

Human and algorithmic decision-making in the personnel selection process: A comparative bibliometric on bias

Humberta Karinne Da Conceição Santos Silva

Liliana Vasconcellos

This article examines, with bibliometrics, the publication on bias in organizations' personnel selection processes, whether they use automated decision-making systems or human-made decisions. While human bias is dynamic, restricted, mutate, and easier to determine the source; algorithmic bias is large-scale, static, and unpredictable. Despite the apparent discrepancy, there is a symbiotic relationship between those two, but somehow only one of them is getting any attention regarding the consequences of fairness on personnel selection and how this influences organizational diversity. So, looking for a better understanding of organizational behaviour, we conduct a bibliometric review to mappings the relations of these two. Here we reviewed 55 articles from the Web of Science Core Collection, from the earliest research published in 1979 to 2021. Only papers of the document type "article" was considered. The tool used for bibliometric data analysis were bibliometrix packages from the RStudio system version 3.6.3. According to our review, the number of studies on the subject is still tiny, and most of them were conducted under controlled conditions without considering the error agent of an organizational environment such as time, organizational culture, and the emotions of the recruiter; this makes it impossible to develop practices to avoid discrimination in these spaces. Concerning the theme, studies on human bias are the most common, with a focus on gender bias, and have recently adopted diversity. Hardly studies on algorithm decision-making consider the process's fairness as a topic for investigation. However, neither study demonstrates a correlation or systematic approach between them. More interdisciplinary and empirical research should be the focus of future studies.

Keywords: *Bibliometrics, Human bias, Personnel selection process, Algorithmic decision-making bias, Organizational behaviour, Personnel selection bias.*

Humberta Karinne Da
Conceição Santos Silva*

Liliana Vasconcellos#
Faculty of Economics,
Administration, Accounting
and Actuarial Sciences (FEA)
University of São Paulo
São Paulo
Brazil

* Humberta@usp.br

Lilianav@usp.br

* (Corresponding Author)

1. Introduction

It is typical for individuals to make a different decision for the same situation and organizational setup, especially where staff recruitment and selection (Caers and Castellyns, 2011), and even promotion is concerned (Isaac et al., 2009).

The reason, according to some authors, can be cultural factors, personality types (Sce-pura, 2020), values, and unrealistic optimism (Makridakis and Moleskis, 2015) that influence individuals, groups, and their own decisions. These factors are contrary to the principles of rational choice, the utilitarian economic view, in which results are gains or losses and, therefore, foster risk aversion or risk appreciation (Tversky and Kahneman, 1986).

Also, considering the elements described above, it is imperative to emphasize selecting people requires a risk-seeking behavior, in which acceptance carries an implicit positive feeling of gain and rejection sounds negative and feels like a loss. On one side, recruiters must know how to delimit the strategies to achieve the goal, find the candidate who has congruence between the positions, requirements, and desired qualifications (Neale, 1987; Huber, Neale, and Northcraft, 1987) and on the other side, pay attention to how emotions frame their decisions, if risky or safe, positive, or negative.

For Kahneman and Tversky (1979), rational decision-making will always be frequently and inevitably influenced by heuristics and mental strategies of system 1 and system 2 of the brain, which, although has never been tested and may not be testable help us understand the functioning of the brain and how individuals process information given the complexity of the human mind (Melnikoff and Barghnos, 2018).

Regardless of the name and origin of the factors (system 1 or 2), everything that comes from the cognitive processes and blurs the perception of what is relevant or central to decision-making, especially when it leads to the discrimination of social groups ("race, nationality, ethnic origin, colour, religion, age, sex, sexual orientation, gender identity or expression, marital status, family status, genetic characteristics, and disability") (Žliobaitė, 2017) is considered bias (Fiske, 1998; Rudman, Glick, and Phelan, 2008).

Human brain function is the point of origin of bias (Kahneman and Tversky, 1979). However, today the novel is a biased algorithm. In the first one, the distorted judgment in decisions occurs casually and randomly (Wihbey, 2015). Second, the algorithm's decisions are based on the machine learning models to support decision-making through historical data based on decisions made by humans. This process can reinforce old bias or even create a new one (Calders and Zliobaite 2013). When human made decisions by judgment, those are biased, but only can occur case-by-case. However, decision produced by algorithms apply to each case and are more systematically with a larger scale than human decision-makers, and this can digitally discriminate (Wihbey, 2015).

In terms of personnel selection can be defined as the most strategic stage of the organization (Ployhart, and Weekley, 2017) which combines jobs and people (Cascio and Scott, 2017), An exchange of roles is perceived in HR professionals from operator to supervisor of the machine (Zerilli et al., 2019) and from passive to active in the sense of isonomy of the consequences.

When the recruiter appropriates the technology (Orlikowski, 1992) to optimize procedures using algorithms, they take some control that allows the measurement of consequences, for example, analysing the results of hidden parameters, the decision of criteria on (ir)relevant information regarding the candidates, including, but not limited to, hometowns and neighbourhoods where they live, the university from which they graduated, the voice, extroversion indicator from photos and the time to get to work (Eaglin, 2017; Danks and London, 2017).

These criteria are currently used to rank candidates for companies worldwide (Chien and Chen, 2008; Cordovés and Suárez, 2009; Jantan, Hamdan, and Othman, 2010; Parrino, 2011; De Freitas Alves et al., 2015; Shehu and Saeed, 2016). One reason is that for most businesses, the people selection strategy is a mystery, particularly what the company must do to find an excellent match between the candidate's capabilities and the company's performance (Cascio and Scott, 2017).

This picture worsens not only because HR professionals rely on technology to determine who they will interview, hire, or promote (Scepora, 2020), but also because these users are professionals with psychological or business backgrounds who are unaware of the programming, requirements, and developer's intentions. The results' accuracy (Giest and Grimmeliikhuijsen, 2020). Everyone holds some of the blame, and HR professionals are still held accountable for the harm caused by technology. Unintentional discrimination in the hiring process results in the individual losing job opportunities and going to suffer the same type of harm as any other victim of intentional discrimination (Scepora, 2020).

Apparently, these algorithms are limited to being an inflexible instrument of power and social control that induces and reproduces discrimination, social apartheid, and inhibits the access of many individuals to the system of production and capital in modernity. Ultimately, this leads to the exclusion of minority groups not only in organizations but also from society (O'neil, 2016). As algorithms are used to model, forecast, and influence human behavior automatically while removing any subjectivity, we are all, in some ways, becoming more standardized (Zerilli, Knott, Maclaurin, and Gavaghan, 2019; Raji, Gebru, Mitchell, Buolamwini, Lee and Denton, 2020).

However, very few empirical studies on personnel selection have been conducted (Highhouse, 1997; Zysberg and Nevo, 2004; Cascio and Scott, 2017); this is especially true for the use of ICT and web-based technologies (Stone and Dulebohn, 2013). Among these issues in personnel selection, fairness is receiving far too much attention, owing to new data management procedures, a lack of precision in decision making, and the outcomes of hidden parameters (Chiao, 2019).

As a result, in this paper, we present the findings of comparative bibliometrics on bias in human and algorithm decision-making, with a focus on traditional and unusual features, in order to get a "photo" of the field and provide a starting point for this critical discussion.

2. Method

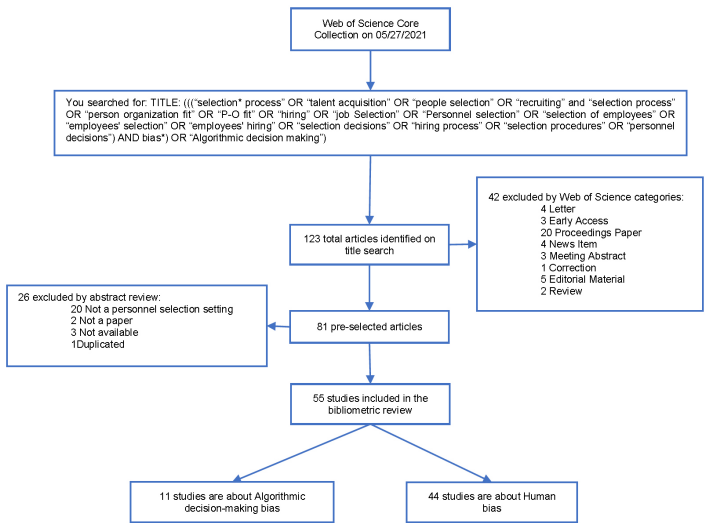
This comparative bibliometric study describes publications about bias in human and algorithms decision-making and its influence on personnel selection decisions from the web of science database from 1979 until 2021.

The systematic search corresponds to the first phase of this study, followed by bibliometric analysis, and finally the presentation of results. The first phase of systematization includes two distinct stages: planning and collection. In the first stage - planning - the 15 most used terms related to the selection of people in an organizational environment were selected. The data collected was from the Web of Science (WoS) Core Collection, from the Institute for Scientific Information (ISI), because of the relevant thematic quantities with a multidisciplinary characteristic.

In the second stage - collection - the search for terms in the title was carried out, among publications between the earliest year to the present day, which allowed us to find 123 articles. As a second filter, we allow only articles as a standard document because it is more rigorously evaluated when submitted to the peer review process (Pinto *et al.*, 2014). The metadata of the remaining 81 articles was compiled and exported manually.

Pre-selected articles were tabulated in Microsoft Excel® software for abstract analysis, which resulted in 55 articles total. After that, the articles were transferred to the bibliometrix packages of the RStudio system version 3.6.3.

Figure 1 illustrates the process for conducting comparative bibliometric research on bias in humans and algorithms.



Source: Developed by the authors

Figure 1
Strategic process for the bibliometrics review

3. Results and discussion

Initially, from 81 articles extracted from the Web of Science database, 23 referred to studies on algorithms and 58 on human biases. However, after a pre-analysis of the abstracts, the number reduced to 11 related to algorithms decision-making and 44 to human bias, totalling 55 articles, were approved.

The compiled descriptive data is presented in “Main Information About Data” (Table 1). The 55 articles chosen were published in 44 peer-reviewed journals. 12 articles have only one author, while the remaining articles have two authors on average. More information can be found in Table [1].

Table 1
Main information about dataSource: the data analysis’s findings

Description	Results
Timespan	1979:2021
Sources (Journals)	44
Documents	55
Average years from publication	12,1
Average citations per documents	28,6
Average citations per year per doc	2,949
References	2183
Document types	
Article	55
Document contents	
Keywords plus (id)	161
Author’s keywords (de)	129
Authors	
Authors	136
Author appearances	144
Authors of single-authored documents	12
Authors of multi-authored documents	124
Authors collaboration	
Single-authored documents	12
Documents per Author	0,404
Authors per Document	2,47
Co-Authors per Documents	2,62
Collaboration index	2,88

3.1 *Publication output*

Annual scientific production has increased from 1979 to June 2021, with 6 in the 1980s, 5 in the 1990s, 7 in the 2000s, 9 in the 2010s, and 9 from 2020 to June 2021. According to the data, the topic “bias in the selection process research” is underexplored. The most common publication is on human bias; however, in 2011, [2] publications on algorithms emerged. 2017 was the most notable year, with 7 studies indexed in databases, 2 of those were about algorithm decision-making bias and 5 about human biases (Figure-2).

The presentation of annual scientific production are shown in table 2.

Table 2
Annual scientific production on Bias in technology and in humans

1970's		1980's		1990's		2000s		2010s		2020s	
Year	Number of Articles	Year	Number of Articles	Year	Number of Articles	Year	Number of Articles	Year	Number of Articles	Year	Number of Articles
1970	1	1980	1	1990	1	2001	1	2011	2	2020	6
		1983	1	1991	1	2005	1	2014	3	2021	3
		1985	1	1992	1	2008	2	2015	3		
		1987	3	1994	2	2009	3	2016	1		
				1996	1			2017	7		
				1998	1			2018	3		
								2019	6		
Total	1	Total	6	Total	7	Total	7	Total	25	Total	9

Source: The data analysis's findings

3.2 *Most globally cited article*

The most cited article on human bias was published by the Journal of Applied Psychol-ogy from the American Psychological Association. As for the characteristics, the article

Table 3
Most Globally Cited Documents

GLOBAL CITATIONS						
Source of bias	Article title	Publication year	Author full names	Times cited, all databases	Journal	Impact Factor
Human	Gender and attractiveness biases in hiring decisions: are more experienced managers less biased?	1996	Marlowe, Cm; Schneider, Sl; Nelson, Ce	186	Journal of Applied Psychology	5.851

Contd...

Algorithmic decision-making	European Union Regulations on Algorithmic Decision-Making and a Right to Explanation	2017	Goodman, B., and Flaxman, S..	175	AI magazine Systems	2.18
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Source: The data analysis's findings

had the purpose to understand the relationship of managerial experience towards gender and examined attractiveness biases in decisions involving suitability for hire and probable organizational progression within a typical financial institution. As for strategy, the researchers applied the quantitative method based on experimental research. The major result of the study shows that with maturity the bias decreases, however, beauty and attractiveness are implicit requirements to the woman for a leadership position.

Regarding bias in algorithms, the most cited article of all time is from the newspaper AI magazine Systems, which through a theoretical essay assesses the potential impact that the European Union's new General Data Protection Regulation will have on the routine use of machine learning algorithms. Table 3 above shows the details.

3.3 Language of publication

The analysis of the articles showed that English was the dominant language adopted in the publication, with 53 articles in the database. We also found articles in Dutch [1] and French [1] which had a version of the abstract in English in which it was possible to perform the analysis. Another observation is that the article in Dutch focuses on algorithms while the one in French on human bias. A summary is displayed below on Table 4.

Table 4
Language of publication

	USE OF TECHNOLOGY IN THE SELECTION PROCESS		
Language	Yes	No	Total
Dutch	1		1
English	10	43	53
French		1	1
Total	11	44	55

Source: the data analysis's findings

3.4 Journals leader in publications

Journal of Applied Psychology from the American Psychological Association publisher [4], Sex roles from Springer Publishing House, and Journal of Applied Social Psychology [3] from Wiley Publishing House are the top three journals that focus on human bias in



Source: The data analysis's findings

Figure 2
Journals leader in publication

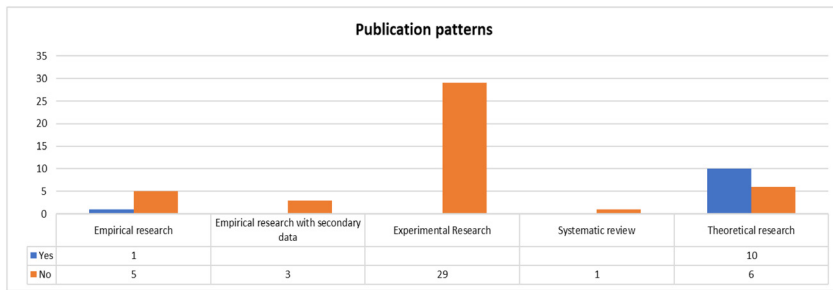
the organizational environment. The Journal of Strategic Information Systems has the most publications about technology, with 2 total. The results are summarized in Figure 2.

We recognize that there is a lack of interdisciplinary in journals, no qual a thematic about technical issues are treated exclusively by technology journals, it is up to social and human sciences journals to compare and contrast the consequences of human or algorithmic bias.

3.5 Publication patterns

When carrying out the analysis on research design, we aimed to draw a profile of the organizations on which practices were clearer, if by humans or machines, and identify the positions, demographic characteristics of the evaluators, country, and the results of the process. However, this was not possible. This is because, of the 55 articles analyzed, 29 were experimental research and 16 were theoretical research, and such studies have their limitations.

Experimental Research is more deductive, which is performed in a controlled environment allows researchers to collect data to evaluate if the results support or reject their hypothesis (Babbie, 1998). On the other hand, theoretical research is a logical exploration of a system of beliefs and assumptions with each investigator going into depth to defend their theory (Thomas, 2017). The details are in Figure 3.



Source: The data analysis's findings

Figure 3

Publication patterns

3.6 Author Keywords

This analysis enabled us to identify the keywords associated with the purpose of this research. It was discovered that the publications primarily focused on gender bias; however, in 2011, the technology theme was implemented with a study on social networks for recruitment and selection, with the emphasis on social network sites; recruitment; selection; Facebook; LinkedIn. In terms of fairness and diversity, the themes are studied beginning in 2017, but only briefly. It is critical to note that 35 of the 55 approved articles lacked keywords. Table 5 shows the details.

Table 4

Author Keywords by year

PUBLICATION YEAR	AUTHOR KEYWORDS
2001	Equal opportunity; adverse impact; test bias; work sample tests
2008	Language abstraction; personnel selection; group decision making; inter-dependence; group membership
2009	Discourse; gender discrimination; hiring decision; gender prejudice
2011	Gender stereotypes; leadership; social roles; sex differences; personnel selection
	Social network sites; recruitment; selection; facebook; linkedin
2014	Body weight bias; obesity stereotype; rational bias; organizational costs; hiring decisions; physical attractiveness stereotype; job type; employability ratings
	Gender discrimination; personnel selection; language abstraction; gender stereotypes
	Individual differences; organizational models; behavioral moderators; organizational performance
2015	Algorithmic decision-making; digital traces; sensors; strategic; social and ethical issues
	Correspondence experiments; gender discrimination; unobserved heterogeneity
	Gender; project manager; selection; stereotypes
2016	Escalation bias; hiring; performance evaluations; experiments

Contd...

2017	Age discrimination; facial age appearance; hireability; fitness impressions; personnel selection
	Discrimination-aware data mining; fairness-aware machine learning; accountability; predictive modeling; indirect discrimination
	Gender disparities in stemm; prejudice reduction; diversity; stemm; interventions; sexism; hiring; gender
	Selection; simulation; residency; interview; nontechnical skills
	Stigma; mental illness; criminal justice; employment; hiring
2018	Gender; in-group bias; perceived discrimination; prototypes
	Online labor markets; hiring bias; gender stereotypes; quasi-experiment; econometrics
2019	Algorithms; artificial intelligence; big data; fairness; accountability; transparency; criminal justice
	Control; artificial intelligence; human-in-the-loop; human-machine systems; human-computer interaction; human factors; ironies of automation; machine learning
	Data ethics; privacy; algorithms; right to explanation; right to be forgotten; bias; public sphere
	Gender roles; masculinity; interpersonal control; hiring decisions; leadership; backlash effect; precarious manhood
	General data protection regulation; automated decision-making; right to explanation; algorithmic transparency; article 22 gdpr; article 11 directive 2016/680
	In-group gender bias; discrimination; field experiment
2020	Algorithms; personnel selection; bias; discrimination; machine learning
	Attraction effect of decoys; choice sets; gender bias; hiring decisions
	Board of directors; ceo compensation; ceo dismissal; cognitive bias; corporate governance
	Transparency; algorithmic transparency; semantic fields; public sphere; publicness; responsibility; democracy; openness
2021	Deadlines; temporal judgments; employment compensation; flat fee bias
	Emotion; affect; ideology; hiring; discrimination

Source: Data from the research

3.7 Author Keywords' Factorial Analysis

This analysis allowed us to identify unobserved underlying factors of 129 Authors' keywords related on bias in personnel selection. The publications focused on 2 major groups, as expected. The red one is predominantly on the human bias, while the blue color group talks about algorithm decision-making.

The findings are even more significant because it based on the Callon *et al.* (1991) Cartesian plane where the x-axis measures the cluster centrality while the y-axis measures the cluster impact. In figure 3, the clusters are represented as themes. In this process, we got 2 large groups independently with parameters ("density" and "centrality").

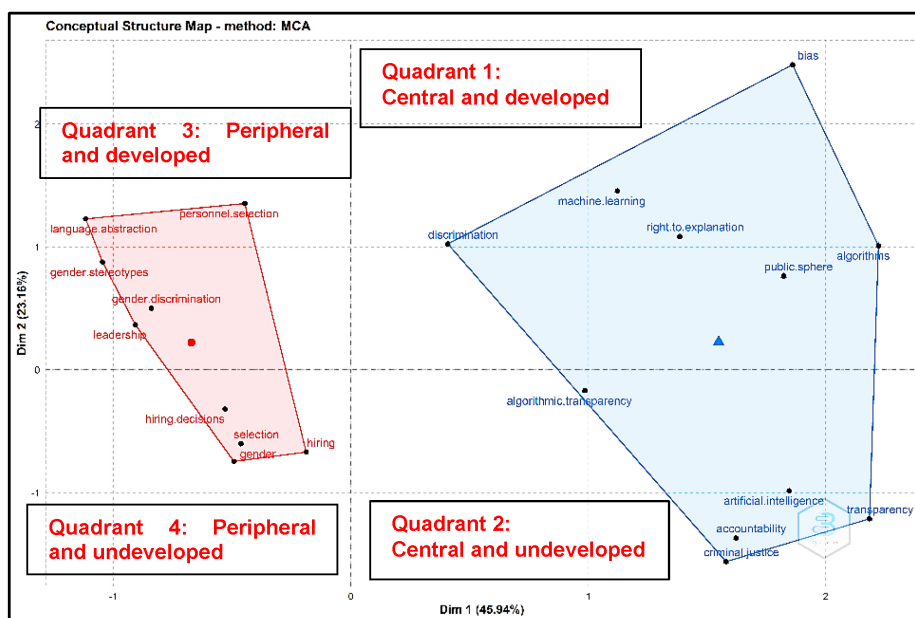
So, according to Callon *et al.* (1991), bias, algorithms, public sphere, machine learning, discrimination, right to explanation, in the first quadrant, are well developed and

represent the motor-themes of the research field, which exhibit deep relations to other clusters. The author further explains that these clusters serve as the file's core. Their position is strategic, and they are undoubtedly studied methodically and over time by a specific team of researchers.

The second quadrant, represented by themes of algorithmic transparency, transparency, artificial intelligence, accountability, and criminal justice, which are strategically important to the file under discussion, such aggregates may actually be the target of investments in other related files. They can also signify the emergence of research issues that are becoming central but have not yet received significant funding.

The third quadrant's cluster, which is represented by recruiting decisions, selection, gender, and hiring, will be referred to as peripheral because they are not essential. They could be clusters that were significant in the past but have now faded into obscurity and have little interest despite still receiving big investments.

The final quadrant is underdeveloped and fragmented. They represent the edges of the network. Only through dynamic research (the development of a network over time) or a comparative analysis will we be able to determine their contribution to the area. Therefore, while being highly specialized, gender stereotypes, gender discrimination, language abstraction, leadership and people selection are of negligible importance for the field. The significance results are below in Figure 4.



Source: The data analysis's findings

Figure 4
Conceptual structure map from Autor Keywords

4. Conclusion

This study investigated comparative bibliometrics on bias in human and decision-making algorithms, focusing on traditional features such as author keywords, type of research, language, and unusual features such as Author Keywords' Factorial Analysis, qualitative keyword analysis, and publication patterns. All of our resources were attentive to capturing a "photo" of the field.

Few studies have focused on investigating bias in humans and machines empirically in the personnel process, especially bias studies related with and without algorithm decision-making. So, in all 11 databases referred to studies on algorithms decision-making and 44 on human biases.

A bibliometric map was made using the following criteria: annual publishing, the most worldwide citations, language, leaders in journal publication, publication trends, and author-keyword analysis, which is described below:

- The most notable year was 2017, with seven studies indexed in databases, two of which were about algorithm decision-making bias and five about human biases;
- Regarding algorithm bias, the most cited article of all time is from the newspaper *AI magazine Systems* in 2017, which assesses the potential impact of the European Union's new General Data Protection Regulation on the routine use of machine learning algorithms through a theoretical essay. The most cited article on human bias was published in 1996 by the American Psychological Association's *Journal of Applied Psychology*;
- In the 54 articles examined, English was the dominant language employed in the publication;
- The American Psychological Association's *Journal of Applied Psychology* published four articles about human, while *The Journal of Strategic Information Systems* published two articles about technology;
- Human bias studies use experiments as methods, whereas decision making algorithms are more theoretical;
- It is important to note that thirty-five of the fifty-five approved articles were missing keywords;
- It was identified that the publications were mostly focused on gender bias; however, the technology theme was later implemented in 2011;
- The motor themes of the research field on bias in personnel selection are bias, algorithms, the public sphere, machine learning, discrimination, and the right to explanation. underdeveloped and fragmented. Although the topics of gender stereotypes, gender discrimination, language abstraction, leadership, and person selection are extremely specialized, they are of minor significance for the study of bias because they have no apparent connection to earlier studies or they are unsystematic.

As a result, we conclude that further qualitative research is necessary to fully comprehend bias phenomena in natural settings and the interpretations that individuals attribute to them through an empirical qualitative study. Also, via the Author Keywords Factorial Analysis exposed, bias is a theme with distinct networks and there is no connection between concerns that linked to algorithms and human prejudice. So, the topic will benefit from receiving greater attention using an interdisciplinary approach.

As a recommendation, it is suggested suggest that futures Research seek to answer questions about “how?”, “where?” and bring proposals for practical applications in particular for algorithm, transparency, artificial intelligence, accountability, and criminal justice topics. Their strategic location in quadrant 2, indicates that they are maturing and that they already have a sizable impact on the topic bias in algorithms.

In terms of bias in people, academic contributions can help map out how and why bias develops in hiring decisions or selection. Notwithstanding, are unexplored subjects that have the potential to have a big impact on societal and organizational practices.

Limitations

The sample size places a strict limit on the ability to discover various findings and linkages and the disconnections between studies, and further limits to perform a co-citation analysis on the entire sample set.

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