

Mitigating Bias in Algorithmic Systems: A Fish-Eye View of Problems and Solutions Across Domains

Kalia Orphanou¹, Jahna Otterbacher¹, Styliani Kleanthous¹, Khuyagbaatar Batsuren², Fausto Giunchiglia², Veronika Bogina³, Avital Shulner Tal³, Alan Hartman³, and Tsvi Kuflik³

¹Open University of Cyprus, CYPRUS

²The University of Trento, ITALY

³The University of Haifa, ISRAEL

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Abstract

Mitigating bias in algorithmic systems is a critical issue drawing attention across communities within the information and computer sciences. Given the complexity of the problem and the involvement of multiple stakeholders – including developers, end-users and third-parties – there is a need to understand the landscape of the sources of bias, and the solutions being proposed to address them. This survey provides a “fish-eye view,” examining approaches across four areas of research. The literature describes three steps toward a comprehensive treatment – bias detection, fairness management and explainability management – and underscores the need to work from within the system as well as from the perspective of stakeholders in the broader context.

Index terms— Algorithmic bias, explainability, fairness, social bias, transparency

1 Introduction

Long before the widespread use of algorithmic systems driven by big data, Friedman and Nissenbaum [47], writing in the ACM TOIS in 1996, argued that “freedom from bias” should be considered equally alongside the criteria of reliability, accuracy and efficiency, when judging the quality of a computer system. Defining biased systems as those that “systematically and unfairly discriminate” against individuals or certain social groups, they emphasized that if a biased system becomes widely adopted in society, that the social biases it perpetuates will have serious consequences.

More than 20 years later, the ACM U.S. Public Policy Council (USACM) and the ACM Europe Policy Committee (EUACM) published a joint Statement on Algorithmic Transparency and Accountability,¹ underscoring the widespread concerns surrounding computer bias, but this time, focusing on the social consequences of *data-driven algorithmic processes and systems*. The statement puts forward seven principles to be considered in the context of system development and deployment, in working toward mitigating the threat of harm to people posed by biases. Despite that the principles are

¹https://www.acm.org/binaries/content/assets/public-policy/2017_joint_statement_algorithms.pdf

articulated in a single page, it is clear that the issue of algorithmic bias is extremely complex. In particular, multiple sources of bias (e.g., data, modelling processes) are mentioned, as well as alternative solutions – from simply raising users’ awareness of the issue, to enabling the auditing of models by third parties. Furthermore, the principles mention a range of stakeholders (the algorithm’s owners, designers, builders, and end-users), alluding to their roles in ensuring the ethical development and appropriate use of algorithmic processes.

Despite the recent surge in attention to the topic, addressing algorithmic bias is not exactly a new concern for researchers. For instance, in the 1990s, machine learning researchers were considering problems of *explainability*, or how to interpret models and facilitate their use (e.g., [28], [29], [36]). In the early 2000s, researchers in the data mining community were developing processes for *discrimination discovery* from historical datasets (e.g., [106]). Similarly, around the same time, information retrieval researchers were considering the issue of bias in training datasets (e.g., [17]) and the resulting impact of this bias on ranking algorithms [26]. Thus, while several research communities were tackling various issues related to algorithmic biases earlier on, they were largely disjoint from one another. Furthermore, they addressed the problems from “inside,” working exclusively from the perspective of the developer. More recently, multiple perspectives on algorithmic bias have come to light, with the increasing influence of algorithmic systems in society. Arguably, a 2016 ProPublica article entitled “Machine Bias” [4] played a key role in stimulating widespread discussion, opening up the conversation to other stakeholders beyond those who develop algorithmic processes and systems.

1.1 Mitigating Algorithmic Bias: The Case of COMPAS

The ProPublica article described the problem of racial bias in the COMPAS system, a proprietary tool developed by Northpointe Inc., which is widely used by courts in the U.S. to predict the risk of recidivism by criminal defendants. The authors, as data journalists assuming the role of *system auditors*, compared the data they collected from public criminal records concerning 10,000 defendants, to the predictions made by the COMPAS system.² Their analysis suggested that the system unfairly discriminates against black defendants over whites; in particular, the system misclassifies black defendants who did not actually reoffend within two years, twice as often as it does their white counterparts.

Although machine learning researchers had already been developing formal definitions of algorithmic fairness in years prior to the ProPublica article, in particular for classification algorithms (e.g., [37]), the COMPAS case highlighted the complex challenges of building socially just systems. In most cases in the “real world,” there are multiple and competing interpretations of “fairness,” which cannot be simultaneously satisfied [76]. At the same time, other researchers emphasized the central importance of *transparency*. It was argued that only the transparency of the methodology and of the training data used, can ensure procedural fairness in a system such as COMPAS [119], by allowing the public to scrutinize the calculations behind recidivism scores. Still, others stressed the role of the user of the COMPAS system. In particular, it was noted that the user’s knowledge, both of data science principles as well as the interworkings of the justice system, will influence her ability to interpret and use the predicted recidivism scores appropriately [114].

In short, the COMPAS case illustrates that mitigating algorithmic bias involves multiple stakeholders and processes as suggested in Fig. 1. *Developers* can internally detect

²<https://www.propublica.org/article/how-we-analyzed-the-compas-recidivism-algorithm>

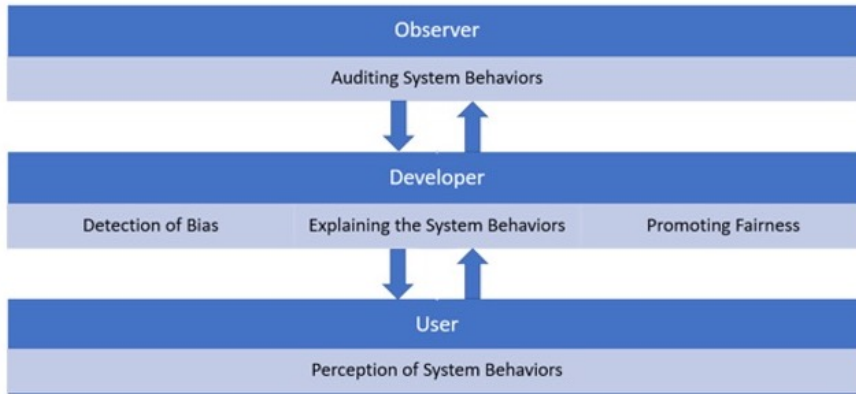


Figure 1: Processes and stakeholders involved in mitigating algorithmic bias.

bias in data and processes, evaluate formal notions of fair treatment of the individuals and groups for whom recidivism scores are predicted, as well as implement methods used by the system for explaining its decisions to users and/or third parties. *System Observers*, who may be regulators, researchers or even data journalists, can conduct their own audits of the system behaviors. However, *Users* of the system have their own perceptions of the system’s behavior, which depend not only on the system itself, but also their own knowledge, experience and attitudes. It is clear from the COMPAS case study, as well as the ACM Statement, that the stakeholders all play a role in mitigating algorithmic bias, and that the processes in which they are involved should have some interaction. However, the work in these areas tends to be undertaken by separate research communities.

1.2 Goal of the Survey: A Fish-Eye View

Integrated solutions for mitigating algorithmic biases are unlikely to be found in one research community alone but rather, must involve work across disciplines. Indeed, this revelation has led to a number of cross-disciplinary initiatives, such as the ACM FAccT Network.³ FAccT⁴ reaches beyond computer science into the social sciences and humanities, as well as law, in addressing fairness, accountability and transparency issues in socio-technical systems. Similarly, many initiatives within artificial intelligence, including workshops and research groups, are focused on FATE (Fairness, Accountability, Transparency and Ethics in AI) (e.g., Microsoft’s FATE group⁵).

In this survey, we aim to facilitate a high-level understanding of the research surrounding the mitigation of bias in algorithmic processes and systems in the information and computer sciences. Recently, a number of comprehensive surveys has emerged on the specific problems and solutions in this area. For instance, Olteanu and colleagues [102] reviewed the literature surrounding data biases; in particular, they address social data sources, given their frequent use in the creation of training data sets. Coming from a fair machine learning perspective, Mehrabi and colleagues [96] provided a survey of common problems and solutions, including those focused on data and processes. Addressing explainability, Guidotti et al. contributed a comprehensive survey and a taxonomy of the various methods used to interpret the behaviors of black box models

³<https://facctconference.org/network/>

⁴Note that in 2020, FAccT became the new acronym of ACM FAT*.

⁵<https://www.microsoft.com/en-us/research/theme/fate/>

[55].

In contrast, our aim is to help the reader achieve a high-level understanding of the current state of this complex topic, across domains. With a view toward promoting more comprehensive solutions, as suggested in Figure 1, we present a *fish-eye view* of the literature surrounding algorithmic bias, its problem and solution spaces. In information visualization, fish-eye views, which balance focus and context (i.e., depth and breadth), are useful for facilitating understanding in information spaces that are very large and diverse [49]. The user maintains perspective of the “big picture,” but can still choose when to drill down into further details. Given the diversity of perspectives on algorithmic bias, we argue that a high-level view is much needed, particularly for researchers and practitioners new to the area.

Thus, we survey related work across four communities – machine learning (ML), human-computer interaction (HCI), recommender systems (RecSys), and information retrieval (IR) – in order to characterize the problems of algorithmic biases that are being addressed, as well as the solutions being proposed, across communities. This allows us to capture perspectives and processes involving multiple stakeholders, as depicted in Fig. 1. For instance, while the ML literature focuses primarily on the developer perspective (and thus, *formal* processes), HCI researchers consider the user’s interaction with the system or how the interface might influence the user’s perception of fairness (more *informal* processes). IR and RecSys represent communities focused on end-user application areas; thus, we can learn the extent to which algorithmic biases have presented challenges to these applications and the nature of the solutions proposed.

Our goal is to produce a more holistic framework describing the problems of algorithmic bias, as well as the processes and stakeholders involved in addressing them. The main contributions of this survey paper are to:

- Provide a methodology for analyzing the work on algorithmic bias, as well as a “live” repository of articles.
- Document the problems and solutions studied across research communities.
- Map the problems to the solutions, as well as the involved stakeholders.
- Describe opportunities for cross-fertilization between communities.

The article is organized as follows. Section 2 describes the methodology used for the literature review and presents an overview of the problem and solution spaces discovered. Following that, we present the detailed analysis of the three categories of solutions described in the literature: Section 3 focuses on Bias Detection, Section 4 details the methods used for Fairness Management, and Section 5 presents a summary of the work within Explainability Management. In each section, we first provide a general overview of the given class of solution and its role in mitigating algorithmic system bias. We then provide specific examples of the respective solution, described in the literature. Each section ends with a table providing a comparison of the specific approaches taken across the four domains studied. Finally, in Sections 6 and 7, we summarize the state-of-the-field, presenting also some open issues for further consideration.

2 Methodology

We first describe the methodology used to identify related articles, as well as the repository we composed. Following that, we describe how we analyzed each article, first

identifying the problem(s) addressed in the article (Section 2.2) as well as the type of solution(s) proposed by the authors (Section 2.3).

2.1 Methodology for collecting and analyzing articles

We followed a methodology involving both bottom-up and top-down processes for collecting articles relevant to *bias in algorithmic systems*. The methodology can be characterized as an adaptation of the standard facet-based methodology used in information science to carry out book and even product classification [60]. In the first phase, a bottom-up, open search process took place, in which each co-author collected relevant literature, adding it to a shared repository. This initial body of material was then used to guide the choice of research domains and publication venues upon which to focus, as well as to identify a set of properties by which to characterize the problems and solutions described.

Following the development of the guiding concept, and the classification scheme for the problems and solutions, a top-down approach was implemented. First, an inventory of the initial article repository was taken, to understand which domains (i.e., research communities) had produced a critical mass of publications related to the mitigation of algorithmic biases. Through this exercise, a list of high-impact publications venues, both conferences and journals, was created for each domain, as presented in Table 1. It should be noted that an “Other” domain was created, as we collected a number of articles published in emerging, cross-disciplinary communities. Also note that some venues publish articles across domains. For instance, while ACM CSCW is generally aligned with the HCI community, some articles describing studies of recommender systems can be found there. Such cases are indicated with parentheses in Table 1.

Domain	Publication Venues Reviewed	# Papers
Machine Learning/AI	AAAI, IJCAI, KDD, SIGKDD, CIDM, AIES, NIPS, MLSP, ACM Data Mining and Knowledge Discovery Journal	86
Information Retrieval	ACM SIGIR, ACM CIKM, ACM WWW, TOIS, JASIS, IR Journal, (AAAI ICWSM)	54
Recommender Systems	ACM RecSys, AAAI ICWSM, UMUAI, ArXive (ACM CSCW, ACM CIKM, ACM FAT*)	37
Human Computer Interaction	ACM CHI, ACM CSCW, ACM CHI Journal, CSCW Journal, Journal of Behaviour and Information Technology	25
Other	AAAI HCOMP, ACM FAT*/FAccT, Others	43

Table 1: Key publication venues reviewed per domain.

The next step was to review each publication venue’s proceedings / published volumes during the ten-year period 2008 - 2019, resulting in a high-recall search for relevant published articles. The key words used were: “accountability,” “bias,” “discrimination,” “fair(ness),” “explain(able),” and “transparen(cy).” In addition, the articles address a particular algorithmic process or system, or class of system. Therefore, articles of a more abstract or philosophical nature were excluded from the survey. Likewise, in the ML category, articles from AI venues (e.g., AAAI, IJCAI) that were not published in the respective ML track, have been excluded, as to focus on algorithmic, data-driven systems.

This survey is based on our current repository of over 245 articles.⁶ The list of publication venues reviewed is not exhaustive; further venues may be added to our repository in the future. However, the problem and solution spaces discovered and

⁶Available at Zotero - https://www.zotero.org/groups/2450986/cycat_survey_collection_public.

detailed below, have proven to be robust across the articles reviewed to date. In our repository, each article is labeled with its respective domain (ML, HCI, RecSys, IR, Other). After reviewing the article, three additional properties, which shall be explained below, were also recorded:

- The problem(s) identified within the system
- The attribute(s) affected by the problem
- The solution(s) proposed to address the problem(s)

These four attributes – domain, problematic system component(s), attribute(s) affected by the problem, and proposed solution(s) – are provided as tags in our Zotero repository. Thus, other researchers may use this resource in various ways, e.g., to focus on a specific problem or type of solution. Table 2 provides examples of the manner in which articles in our repository were analyzed; further details are provided in the following subsections.

Domain	Example	Problem(s)	Attribute(s)	Solution(s)
ML	Word embeddings trained on Google News articles were found to perpetuate prevalent gender biases. [13]	Data	gender	Discrimination discovery - indirect
IR	Users of Mendeley search were shown to disproportionately favor articles written by authors sharing their national origin. [136]	User	national origin	Discrimination discovery - direct
RecSys	Profiles of women and people of color in online freelance marketplaces were found to be systematically lower-ranked than others; reasons included bias in training data and lower evaluations by other users. [56]	User, Data Third parties	gender, race	Auditing
HCI	Authors provided various explanations to users about their Facebook feeds. Explanations were found to shape beliefs on how the system works, but not in understanding its specific outputs. [110]	User Output	information	Explainability - model, output
Other	Authors addressed the issue of human bias in computer vision training data, through an algorithm that filters human reporting bias from labels that are visually grounded. [98]	Data	information	Fairness learning

Table 2: Example analyses of articles in the repository.

2.2 Problem space

To explore the problem space within the literature addressing algorithmic bias, we characterized, for each article, the system component(s) deemed problematic by the authors, as well as the attribute(s) affected by the bias.

2.2.1 Problematic system component(s)

We recorded the macro component(s) of the algorithmic system or process,⁷ considered by the author(s) as being the source of the problem. Fig. 2 provides a general characterization of an algorithmic system, with its macro components, which we have used to

⁷Henceforth, we shall refer to a “system,” although as previously mentioned, we consider articles that describe particular algorithmic processes as well as those describing deployed systems.

examine the problem space of algorithmic bias. Note that some components are optionally present. This includes a User (U), who interacts directly with the system’s inputs and/or outputs. For instance, an API may be in place, to allow the system to interact with other systems and applications.

In this generic architecture, the system receives input (I) for an instance of its operation. This is provided by a user (U), or another source (e.g., the result of an automated process). The algorithmic model (M) makes some computation(s) based on the inputs and produces an output (O). The model learns from a set of observations of data (D) from the problem domain. It may also receive constraints from third-party actors (T) and/or internal fairness criteria (F) which modify the operation of the algorithmic model (M). Finally, some systems have direct interaction with a user (U) who, as previously discussed, will bring her own knowledge, background and attitude when interpreting the system’s output.

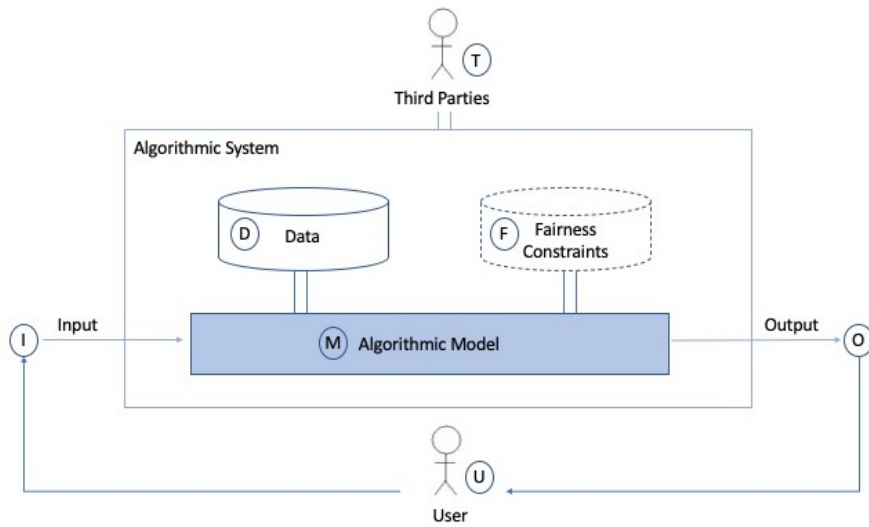


Figure 2: Generic architecture of an algorithmic system.

Thus, as depicted in Fig. 2, bias may manifest and/or be detected in one or more of these components:

- Input (I) - Bias may be introduced in the input data, e.g., as incorrect or incomplete information input by the user.
- Output (O) - Bias may be detected at the outcome (value(s)/label(s)) produced in response to the input.
- Algorithm (M) - Bias can manifest during the model’s processing and learning.
- Training Data (D) - Training data may be inaccurate, imbalanced, and/or unrepresentative. Furthermore, it may contain information about sensitive attributes of people.
- Third Party Constraints (T) - Implicit and explicit constraints, given by third parties, may impact the design and performance of the algorithm and cause discrimination and fairness issues. These include operators of the system, regulators, and other bodies which influence the use and outcomes of the system.⁸

⁸An example was described in Table 2 of a RecSys in which other users’ ratings of workers affected sys-

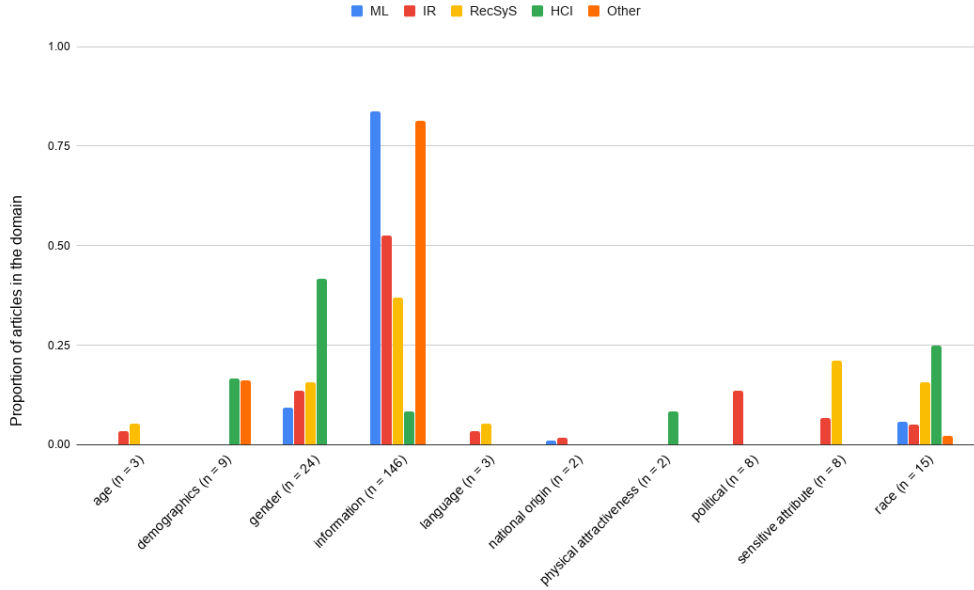


Figure 3: Affected attributes in the surveyed articles.

- Fairness Constraints (F) - Fairness constraints may be introduced within the system, such that one interpretation of fairness is prioritized over others [76].
- User (U) - When users interact directly with a system, they may contribute to bias in a number of ways, such as through the inappropriate use of the system or misinterpretation of system output.

2.2.2 Affected attribute(s)

We also characterized, for a given article, the attribute(s) affected by the problematic system behavior. While early technical works often discussed generic *sensitive attributes* [107], we recorded the specific attribute of interest in the respective research. Thus, we follow the more recent work in socio-technical systems that considers how specific dimensions, such as the social, cultural, and political attributes of the content or person being processed, may be affected by algorithmic behaviors. As can be observed in Table 2, given the breadth of our survey, we also find that in addition to demographic and other personal attributes, ‘information’ is often an affected attribute.

Fig. 3 analyzes the frequency with which specific attributes were examined in the literature we surveyed, across the respective domains. In particular, the chart presents the proportion of articles within a given domain, that discussed each attribute. As can be observed, across all articles, we find 10 attributes described; note that some researchers describe more/less specific attributes (e.g. demographics or sensitive attribute vs. gender, race or natural origin). Frequencies across the entire corpus are detailed on the horizontal axis.

Information is the most frequently studied attribute in our corpus, and is the primary dimension addressed in the ML literature. For instance, in the explainability literature, a primary concern is the extent to which information is effectively conveyed to the user. Likewise, IR articles often consider information as the affected dimension under

tem performance during a given user’s instance. Another example might be a search engine suppressing some ranked results to comply with laws in the user’s geographical region.

study; here, the classic example is the large body of work on search engine biases. In contrast, the literature in HCI and RecSys do not often address information as an affected dimension. In these fields, articles on mitigating algorithmic biases more often consider social and cultural dimensions, such as demographics (generally), gender, and race, with a few studies on attributes such as age, language and physical attractiveness also emerging.

2.3 Solution space

The literature suggests that a comprehensive solution for mitigating algorithmic bias consists of three main steps:

- **Detection of Bias:** this involves scrutinizing the system to detect any type of systematic bias. As will be explained, Observers, Developers and Users have different tools at their disposal for bias detection. Bias detection is reviewed in detail in Section 3.
- **Fairness Management:** includes the techniques Developers use to mitigate the detected bias and certify that the system is fairness-aware. Section 4 reviews the techniques described in the literature for Fairness Management.
- **Explainability Management:** is applied to the system to facilitate transparency and to build trust between Observers/Users and the system. The literature on Explainability is presented in Section 5.

Fig. 4 aligns the three steps involved in mitigating biases, with the taxonomy of solutions found in the literature surveyed. Bias detection can be achieved through *Auditing* and/or *Discrimination Discovery* methods. As will be explained, while Auditing can be used by any stakeholder, Discrimination Discovery is typically used by Developers. Fairness management approaches are used by Developers to tackle bias in different parts of the system and they are divided into *Fairness sampling or pre-processing*, *Fairness Learning or in-processing* and *Fairness certification or post-processing* methods. Fairness certification is a method used to (internally) certify that a system is fairness-aware. Explainability management approaches are used to provide transparency of the system and to build trust between end users and other observers, and the system. In ML and AI systems, these approaches are divided into white-box and black-box explainability methods regarding the interpretability of the algorithm that is used in the system. In the user-focused systems, explainability aims to provide transparency to the user for the outcome decision of the system.

2.4 Summary

Before describing each set of techniques in detail, we provide a summary overview of the problems and solutions documented within each of the four domains surveyed. The distribution of problems addressed across the four domains illustrates the insights gained from our ‘fish-eye view’. As expected, the ML literature addresses problems concerning the training data, the algorithmic model and the system output. The RecSys and IR literature, as user-focused application areas, consider problems both inside and outside the system, while HCI naturally addresses the interactions between the user and the algorithmic system.

Similarly, we find that across domains, researchers are engaged in all three steps in bias mitigation – detection, fairness and explainability management. In the following

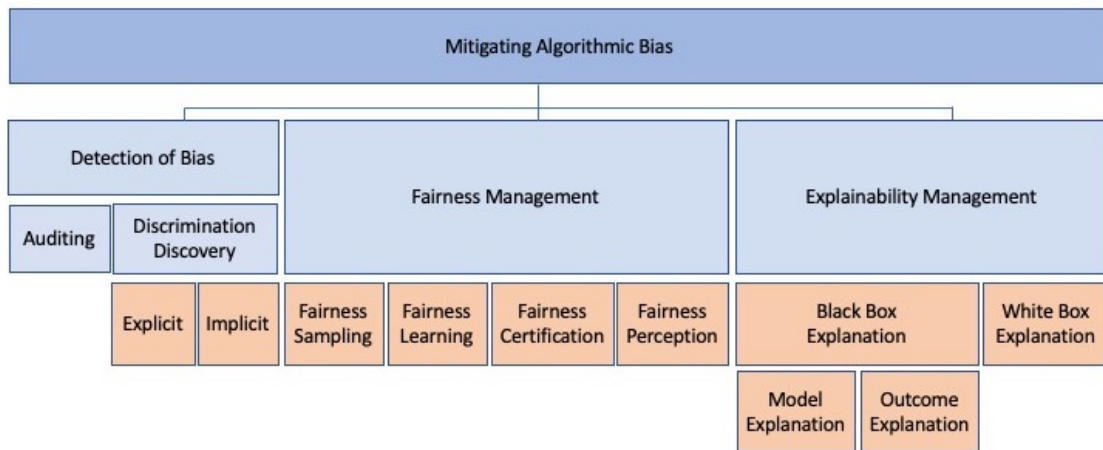


Figure 4: The solution space - tools for mitigating bias in algorithmic systems.

sections, we shall provide a detailed overview of each of the three steps, as described in the literature. We shall also provide specific examples of the approaches, from across domains, and shall compare the techniques used.

3 Detection of Bias in Algorithmic Systems

3.1 Definitions: Computer bias and discrimination

Discrimination is the intentional or unintentional distinction of individuals in a particular group or social category without justification.⁹ Protected group refers to a group or a category of people who are the subject of discrimination analysis. The most common characteristics on the basis of which an individual can be discriminated are the gender, race/ethnicity and age. Multiple discrimination refers to cases where an individual is discriminated against on the basis of two or more characteristics, sometimes referred to as *sensitive attributes*. [117].

The underlying cause of discrimination is typically unintentional prejudice in an individual or group, or when economic agents (e.g., consumers, workers, employers) lack adequate information about individuals with which they interact (i.e., statistical thinking). It is divided into direct and indirect discrimination. Direct discrimination is intentional and direct to a particular group of individuals, e.g., a restaurant that refuses service to Muslims. Indirect discrimination or disparate treatment is unintentional and indirect. It happens when decisions take into account characteristics that are correlated to indicators of sensitive attributes such as race, gender and others upon which discrimination occur [117].

The main approaches described in the literature for understanding and detecting bias in an algorithmic system are classified into two categories: *Auditing* and *Discrimination Discovery*.

3.2 Auditing Approaches for Bias Detection

Auditing can involve making cross-system or within-system comparisons, and is typically done by an analyst / observer or a regulator who does not have access to the inner-workings of the system [122]. There are variations in the extent to which the auditing approaches are formalized. In some cases, auditing uses the tools of discrimination discovery. In this sense, auditing as a term refers to who is doing the discrimination discovery and why; but not to a different set of tools and techniques. In other cases, auditing is used in a more formal way to detect any fairness issues in the system (*fairness formalization*).

Auditing approaches that are used on any algorithmic system for detecting bias through the data are described in [117]. The simplest case is when auditors (testers) search through the dataset to detect any discrimination bias based on specific criteria or for a given group of individuals. Special cases of auditing approaches are situational and corresponding testing approaches. The most common auditing approach used for discrimination detection in algorithmic systems is the conduction of studies where humans (external testers, researchers, journalists or the end users) are the auditors of the system. In [117], the authors describe many approaches for discrimination discovery in data mining systems. One of these approaches is to use auditing where auditors (testers) search through the dataset. Also, they propose situational and corresponding testing approaches which are special cases for auditing.

In information retrieval systems, researchers usually perform an audit by submitting queries to search engine/s and analyzing the results. For instance, Vincent et. al. [141] performed an audit on Google result pages, where six types of important queries (e.g., trending, expensive advertising) were analyzed. The goal was to examine the importance

⁹<https://www.dictionary.com/browse/discrimination?s=t>

of user-generated content (UGC) on the Web, in terms of the quality of information that the search engines provide to users (i.e., if there was a bias in favor/penalizing such content). Similarly, Kay et. al. [72], Magno et. al. [92], and Otterbacher et. al. [103] submit queries to search engines to study the perpetuation of gender stereotypes in image search engines. Another example of bias detection in a search engine via auditing is the work of Kilman-Silver et. al. [77] who examine the influence of geolocation on Web search (Google) personalization. They collect and analyze Google results for 240 queries over 30 days from 59 different GPS coordinates, looking for systematic differences. In addition, Robertson et. al. [115] audited Google search engine result pages (SERPs) collected by study participants for evidence of filter bubble effects. Participants in the study completed a questionnaire on their political leaning and used a browser extension allowing the researchers to collect their SERPs.

Kulshrestha et al. [82] propose an auditing technique where queries are submitted on Twitter, to measure bias on Twitter results as compared to search engines. The proposed technique considers both the input and output bias. Input bias allows the researchers to understand what a user would see if shown a set of random items relevant to her query. The output bias isolates the bias of the ranking mechanism. Johnson et. al. [68], also, investigate the demographic bias detection in Twitter results using as an auditing technique, the retrieval of geotagged content using Twitter API. Another example where researchers are the auditors is the study of Edelman et. al. [38] where authors run an experiment to audit Airbnb applications to detect racial bias in ranked results, and more specifically, for African American names.

Another cluster of user-based studies in IR systems concerned the detection of perceived biases about search and/or during a search for information. In these studies, users are the auditors. For instance, Kodama et al. [78] assessed young people’s mental models of the Google search engine, through a drawing task. Many informants anthropomorphized Google, and few focused on inferring its internal workings. The authors called for a better understanding of young people’s conceptions of search tools, so as to better design information literacy interventions and programs. In addition, Otterbacher et al. [104] described a study in which participants were the auditors for detecting perceived bias. They were shown image search results for queries on personal traits (e.g., “sensitive person”, “intelligent person”) and were asked to evaluate the results on a number of aspects, including the extent to which they were “biased”.

Auditing approaches have also been widely used to detect discrimination in data mining and other algorithmic systems. A situational testing auditing approach has been proposed by Luong et. al. [90], to detect discrimination against a specific group of individuals, using data mining algorithms. K-nearest neighbors were combined with the situation testing approach to identify a group of tuples with similar characteristics to a target individual. Zhang et. al. [157] proposed an improvement over the method of Luong et. al. [90], by engaging Causal Bayesian networks (CBNs), which are probabilistic graphical models used for reasoning and inference. For the development of a CBN, the causal structure of the dataset and the causal effect of each attribute on the decision are used to guide the identification of the similar tuples to a target individual. Robertson et. al. [116], present an auditing approach in the form of a black-box algorithm, called “recursive algorithm interrogation”. The auto-complete functions of Google and Bing are treated as black-box algorithms. They recursively submitted queries, and their resulting child queries, in order to create a network of the algorithm’s suggestions.

Hu et. al. [64] audited Google SERPs snippets, for evidence of partisanship where the generation of snippets is a black-box process. Moreover, Le et. al. [85] audit Google News Search for evidence of reinforcing a user’s presumed partisanship. Using a sock-

puppet technique, the browser first visited a political web page, and then continued on to conduct a Google news search. The results of the audit suggested significant reinforcement of inferred partisanship via personalization. In addition, Eslami et. al. [43] use a cross-platform audit technique that analyzed online ratings of hotels across three platforms, in order to understand how users perceived and managed biases in reviews.

In the HCI literature, auditing often involves characterizing the behavior of the algorithm from a user perspective. For instance, in Matsangidou and Otterbacher [94], the authors consider the inferences on physical attractiveness made by image tagging algorithms on images of people. They audited the output of four image recognition APIs on standardized portraits of people across genders and races. Another example is the work of Eslami et. al. [44], where the authors describe a qualitative study of online discussions about Yelp on the algorithm existence and opacity. The authors further enhanced the results by conducting 15 interviews with Yelp users who acted as auditors of the system, in an attempt to understand how the reviews filtering algorithm works.

An automatic auditing tool, the Aequitas, has also been proposed in [120]. The Aequitas is an open source bias and fairness audit toolkit that can be used to detect discrimination in AI systems. Another toolkit proposed is the AI Fairness 360 toolkit which includes discrimination measures for detecting, understanding discrimination bias and data mining algorithms for mitigating algorithmic bias [9].

3.3 Direct or Indirect Discrimination Discovery

Discrimination discovery (direct or indirect) approaches are used across all domains, and can be applied to the study of particular tasks and/or algorithms (e.g., a top-k ranking algorithm) as well as to deployed systems, which may consist of a whole collection of algorithmic processes (e.g., a proprietary search engine, which uses not only relevance ranking, but also personalization / localization algorithms, among others). In sum, discrimination discovery consists of tools and practices for detecting unfair treatment by data / algorithms / systems.

A common approach for discrimination discovery is to compute discrimination measures in order to detect any direct/indirect discrimination bias in the data. Discrimination measures [163] can be absolute measures, conditional measures or statistical tests. Absolute measures define the magnitude of discrimination over a dataset by taking into account the protected characteristics and the predicted outcome. Statistical tests, rather than measuring the magnitude of discrimination, indicate the presence or absence of discrimination at a dataset level. Conditional measures compute the magnitude of discrimination which cannot be explained by any non-protected characteristics of individuals.

The research in recommender systems uses an implicit or explicit discrimination method to discover discriminatory bias in the evaluation of the system. Bellogin et. al. [10] studied the effects of sparsity and popularity bias on evaluation metrics in recommender systems. In a similar vein, Ekstrand et. al. [41] researched the effect of demographics on evaluation metrics in recommender systems.

In information retrieval systems, discrimination discovery is primarily used in user-focused studies. Weber and Castillo [143] conducted a study of user search habits, which involved a large-scale analysis of Web logs from Yahoo!. Using the logs, as well as users' profile information and US-census information (e.g., average income within a given zip code), the authors were able to characterize the typical behaviours of various segments of the population and detect any discrimination bias related to the users' sensitive demographic attributes. In a similar manner, Yom-Tov [153] used search query

logs to characterize the differences in the way that users of different ages, genders and income brackets, formulate health-related queries. His driving concern was the ability to discover users with similar profiles, according to their demographic information (user cohorts), who are looking for the same information e.g., a health condition.

Pal et. al. [105] considered the identification of experts in the context of a question-answering community. Their analysis revealed that as compared to other users with less expertise, experts exhibited significant selection biases in their engagement with content. They proposed to exploit this bias in a probabilistic model, to identify both current and potential experts. Finally, in a study of information exposure on the Mendeley platform for sharing academic research, Thelwall and Maflahi [136] illustrated a *home-country* bias. Articles were significantly more likely to be read by users in the home country of the authors, as compared to users located in other countries. Chen et. al. [23] looked into direct and indirect (implicit) gender-based discrimination in the context of resume search engines, by a system towards its users. Direct discrimination happens when the system explicitly uses the inferred gender or other attributes to rank candidates, while indirect discrimination is when the system unintentionally discriminates against users (indirectly via sensitive attributes). The results suggested that the system under review is indirectly discriminating against females, however, it does not implicitly use gender as a parameter.

Another method for detecting bias in search engine results involves the use of metrics that quantify the search engine bias [100]. A series of articles by Wikie et. al. [147, 146, 148] and a paper of Bashir and Rauber [8] investigates the identification retrieval bias in IR systems. Bashir and Rauber study the relationship between query characteristics and document retrievability using the TREC Chemical Retrieval track. In Wilkie and Azzopardi [147], they examined the issue of fairness vs. performance. Wilkie and Azzopardi [146] consider specific measures of retrieval bias and the correlation to the system performance. Wilkie and Azzopardi [148] consider the issue of bias resulting from the process of pooling in the creation of test sets.

Another set of works in the HCI domain, analyzes crowdsourced data from the OpenStreetMap to detect any potential biases such as gender and geographic information bias [30, 109]. In a similar vein, two other studies run a crowdsourcing study to detect any bias on human versus algorithmic decision making [52, 7]. Green and Chen [52] run a crowdsourcing study to examine the influence of algorithmic risk assessment to human decision making, while Barlas et. al. [7] compared human and algorithmic generated descriptions of people images in a crowdsourcing study in an attempt to identify what is perceived as fair when describing the depicted person. The execution of a crowdsourcing study for discrimination detection has also been used in IR systems [40, 88].

Many works study the problem of bias detection in textual data using data mining methods concerning specific protected groups. The typical approach is to extract association or classification rules from the data and to evaluate these rules according to discrimination of protected groups [117, 107]. For instance, Datta et. al. [31] analyse the gender discrimination in online advertising (Google ads) using machine learning techniques, to identify the gender-based ad serving patterns. Specifically, they train a classifier to learn differences in the served ads and to predict the corresponding gender. Similarly, Leavy et. al. [86] detect gender bias in natural-language processing (NLP) data by identifying linguistic features that are gender-discriminative. Zhao et. al. [159] detect gender bias in coreference resolution systems. They introduce a new benchmark dataset, WinoBias which focuses on gender bias. They also use a data augmentation approach that in combination with existing word-embedding debiasing techniques, removes the gender bias demonstrated in the data.

Madaan et. al. [91] detect gender discrimination in movies using knowledge graph and word embedding for bias detection and removal after analysing the data (i.e., mentions of each gender in movies, emotions of the actors during the movies, occupation of each gender in the movies, screen time). Pedreshi et. al. [107] use a black-box predictive model to extract frequent classification rules based on an inductive approach. Background knowledge is used to identify the groups to be detected as potentially discriminated. On the other hand, Zhang et. al. [158] use a causal Bayesian network and a learning structure algorithm to identify the causal factors for discrimination. The direct causal effect of the *protected variable* on the dependent variable represents the sensitivity of the dependent variable to changes in the discrimination grounds while all other variables are held fixed. They also detect discrimination in the prediction/classification outcome by computing the classification error rate (error bias).

Similarly, a cluster of works in the IR domain study the detection of bias in classification algorithms such as age-based bias, text-frequency and stylistic biases in sentiment classification algorithms [33, 111, 126], cultural biases at Wikipedia using sentiment analysis [19] and the under-representation of sensitive attributes in the summarization algorithms [125]. Another example is the detection of bias in the automated hate speech detection algorithms such as the existence of offensive language or stereotyping of sensitive attributes [32, 5].

In addition, many works in the recommender systems community, use discrimination discovery to investigate the racial bias in advertising recommendations systems. For instance, Sweeney [133] investigates the racial bias in advertising recommendations by an ad server when searching for particular names in Google and Reuters search engines. She finds that ads for services providing criminal records on names were significantly more likely to be served if the name search was on a typically black first name. Ali et al. [3] and Speicher et. al [130] detected significantly skewed ad delivery on racial lines in Facebook ads for employment, financial services and housing.

3.3.1 Direct Discrimination Detection of Perception Bias

In IR systems, a common type of bias is the cognitive or perception bias that arises from the manner in which information is presented to users, in combination with the user’s own cognition and/or perception. For example, Jansen and Resnick [65] analyzed the behaviours of 56 participants engaged in e-commerce search tasks, with the goal of understanding users’ perceptions of sponsored versus un-sponsored (organic) Web links. The links suggested by the search engine were manipulated in order to control content and quality. Even controlling for these factors, it was shown that users have a strong preference for organic web links. In a similar vein, Bar-Ilan et al. [6] conducted a user experiment to examine the effect of position in a search engine results page. Across a variety of queries and synthetic orderings of the results, they demonstrated a strong placement bias; a result’s placement, along with a small effect on its source, is the main determinant of perceived quality.

Ryen White, of Microsoft Research, has published extensively on detecting users’ perception bias during and after a search, particularly when trying to find information to answer health-related queries. In an initial work [144], a user study focused on finding yes-no answers to medical questions, showed that pre-search beliefs influence users’ search behaviours. For instance, those with strong beliefs pre-search, are less likely to explore the results page, thus reinforcing the above-mentioned positioning bias. A follow-up study by White and Horvitz [145] looked more specifically at users’ beliefs on the efficiency of medical treatments, and how these beliefs could be influenced by

a Web search. An example of searching for user perception bias in recommender systems was studied in [118], where the driver perception regarding Uber application was investigated, given drivers profiles and their history performance.

3.4 Comparison of Approaches for Bias Detection

The first step in mitigating bias in an algorithmic system is that of bias detection. Analysts search for evidence of any systematic, informational or discriminatory biases, and may attempt also to detect the precise source of the bias. The two main approaches for detecting bias in an algorithmic system, which are described in the literature are: Auditing and direct/indirect Discrimination discovery.

Table 3 summarizes the methods used for auditing and discrimination discovery on each of the research domains analyzed in this survey. In machine learning systems, discrimination detection is mostly done by implicit/explicit discrimination discovery methods which include measuring discrimination or using a causal Bayesian network. Auditing in ML systems is mostly done by a black-box auditing software tool or when auditors search for any bias through the dataset. In IR, HCI and RecSys systems, users mostly act as auditors by submitting different queries in search engines and social networks or by taking the role of crowdworker in the crowdsourcing conducted studies.

Domain	Problem	Solution Space	Reference(s)
Detection of Bias			
ML	Data/Model	Auditing	Situational and testing auditing [90, 158] Automatic auditing tool [120]
ML	Data Data/Model/Output	Discrimination Discovery	Discrimination metrics [163, 154] Data mining methods [86, 158, 107, 31, 27]
IR	User/Data/Output	Auditing	Submit queries to search engines/ Twitter [141, 72, 92, 103, 82, 64, 85]
IR	User/Data/Output User/Third Party/Data User/Third Party	Discrimination Discovery	Analysis of web logs [143, 153, 105, 23, 147, 146, 148, 8] Crowdsourcing studies[40, 88] Direct discrimination of perceived bias [65, 6, 144, 145]
HCI	Output/Model/User	Auditing	Analysing system behavior [94, 68]
HCI	Data/User/Third Party	Discrimination Discovery	Crowdsourcing studies [30, 109, 52, 7]
RecSys	Data/User	Auditing	Auditing application systems [43, 38]
RecSys	User/Model/Output Output/Model	Discrimination Discovery	Discrimination detection in advertising recommendation systems[3, 130, 133] Discrimination detection in evaluation metrics [10, 41]

Table 3: Comparison of Discrimination Detection approaches on different domains

4 Fairness Management

The second set of tools used in mitigating algorithmic system bias concerns processes of *Fairness Management*. One consideration is to use fairness management approaches to mitigate the bias detected in any part of an algorithmic system. However, in order to make sure that an algorithmic system can be considered "fair," it is not enough to

simply mitigate the detected bias – the design of the system should be “fairness-aware”. The fairness management approach consists of the following steps:

- *Auditing (Fairness formalization)* where the fairness constraints or any fairness measures, specifications and criteria for the system design are defined. Different ways of addressing fairness in the system are also defined.
- *Fairness sampling (pre-processing methods)* usually concerns the pre-processing of imbalanced input data where the data are re-sampled using different methods e.g., oversampling. Fairness sampling is a suggested method for addressing discrimination bias detection problems in input data for both end-user application systems and machine learning/data mining systems.
- *Fairness learning (in-processing methods)* is most commonly used in machine learning/data mining systems aiming to train a fair algorithm. In user-focused systems, fairness learning solutions impose constraints that force the learner to result in fairer models.
- *Fairness certification (post-processing methods)* is provided by the developer in the case where no unintended bias has been detected in the system. The developer verifies whether the output satisfies the fairness constraints that were defined in fairness formalization, and if so, can certify the algorithmic system as ‘fair’. In general, fairness certification solutions aim to test algorithmic models for possible disparate impact, according to the fairness internal discrimination detection results, ‘certifying’ those that do not exhibit evidence of unfairness.

4.1 Auditing (Fairness Formalization)

Auditing approaches in ML systems can also be used for auditing fairness of the system. Aequitas [120] is an auditing toolkit designed to bring together data scientists and policymakers for developing, maintaining and deploying an algorithmic system. It provides systematic audits for detecting bias and fairness issues in a system in order to make it easier for data scientists and policy makers to make model selection decisions considering fairness management and to better understand the causes of bias against specific discrimination groups.

4.2 Fairness Management

The fairness management are divided into: pre-processing (i.e., data-focused), in-processing (i.e., model-focused) and post-processing methods (i.e., output-focused). The pre-processing methods modify the input datasets so that the outcome of the algorithm applied to the data will be fair. The in-processing methods are applied during the learning phase of the model and their goal is to modify an existing algorithm or create a new one that will be fair when applied to any input. The post-processing techniques modify the output of the model to be fair.

Recently, IBM released an open source toolkit, the AI Fairness 360 (AIF360) [9] with the aim to incorporate both bias detection and bias mitigation using state-of-the-art fairness solutions. The toolkit includes a comprehensive set of bias metrics, bias mitigation algorithms, bias metric explanations, and industrial usability.

4.2.1 Fairness Sampling (Pre-processing Methods)

Many of the articles that concern the discrimination discovery and fairness problems use pre-processing methods to remove the discriminatory bias of the input training data. An idea is to remove sensitive attributes that may be involved in discrimination. However, in some cases, the inclusion of sensitive characteristics in the data may be beneficial to the design of a fair model [164]. To handle this issue, some approaches remove information about the protected variables from the training data but they also transform the training data using data mining methods. For instance, Kamiran and Calders [69] use a naive Bayes classifier to generate rankings of each observation in the training data based on its probability of belonging to the desirable class category. The outcome variable in the training data is adjusted until there is no remaining association between the protected variable and the intended outcome variable. The drawback of this solution is that it is limited to a binary outcome variable and the transformed training data cannot be used with other outcome variables. Calders and Verwer [18] eliminate the above drawbacks by presenting three algorithms that transform the training data based on an objective function that is minimized when the outcomes from a model that fit to the transformed data are independent of the protected variable. This class is also restricted to binary outcome and protected variables. Another approach that can be applied to both discrete and continuous outcome variables has been proposed by Johndrow and Lum [67]. The authors suggest a statistical framework where the models trained to the data will be mutually independent of protected variables.

Moreover, another frequently used technique for mitigating data bias is the use of directed acyclic graphs (BN) and causal reasoning that capture the dependencies between the features and their impact on the outcome. For instance, Zhang et al. [158] discover and prevent discrimination bias in decision support systems using a causal Bayesian network to identify pairs of tuples with similar characteristics from the dataset. Then, they generate a new dataset sampled from the learned BN. Cardoso et al. [84] also use a Bayesian network estimated from real-world data to generate biased data that are learned from real-world data. Rather than adjusting the observations of the training data, Cardoso et al. [84] propose the use of a black-box auditing tool to repair the dataset by changing attribute labels. Kamiran and Calders [69] also massage the data by swapping some of the labels in such a way that a positive outcome for the disadvantaged group is more likely and then they re-train the model. Feldman et al. [45] proposed the *disparate impact removal* solution approach which manipulates individual data dimensions in a way that depends on the protected attribute.

The aim of fairness sampling methods is to generate a balanced dataset that will not under- or over-represent a particular protected group. Fairness sampling is usually achieved by re-balancing the data using various data re-sampling techniques that can be applied to any type of algorithmic system [35, 126, 33, 68, 51]. In recommender systems, an example of fair sampling approach is to balance the neighborhoods before producing recommendations or re-balance the input data according to the protected attributes e.g., gender [90].

4.2.2 Fairness Learning (In-processing Methods)

The proposed in-processing methods consider the problem of discrimination discovery and fairness in the algorithm itself. Therefore, the methods modify the classification/predictive algorithm mainly by introducing some fairness constraints [156, 21, 76, 34] or by introducing new fairness metrics such as FACE and FACT [74], feature-apriori fairness, feature accuracy fairness and feature-disparity fairness [53]. Wu et al. [150]

propose a framework that uses many of these fairness metrics as convex constraints that are directly incorporated into the classifier. They first present a constraint-free criterion (derived from the training data) which guarantees that any learned classifier will be fair according to the specified fairness metric. Thus, when the criterion is satisfied, there is no need to add any fairness constraint into optimization for learning fair classifiers. When the criterion is not satisfied, a constrained optimization problem is used to learn fair classifiers.

Kuhlman et al. [81] identify fairness specifically in ranking algorithms used for decision making. The authors use an auditing methodology FARE (Fair Auditing based on Rank Error) for error-based fairness assessment of ranking. They propose three error-based fairness criteria which are rank-appropriate. Zehlike et al. [155] and Singh and Joachims [129] propose fair top-k ranking algorithms for recommender systems that makes the recommendations subject to group fairness criteria and constraints.

In a similar manner, Xiao et al. [151] suggest an optimization framework for fairness-aware group recommendations. Optimization approaches with fairness weights have also been used in recommendation systems for two-sided marketplaces [97]. In that scenario, the developed recommendation systems should be fair on both the demand and supplier state. Thus, Mehrotra et al. [97] propose different recommendation policies that jointly optimize the relevance of recommendations to consumer (i.e., user) and fairness of representation of suppliers. Another suggestion for a fair ranking system proposed by [22] who attempt to find a fair ranking for crowd-sourced recommendations taking into account that the vast majority of potential voters are silent, that some people vote multiple times, and that votes for similar topics are split, leading to a bias towards extreme viewpoints. Regarding the fairness of image ranking recommendations, Karako and Mangala [71] incorporated fairness in the system by choosing a sample of labeled images, based on gender, though their method is suitable for any attribute of interest.

A regularization approach has also been proposed by Kamishima et al. [70] where they introduce a fairness-focused regularization term and apply it to a logistic regression classifier. Kusner et al. [83] use an alternative fairness approach, the counterfactual fairness, that captures the social biases that may arise towards individuals based on sensitive attributes. They provide optimization of fairness and prediction accuracy of the classifier using a causal model. Kilbertus et al. [75] aim to provide fairness learning and certification without access to users' sensitive data. To achieve this, they use an encrypted version of sensitive data, privacy constraints and decision verification by employing secure multi-party computation (MPC) methods.

An in-processing method that has been proposed in information retrieval systems considers the interaction between the user and a system, or a particular system component, as possible insight in solving information biases. Mitra et al. [99] presented the first large-scale study of users' interaction with the auto-complete function of Bing. Through an analysis of query logs, they found evidence of a position bias (i.e., users were more likely to engage with higher-ranked suggestions). They were also more likely to engage with auto-complete suggestions after having typed at least half of their query. In a follow-up study, Hofmann et al. [62] conducted an eye-tracking study with Bing users. In half of their queries, users were shown ranked the auto-complete suggestions whilst in the other half of queries, the suggestions were random. The authors confirmed the position bias in the auto-complete results, across both ranking conditions. They found that the quality of the auto-complete suggestions affected search behaviours; in the random setting users visited more pages in order to complete their search task.

In addition, Maxwell et al. [95] investigated the influence of result diversification on users' search behaviours. Diversification is meant to reduce search engine biases

by exposing users to a broader coverage of information on their topic of interest. A within-subject study with 51 users was performed, using the TREC AQUAINT collection. Two types of search tasks - ad hoc versus aspectual - are assigned to each user using a non-diversified IR system as well as a diversified system. Results indicated significant differences in users' search behaviours between the two systems, with users executing more queries, but examining fewer documents when using the diversified system on the aspectual (i.e., more complex) task. An alternative method proposed in the HCI domain is to use a human-in-the-loop approach for decision making when sensitive attributes are involved rather than the statistical model approach [16]. In addition, in HCI research, the use of automatic gender recognition can be discriminated upon trans gendered people. For systems to be fair, Keyes [73] proposed alternative methods and the development of more inclusive approaches in the gender inference process and evaluation.

4.2.3 Fairness Certification (Post-processing Methods)

The post-processing methods concern the modification of the output of the learned classifier. Examples are proposed by Pedreschi et al. [107] who alter the confidence of classification rules inferred by the CPAR algorithm, whereas Kamiran et al. [69] re-label the class which is predicted at the labels of a decision tree. In [57], the authors propose a framework to construct classifiers from any Bayes optimal regressor following a post-processing step which avoids modifying the training process. They discover discrimination against a specified sensitive attribute in supervised learning.

Epstein et al. [42], rather than removing the bias on the output of the search engine results, proposed to raise users' awareness. They aimed to develop solutions for the Search Engine Manipulation Effect (SEME), citing recent evidence of its impact on the views of undecided voters in the political context. In a large-scale online experiment with 3,600 users in 39 countries, they showed that manipulating the rankings in political searches can shift users' expressed voting preferences by up to 39%. However, providing users with a "bias alert," which informed them that "the current page of search rankings you are viewing appears to be biased in favor of [name of candidate]," reduced the shift to 22%. They found that this could be reduced even further when more detailed bias alerts were provided to users. Nonetheless, they reported that SEME cannot be completely eliminated with this type of intervention, and suggest instituting an "equal-time" rule such as that used in traditional media advertisements.

4.3 Perceived Fairness Management

The perceived bias of the outcome can impact the perceived fairness of both user-focused systems as well as those interfacing with other systems and processes. Perceived fairness concerns the perception of users with the decision making outcome and it can be measured through questionnaires and statistical tests [87]. According to [87], the perceived fairness of decisions depends on the task and whether the decision maker is a human or an algorithm. For mechanical tasks, user perception on fairness and trust of the system is similar, whether the decision is taken by a human or an algorithm. However, in tasks of a more social nature, a user perceives the human decision making outcome as more fair and trustworthy rather than a decision outcome made by an algorithm.

Woodruff et al. [149] explore, in a qualitative study, the perception of algorithmic fairness by populations that have been marginalized. In particular, they consider how race and low socioeconomic status was used in stereotyping and adapting services to

those involved. Most participants were not aware of algorithmic unfairness even though they have experience with discrimination in their daily lives. Brown et al. [16] also present a qualitative study for understanding the public’s perspective on algorithmic decision making in public services. They discovered that many participants mentioned discrimination and bias based on race, ethnicity, gender, location, and socioeconomic status. A descriptive approach for identifying the notion of perceived fairness for machine learning was suggested by Srivastava et al. [131]. They argued that the perceived fairness of the user is the most appropriate notion of algorithmic fairness. Their results show that the formal measurement, demographic parity, most closely matches the perceived fairness of the users and that in cases when the stakes are high, accuracy is more important than equality.

4.4 Comparison of Fairness Management Solutions

Fairness management approaches can be classified into pre-processing, in-processing and post-processing methods. Pre-processing methods handle bias in input data, in-processing methods concern the mitigation of bias in the algorithm and post-processing methods concern the elimination of bias in the outcome. As displayed in Table 4, in machine learning algorithmic systems, data mining techniques are used to mitigate bias either in the data, in the model processing or at the outcome decision. User-focus systems such as information retrieval, recommender systems and human-computer interface systems use mostly pre-processing approaches such as fairness sampling and feature selection to handle bias in data. Researchers in this area also proposed some in-processing methods to handle bias in ranking algorithms and to raise users’ awareness of the algorithm’s behavior.

Fairness Management			
Domain	Problem	Solution Space	Reference(s)
ML	Data	Fairness Sampling	Removing protected attributes & transform the training data [18, 67] Causal BN[158, 84, 69]
ML	Model/Third Party Model/Output Model/Output Model/Output Data/Model	Fairness Learning	Fairness constraints [156, 21, 76, 34] Fairness metrics [74, 53, 150] Regularization approach [70] Counterfactual fairness [83] Encrypted version of sensitive data [75]
IR	Data	Fairness Sampling	Data sampling [51, 35, 126, 33]
IR	User/Output Model	Fairness Learning	User’s interaction with system [99, 61] Mitigating search engine bias [95]
HCI	Data Model	Fairness Sampling	Data sampling [68] Automated generated data [121]
HCI	Model	Fairness Learning	Human in the loop approach[16, 73]
RecSys	Data	Fairness Sampling	Data sampling [90, 71]
RecSys	Model Model Model/Output	Fairness Learning	Error-based Fairness Criteria [81] Fair top-k ranking algorithm [155, 129, 22] Optimization approaches [151, 97]
ML	Third Party/Output Output User/Third Party	Fairness Certification	Altering of labels [69, 57] Altering of confidence of classification rules [107] Perceived fairness management [131]
IR	Output/User	Fairness Certification	Raise user awareness[42]
HCI	Output/User	Fairness Certification	Perceived fairness management [149, 87]

Table 4: Comparison of fairness management methods in the different domains

5 Explainability Management

The third step in a comprehensive approach to mitigating algorithmic system bias, is to ensure the transparency of the system by providing a reliable explanation about its process and outcomes. In most of the papers in the literature, the design of an interpretable system aims to enhance the trust and confidence of the user in the system. Shin and Park [127] stress the importance of helping the user to understand algorithmic affordances in the adoption and use of a system. They have identified that the user experience is affected by the lack of system transparency and demonstrate statistically that fairness, accountability and transparency in algorithmic systems can help the user to understand how the system takes decisions e.g., recommendations, in turn enhancing their trust in the system.

According to Eslami et al. [44], full transparency is neither necessary nor desirable in most systems. One reason is that full transparency may affect negatively the user's information privacy [24]. Moreover, users need to be provided with judgments on the decisions made, and not simply with explanations of the outcome. They argue that this raises the importance of searching for explainability methods for designing more interpretable systems. Friedrich and Zanker [48] classify explainability into two types: *white-box* and *black-box*. *How* explanations are white-box explanations of the input, output and the process leading to the particular outcome. They provide information focusing on the system's reasoning and data source, which enhances the user satisfaction of the system. *Why* explanations treat the systems as black-boxes and they do not provide any information on how a system works. Instead, they give justifications for outcomes and explain the motivations behind the system, to fill the gap between the user's needs and system's goals. Rader et al. [110] proposed two additional types of explainability, "What" and "Objective". *What* explanations only reveal the existence of algorithmic decision-making without providing any additional information of how the system works. This type of explainability aims to raise the users' awareness of the algorithm. *Objective* explains the process of the development of the system and its potential improvement with the objective of ending on an unbiased system.

Important aspects of explanations in algorithmic systems include the presentation format of the different types of explanations (e.g., graphical, textual, bullet points), the length of each explanation, and the adopted vocabulary if natural language is used for the explanations. The range of explanations is based on the domain; for example, decisions in the health domain are more critical than in movie recommendations and may need a wider range of explanations of how a system derives its predictions/classifications. Regarding the presentation format, Eiband et al. [39] proposed a participatory design methodology for incorporating transparency in the design of user interfaces such as to make intelligent systems more transparent and explainable. The process used in the design methodology consists of two main parts. The first part defines the content of an explanation (what to explain) while the second focuses on the presentation format of the explanation (how to explain). In a similar vein, Binnis et al. [11] classify a set of explanation styles into four categories based on the type of information they would like to present to the end-user:

- **Input influence style:** A set of input variables are presented to the user along with their positive or negative influence on the outcome.
- **Sensitivity style:** A sensitivity analysis shows how much each of the input values would have to differ in order to change the outcome (e.g., class).

- **Case-based style:** A case from the model’s training data that is most similar to the decision outcome is presented to the user.
- **Demographic style:** Using this style, the system presents to the user, statistics regarding the outcome classes for people in the same demographic categories as the decision subject e.g., age, gender, income level or occupation.

In the following subsections, we describe the machine learning approaches where model or outcome explanations are provided to interpret the behavior and outcome of the algorithm.

5.1 Explainability Management

Over the years, there have been many attempts to make machine learning models interpretable [61], however, the research areas of explainable AI [2] and black-box explainability [55] have recently raised much interest in ML communities. Explainability and interpretability in ML systems aim to ensure compatibility with social values such as fairness, privacy, causality and trust. Completely interpretable ML models are able to justify the predictions made and search for potential biases or mistakes. To measure the level of interpretability of a machine learning model, state-of-the-art works use global and local interpretability metrics such as the model complexity, accuracy and fidelity [55].

Nowadays, many systems developed for problem-solving use black-box models such as neural networks, ensemble classifiers and deep learning, due to the fact that they make it feasible to process and automatically transform complex types of data e.g., images. However, the internal processes of a black-box model are either unknown to the observer or are un-interpretable by a human [55]. To handle this issue, many researchers study approaches for explaining the internal process (model) or the outcome of a black-box model or to inspect the black-box internally. These approaches represent the interface between a decision-making algorithm and a human (observer/user). The predominant approaches for explaining black-box models are surveyed by Guidotti et al. [55].

In general, explainability-aware ML techniques can be divided into two main categories [1]:

- Models that incorporate a white box (interpretable) model to explain the process of the algorithm in order to reach a given outcome e.g., using rules or feature importance weights (*Model Explainability*).
- Models that explain their outcome in an understandable way to the user. These types of methods explain only their output, and they do not provide explanations for the process of the ML algorithm. This form of explanation is usually helpful when the user of the system is not an expert such as in the case of recommender systems (*Outcome Explainability*).

5.1.1 Black-box Model Explainability

The main approach for explaining a black-box model is through a white-box model that should mimic the black-box model behavior and be interpretable by humans. Fidelity is a metric used to measure the predictive accuracy of the interpretable model and to which extent it is able to mimic accurately the black-box. Examples of white-box interpretable models are decision trees, Bayesian networks, and rule-based classifiers.

A set of papers proposed the use of a decision tree to mimic the behavior of a black-box model such as a neural network [29, 80, 15, 66] and tree ensemble models [36,

50, 160, 123, 134]. The use of decision trees for explaining neural networks was first presented in [29] where the *Trepan* network implements the algorithmic process of the neural network and returns the representations of the model. It queries the neural network in order to induce a decision tree model. An extension of Trepan is presented in [15], called *DecText*. The DecText uses a four-splitting method to select the most relevant features. A fidelity-based pruning strategy was proposed to reduce the size of the tree. In a similar line, Krishan et al. [80] and Johanson et al. [66] use genetic programming to evolve decision trees in order to mimic the behavior of a neural network and generate more understandable and accurate decision trees. Krishan et al. [80] explain the outcome of a black-box model by extracting decision trees from the data. A genetic algorithm was applied to predict membership queries to the trained neural network and obtain prototypes to control the size of the decision tree.

Chipman et al. [25] use decision trees as an interpretable predictor model for tree ensemble models by summarizing the forest of trees through clustering and use the associated clusters as explanation models. Domingos [36] propose the training of a decision tree with an increased amount of training data after applying an ensemble meta-algorithm (e.g., boosting) to the tree ensemble models. The decision tree acts as the interpretable predictor that mimics the tree ensemble models. Scetinin et al. [123] present an approach for the interpretation of the black-box Bayesian decision tree ensemble model by evaluating the uncertainty of a Confident Decision Tree (CDT) for medical domains. A selection procedure was proposed for extracting CDT from the Bayesian decision tree ensemble model.

Another set of papers proposes the use of decision rules to explain a black-box model, for instance, by extracting rules from a trained black-box model such as a neural network (NN), and then using the NN to refine existing rules [29, 66, 161]. Lu et al. [89] also uses genetic programming to the output of the neural network, but rather than using this to evolve decision trees, it generates classification rules. Classification rules have also been used in [161]. Zhou et al. propose the REFNE framework that extracts symbolic rules from trained neural network ensembles. Tan et al. [135] propose a model distillation using a rule-based classifier to mimic the black-box, and then compare the transparent mimic model to a rule-based classifier trained using the same features on true outcomes instead of the labels predicted by the black-box.

A more recent black-box explainability approach proposed by Card et al. [20] uses transparent explanations for classification decisions as well as an intuitive notion of the credibility of each prediction using a new measure of non-conformity. They also develop a deep weighted averaging classifier replacing softmax in order to provide a transparent version of any successfully developed deep learning architecture. Although many approaches have been proposed for explaining black-box models, the most common explanation style used in classification systems is the feature-based explanation. Feature-based explanation reports to the user, the importance of each feature for the classification/prediction outcome. Horne et al. [63] use this explanation approach to explain the spread of fake news and misinformation online. They used an AI assistance framework for providing these explanations to users. This has been shown to improve the user perception of bias and reliability on online news consumption. In another approach, Henelius et al. [59] search for a group of attributes whose interactions affect the predictive performance of a given classifier and they evaluate the importance of each group of attributes using the fidelity metric. In addition, Vidovic et al. [140] propose the measure of feature importance (MFI) which is model-agnostic, it can be applied to any type of model.

In addition to the aforementioned approaches for explainability of black-box ML al-

gorithms, many articles, especially in the domain of recommender systems propose some approaches for interpreting the ranking algorithms. In such systems, the authors aim to provide explanations based on user opinions and evaluation of previous purchases, rather than on the analysis of the ranking algorithm [142]. The aim is to provide personalized explanations by selecting the most appropriate explanation style. Nunes et al. [101] presented a systematic review on explanations for recommendations in decision support systems where they proposed a taxonomy of concepts that are required for providing explanation. According to Tintarev and Masthoff [137], there are seven purposes for providing explanations in a recommender system: transparency, scrutability, trust, effectiveness, persuasiveness, satisfaction and efficiency. In the early studies of providing explanations in recommender systems, a uniform explanation style was provided for single-source collaborative filtering whereas in more recent works, explanations are derived based on hybrid multiple sources [79] and matrix factorization [24]. Hybrid explanations focus on proposing graphical interfaces to visualize the different explanation styles. TalkExplorer [139] combines content, tag, and social-based filtering techniques to provide an interactive interface in the form of clustermaps. In a similar vein, Bountouridis et al. [14] proposed a simulation framework of news consumption in order to provide visualization for the recommender systems.

5.1.2 Black-Box Outcome Explainability

In contrast to model inspection, some approaches attempt to provide a local interpretation, focusing on explaining a particular outcome generated by the model. A recent work focuses on providing both local and pedagogical explanations for the output of ML models [93]. Pedagogical explanations are those that teach something about how the model works rather than attempting to represent it directly.

A general method for explaining the output of a classifier (either a black-box or white-box model) is by using only the input and output of the model to decompose the changes in the algorithm’s prediction outcome into contributions of individual feature values. These contributions correspond to known concepts from coalitional game theory [132]. Similar approaches applied to complex machine learning models that the logic and output are hard to explain are called “model-agnostic” approaches that explain the output of any classifier, regardless of the machine learning algorithm used to train it and the type of input data. Example approaches are the Local Interpretable Model-Agnostic Explanations (LIME) [112] for the outcome explanation and the Qualitative Input Influence (QII) [31] for the model inspection. The explanations in LIME are only provided through linear models and their respective feature importance. Extensions of LIME use decision rules for explaining any type of a black-box model [54, 113, 138]. Ribeiro et al. [113] propose the use of anchors which are decision rules that anchors the prediction of the black-box model sufficiently. Turner et al. [138] design the model explanation system (MES) that uses the Monte Carlo algorithm to explain black-box predictions. *ExplainD* is a framework presented in [108] for interpreting the outcome of any black-box model. ExplainD uses generative additive models (GAM) to weight the importance of the input features.

Another set of papers consider the use of visualization techniques to inspect the training process of a deep neural network (DNN) behavior on images [12, 162, 152]. In these works, a Saliency Mask (SM) is used as the interpretable local predictor e.g., a part of an image. Similarly, Fong et al. [46] propose a framework of explanations as meta-predictors for explaining the outcome of deep learning models. The meta-predictor is a rule that predicts the response of a black-box model to certain inputs such as highlighting

the salient parts of an image. Another set of works use saliency masks to incorporate the DL network activation into their visualizations [124, 160, 128].

A different approach for explaining the outcome of black-box models has been proposed in [58]. Haufe et al. transform the non-linear black-box model into a linear interpretable model where the features for a specific prediction are easily to be explained. While there is a large amount of solutions for providing explainability in a ML system, there are also some desired characteristics for explainers. Explainability methods should enrich the trust in the system including the trust in the model as well as in the local predictions. To achieve this trust, an essential criterion for explainability methods is the local fidelity which measures the local fairness of the explanation i.e., how the model behaves based on the predicted instance. In addition, the explainer should be able to explain any model (i.e., be model-agnostic). Moreover, explanations must be interpretable considering the user’s limitations [112].

5.2 Comparison of Explainability Management Approaches

Table 5 provides a comparison of the solutions focusing on Explainability Management. Explainability approaches have primarily been developed in the context of ML algorithms and systems. However, there is a growing literature within the HCI and IR communities. These works suggest that explainability and judgement of the outcome or decision of the system should be provided in order to enhance the trust of the end user in the system. In ML systems, the explainability method is usually based on the algorithm used in the system, considering whether it is an interpretable algorithm (white-box) or a black-box model such as deep learning. The explainability approaches also concern either the explainability of how the algorithm works or of the algorithm’s outcome. There are also the *model-agnostic* explanation approaches that explain the output of any classifier, regardless of the machine learning algorithm used to train it.

Finally, explainability approaches have also been widely discussed in recommender systems. The difference between these approaches and the ones used in ML are that they take into consideration the user’s perception and specific goal of increasing the trust of the end-user in the system. In RecSys literature, various explanation styles have been reviewed according to the purpose of providing explanations in a recommender system e.g., transparency, scrutability, trust, etc.

6 Discussion

We conducted a survey of literature across four domains within the information and computer sciences, to understand the various approaches in mitigating algorithmic biases. Our survey was intentionally broad, as we aimed to provide a “fish-eye view” of this complex topic. Furthermore, we did not restrict our review to the literature on fairness and/or discriminatory bias in a social sense; rather, we considered articles describing the problems and solutions surrounding bias, which affect any number of attributes including the quality of information provided by a system. Fig. 5 presents an overview of the problem and solutions spaces revealed by the survey, from the point of view of the observer (i.e., researcher). This framework integrates the concepts presented earlier on, including the involvement of multiple stakeholders (Fig. 1), the components of a system that can be problematic (Fig. 2), and the solutions described across communities (Fig. 4).

Explainability Management			
Domain	Problem	Solution Space	Reference(s)
ML	Model	Black-box Model Explainability	Decision tree mimic black-box [80, 15, 36, 50, 25, 160, 123, 134]
	Model		Decision rules explaining black-box [29, 66, 161, 135, 89]
	Model Data/Model		Deep weighted averaging classifier [20] Feature-based explanation [59, 140]
ML	Output	Black-box Outcome Explainability	Model-agnostic explanations [132, 112, 31, 108]
	Output		LIME Explanations [112, 54, 113, 138]
	Output/User		Visualization methods [12, 162, 152, 46, 124, 160, 128] Convert to a linear model [58]
HCI	Output/Data User/Output User/Output User/Output	White & Black-box Outcome Explainability	Feature-based explanation [63] Taxonomy of explanations [48] Raise user awareness [110] Explanation styles [39, 11]
RecSys	Model/User	Black-box Model Explainability	Taxonomy of concepts [101]
	Model/User		Based on user opinions [142]
	Output/User		Uniform explanation style [137]
	Output/User		Hybrid explanations [79, 139, 14]
	Output/User		Matrix-factorization [24]

Table 5: Comparison of explainability management approaches for different research domains

Stakeholders Three classes of stakeholders were discussed in the literature surveyed: Observers, Users and Developers. Observers and Users play a different role as compared to Developers, typically working “outside” of the system (i.e., having limited or no access to its data and interworkings). They can typically apply only Auditing to the detection of bias, while Developers can also apply Discrimination Detection upon the training data and/or the algorithmic model. Nonetheless, as highlighted in the COMPAS case, all stakeholders can play a key role in raising awareness of the problem of algorithmic bias.

Sources of Bias Articles reviewed in our survey mentioned at least one of seven problematic components and/or points at which bias can be detected. These are shown in Fig. 5, which also groups them into four main types: data bias, user bias, processing bias, and human bias. In reality, all biases are at least indirectly *human biases*; for instance, datasets and processing techniques are created by humans. However, we believe that it is helpful to distinguish the biases that are directly introduced into the system by humans, such as third-party biases, those resulting from conflicting fairness constraints, as well as those due to the choices of the developer. User bias is distinguished from other human biases in our framework; as detailed in the literature, since users can both introduce bias (e.g., in biased input), but can also perceive bias in the output. Finally, Fig. 5 also incorporates at a high level the three steps in a comprehensive solution to mitigate algorithmic bias: detection, fairness management and explainability.

Detecting Bias In most of the articles in our repository, auditing processes concern the model, as well as system inputs and outputs. Auditing can involve making cross-system or within-system comparisons, and is typically done by an analyst-observer who does not have access to the inner-workings of the system. Auditing uses the same tools

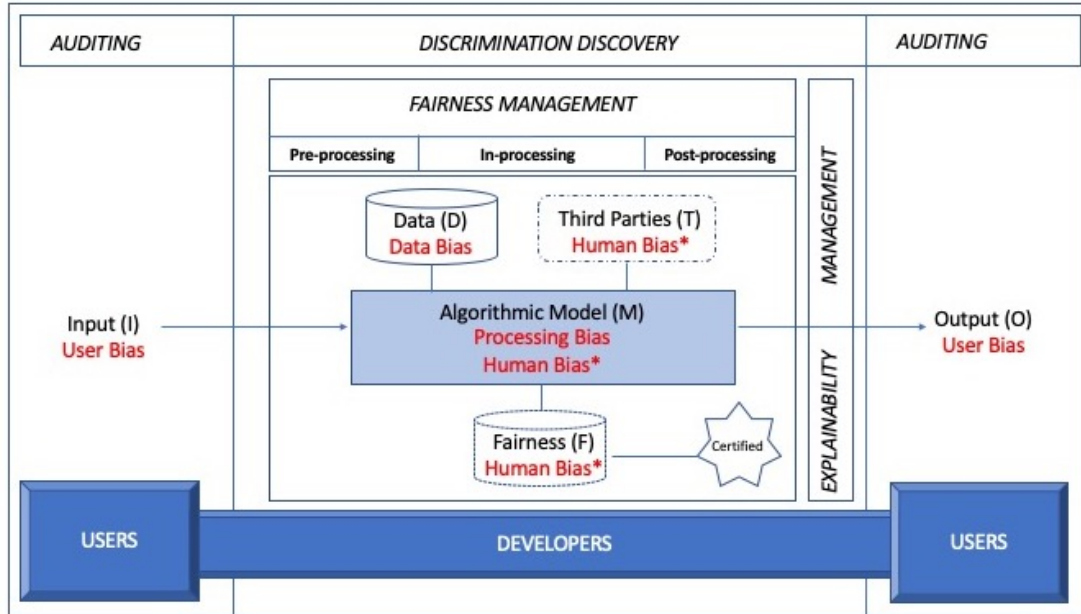


Figure 5: Observers’ fish-eye view of mitigating algorithmic bias: problems, stakeholders, solutions.

as discrimination discovery. The term does not refer to a different technique; however, auditing specifies who is doing the auditing process and why. It should also be noted that within ML, beyond involving the model, inputs and outputs, auditing can also involve fairness management pre-processing, such as the generation of biased datasets for conducting a black-box audit. In three domains, both auditing and discrimination discovery are done by observers. The exception is ML, where developers implement automated auditing and discrimination discovery tools, and also use auditing for fairness formalization (to detect fairness issues in the system).

Fairness Management The issue of ensuring that people and/or groups of people are treated fairly by an algorithmic system was found to be of interest to researchers across all domains considered. However, the tools stakeholders have at their disposal vary. For instance, those working ‘inside the box’ (i.e., those involved in development) may take pre-processing measures (i.e., ensure fair sampling when building training datasets) or during-processing measures (i.e., introduce fairness constraints within the learning process). Developers also have methods to “certify” that their algorithms are fair, using internal processes. On the other hand, the HCI literature typically describes system observers from the outside (i.e., those who study or use the system, but who are not involved in the system’s development), and thus presents a challenge to our initial taxonomy of solutions. This is because HCI studies often concern the user’s perceptions of a system’s behaviours and/or decisions (e.g., Grgic-Hlaca et al., 2018; Lee 2018), which can be difficult to measure and for which there are no established standards or techniques. In ML systems, the developers manage the fairness of the system using the aforementioned fairness techniques. In contrast, in HCI and IR systems, the stakeholders are the system observers, who are not involved in the system’s development but rather, manage fairness by observing the system’s behaviour or the output of the system. In addition, the users of the system participate in the conducted studies for managing system fairness concerning the users’ perception. In RecSys, observers are the main

stakeholders who are involved in making sure that the algorithm is fair, apart from the fairness learning approaches where the developers are involved to develop a fair system.

Explainability Management With respect of the transparency of the algorithmic system, a set of explainability approaches has been introduced in the literature, to encourage trust in the system by the end user, while at the same time maintaining the effectiveness of the system. Explainability of the system mostly concerns the HCI and ML communities. In HCI articles, the most appropriate presentation and format of explainability is examined for enriching the transparency of the systems and the trust of the end user. Moreover, multiple papers study specific explainability approaches for explaining the matching/ranking algorithm in recommender systems. In ML systems, the developers implement algorithms or methods for providing transparency for the black-box model and outcome. In HCI systems, the observer in collaboration with the user conduct experimental studies using various explanation presentation styles for providing the user with some transparency of the system. In RecSys, some explainability approaches are based on User’s opinion where as for some other approaches, the developer of the system has to implement a method for providing transparency of the model and the outcome of the system i.e. matrix factorization.

While producing models and/or outcomes that are easily interpretable to the user is, in and of itself, viewed as a positive characteristic, it is important to emphasize the particular role of explainability management for bias mitigation. Specifically, in this context, explainability can be viewed as a means rather than an end; complex algorithmic systems can become more transparent to users, the more interpretable their models and outcomes are. Clearly, explainability has a tight relationship to the user’s perception of fairness.

6.1 Limitations

We must note some challenges faced when reviewing the literature on mitigating algorithmic bias. First, the field is becoming highly interdisciplinary. It was often difficult to categorize the articles we collected into one domain; for instance, RecSys researchers often publish in HCI venues, or even ACM FAccT. Thus, while we aimed to collect articles from across four domains, one should keep in mind that there is some overlap between them. Thus, it was more difficult than expected to characterize how each community has contributed to the work on addressing algorithmic bias. This challenge, however, does not affect the development of a “fish-eye view” on the field.

Secondly, the framework presented in Figure 5 does not yet explicitly incorporate *accountability* into the solutions for mitigating algorithmic bias. Because we focused on literature in the information and computer sciences, studying articles describing particular algorithms and/or systems, the issue of accountability was not often discussed. Going forward, the literature search could be expanded into law and the social sciences as to further investigate the role of the Observer – Regulator in the landscape of solutions.

7 Conclusion

In this survey, we provided a “fish-eye view” of research to date on the mitigation of bias in any type of algorithmic system. With the aim of raising awareness of biases in user-focused, and algorithmic-focus systems, we examined studies conducted in four different research communities: information retrieval (IR), human-computer interaction (HCI), recommender systems (RecSys) and machine learning (ML). We outlined a classification

of the solutions described in the literature for detecting bias as well as for mitigating the risk of bias and managing fairness in the system. Multiple stakeholders, including the developer (or anyone involved in the pipeline of a system’s development), and various system observers (i.e., stakeholders who are not involved in the development, but who may use, be affected by, oversee, or even regulate the use of the system) are involved in mitigating bias. In future work, we aim to further refine the various roles of individual stakeholders and the relationships between them.

A second consideration to be explored, is that while many solutions described in the literature have been formalized (e.g., discrimination detection methods, fairness management, internal certification), there are many other issues surrounding *perceived fairness*. The perceived fairness of the user is somewhat subjective and it is not clear how the internal, formal processes relate to users’ perceptions of the systems and their value judgements. Finally, in this survey, we recorded the attribute(s) affected by the problematic system in each of the reviewed domains. As a future work, we aim to find connections between these attributes and the solution approaches for detecting and mitigating bias.

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