up. Initially, I pursued this investigation independently resulting in a narrow examination of the literature. My focus was confined to particular ideas that were explored solely by myself. Perhaps if conducted as part of a collective effort involving several individuals, a more comprehensive analysis could have been achieved. Secondly, I solely relied on existing literature and did not perform any empirical research. Third, I limit my search to specific academic databases, which may result in the omission of some important studies from this research. Fourth, I did not include technical research papers as they were beyond the scope of my study. Future research may find ways to overcome this subjective bias while performing a Narrative literature review on algorithmic decision support systems.

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