KAHRAMANMARAŞ İSTİKLAL ÜNİVERSİTESİ PSİKOLOJİ DERGİSİ

# Unveiling missing themes: An analysis of gender bias through artificial intelligence assisted bibliometric analysis

# Eksik temaların ortaya çıkarılması: Yapay zeka destekli bibliyometrik analiz yoluyla cinsiyetçi önyargının analizi

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**ÖZET:** *Bu çalışma, literatürdeki eksik temaları ortaya çıkarmak için yapay zeka ve bibliyometrik analizden yararlanarak, literatürde cinsiyet yanlılığı odaklarının az araştırılmış alanlarını araştırmaktadır. Çalışmada Web of Science Core Collection'dan derlenen veri setine yapay zeka destekli nitel araştırma teknikleri uygulanmıştır. Bulgular, zihinsel sağlığın, çeşitli kimliklerin ve teknoloji ve medyadaki önyargıların azaltılmasının önemini vurgulayan, belirlenen eşitsizlikleri ele alan daha toplum merkezli araştırmaları ve kapsayıcı literatürü savunmaktadır. Ayrıca bu çalışma, toplumsal cinsiyet yanlılığı ve şiddetle etkili bir şekilde mücadele etmek için akademik araştırmaları toplulukların gerçek kaygılarıyla uyumlu hale getirmenin gerekliliğinin altını çizmektedir.*

**Anahtar sözcükler:** *Toplumsal cinsiyet ayrımı, bibliyometrik analiz, yapay zeka -AI- destekli metin analizi, GPT-4, claude-AI, voyant araçları*

**ABSTRACT**: *This study explores the under-researched areas of gender bias foci in literature, employing AI and bibliometric analysis to uncover overlooked themes. The periods and techniques of qualitative research paradigm were conducted to the data set gathered from Web of Science Core Collection. The findings highlight the need for more community-centric research and inclusive literature that address the existing disparities, emphasizing the importance of mental health, diverse identities, and the reduction of biases in technology and media. Moreover, this study underscores the necessity of aligning academic research with the actual concerns of communities to effectively tackle gender bias and violence.*

**Keywords:** *Gender Bias, bibliometric analysis, artificial intelligence -AI- assisted text analysis, GPT-4, claude-AI, voyant tools*

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# 1. INTRODUCTION

Sex refers to the biological and genetic differences between women and men, while gender is shaped not only by these biological foundations but also by the roles, expectations, and behavioral norms that a society assigns to concepts of femininity and masculinity. Although gender plays a significant role in determining individuals' identities and positions within society, these roles and expectations can vary across different cultures, geographies, and historical periods. For instance, in some matriarchal societies, gender roles are shaped in accordance with the community's historical and cultural makeup, making it problematic to label such arrangements as inherently "right" or "wrong." Recognizing the distinction between sex and gender is essential for understanding inequalities observed in various domains, including education, law, employment, health, religion, family, economy, politics, and language (Bhasin, 2003; Yaşin-Dökmen, 2016). These inequalities often create gender-based barriers to accessing resources, opportunities, and representation. In this context, language emerges as a powerful tool that both reflects and perpetuates societal gender expectations. Through language use, norms, values, and assumptions related to gender are expressed, helping individuals comprehend their roles in society. Historically, language has reinforced gendered patterns and stereotypes, contributing to their normalization and acceptance.

The emergence of Artificial Intelligence (AI) and its growing incorporation into linguistic fields has become the interplay between language, gender, and technology a central concern. Artificial intelligence, integrated into society and its cultures, significantly influences human relationships and societal standards. AI-supported language models are engineered to understand and produce human-like writing, reflecting the linguistic structures prevalent in culture. This encompasses gendered linguistic patterns that may inadvertently reinforce prejudices and biases inherent in the training data. Artificial intelligence and associated technologies, frequently considered intelligent socio-technical systems (Gonzales & Rampino, 2024; Jones et al., 2013), may unintentionally include societal prejudices into their algorithms. The biases referred to as "Algorithm Bias," "Artificial Intelligence Bias," or "Machine Learning Bias" arise from the intricate interaction between the data utilized for training AI models and the inherent biases present in society (Pathak et al., 2024).

The impact of these biases is especially alarming when examining the perpetuation of gender inequities via AI technologies. AI systems, prevalent in industries like recruiting, healthcare, banking, and content moderation, possess the capacity to exacerbate and entrench gender inequalities by reinforcing biased decision-making tendencies. The perpetuation of stereotypes via AI threatens to reverse advancements in gender equality, so jeopardizing one of the 17 Sustainable Development Goals (SDGs) established by all United Nations Member States: the attainment of gender equality and the empowerment of all women and girls (UN, 2015). The eradication of gender inequities is crucial for societal progress and is important to sustainable development (Vinuesa et al., 2020).

The EU Commission is among the many international organizations that recognize the pivotal role of AI in maintaining or mitigating gender biases and has initiated programs that aim at addressing the possible negative effects of biased AI. Yet, this does beg the question of how equal conditions and opportunities do not translate into the execution of precisely identical duties and tasks by any member irrespective of gender. While the European Commission underlines that the need to increase women's representation in AI development as developers and consumers (EIGE 2020; European Commission 2020), it is similarly important to discuss the disadvantages faced by men. It is claimed that the debate on gender equality fails to express these dimensions, which is a distortion of the truth. Moreover, the criticism questions the definition of gender inequality, stating that it can only be considered as such if one is being deprived of something they should have because of their gender. If a man is the best fit for a certain position, for example, it is not correct to call that situation gender inequality or to use such a situation for advocacy purposes unless proven that there is discrimination. The fact that the European Commission identifies this lacuna within AI development teams and recognizes how it is, in part, contributing toward gender prejudice is important; how such bias is overcome by acknowledging and analyzing disparities for all genders, and not just female ones. Without such an approach, the solutions may actually build new inequalities into our environments.

The analysis of Gonzales and Rampino (2024) identifies three principal variables contributing to AI gender bias: the endurance of gender preconceptions, the insufficient representation of women in AI development positions, and the inadequate quality of training data. These factors collectively foster a biased technical environment in which gender prejudices are entrenched within algorithms. Moreover, researchers contend that the male dominance in AI development leads to biased algorithmic results, as male-centric viewpoints may unintentionally influence technological advancement (Agudo et al., 2022; Font & Costa-Jussa, 2019; Leavy, 2018; Swift, 2015; Watkins & Pak, 2020). AI-induced prejudices can marginalize women, disadvantaging them in economic, political, and social domains (UNESCO, 2020). As AI advances, it is imperative to overcome these prejudices to provide equitable technology that fosters inclusivity and fair representation among all genders.

## 1.1. Text Analysis Through AI Assisted Technologies Regarding Gender Bias

Looking at the current literature, it is seen that the increasingly growing digitalization in each and every walk of life, and rapidly increasing tendency towards artifical intelligence (hereinafter AI) lead to a great variety number of publications discussing AI and society. For instance, the system and/or machine can associate “computer science” with man and “homemaker” with woman (Bolukbasi et al., 2016); or “doctor” with man and “nurse” with woman (Lu et al., 2018), which is an example to see how gender ideology is embedded in language. The studies of Caldas-Coulthard and Moon (2010), Litosseliti and Sunderland (2002) and Motschenbacher (2013) underline that it is possible to make text analysis through AI.

However, to date, most of the studies seeking the relation between society and machines ignore or have quite limited foci on the ideology on gender bias embedded in language and algorithm. In order to fill this gap in literature, this research aims to identify missing themes through AI -such as GPT-4, Claude-AI, voyant tools- using bibliometric analysis. In this context, the research questions are:

1. What are the descriptive results of the bibliometric analysis regarding gender perception in WoS in terms of categories?
2. How does AI- assisted bibloimetric analysis reflect the gender bias and gender perceptions in in Bibliometric Analysis in WoS in term of keywords in author keywords, keywords and abstracts?
3. How does AI- assisted bibloimetric analysis reflect the gender bias and gender perceptions in Bibliometric Analysis in WoS in terms of full abstracts via Claude-AI and GPT-4?

## 2. METHODOLOGY

This study is a product of qualitative research paradigm, the periods and techniques of which were conducted to the data set. Both traditional qualitative data analysis techniques and current technologies such as text mining and AI such as GPT-4, Claude-AI, voyant tools were used together.

### 2.1. Data Collection, Procedure and Analysis

In this study, the bibliometric analysis method was used to examine the literature. Bibliometric analysis is the comprehensive approach using statistical tools in assessing the breadth and depth of literature on various dimensions within specific subject areas. This method forms part of the more general domain of "infometrics" and thus is related to, among others, "scientometrics"-dealing with scientific publications alone-and "webometrics"-concerned with other aspects of the web-see for example (Donthu et al., 2021; Ellegaard& Wallin, 2015). We used AI tools or chatbots, including GPT-4 and Claude

1.First Bibliometric Analysis:

• Conduct bibliometric analysis on the WoS database, focusing on gender perception. The focus of this study is how gender is represented and discussed.

2. Detailed Bibliometric Analysis:

• Expand the bibliometric analysis in the same database to understand the gender perceptions by further analyzing the data associated with authors, keywords, and abstracts. Apply GPT-4 to find out which themes are not covered by these dimensions.

3. Full Text Analysis:

• Analyze full-text versions of the abstracts with Claude-AI and GPT-4. Identify the missing themes that were not clear from the earlier analyses when just the abstracts, key words, and authors details were available.

4. Synthesis and Identification of Common Themes:

• Put together information obtained from all the steps and identify common missing themes for all types of analyses done so far.

From these frequency words, codes, categories, and themes were created using the GPT-4 AI program. The missing themes that were not present in these themes were removed. In particular, it covers the following qualitative research methods:

•Word/theme analysis (content analysis): It deals with the presence of some words and themes in the text, their meanings, and contexts. In the example, the words "violence", "woman" and "man" were frequency analyzed (Hsieh & Shannon, 2005; Weber, 1990).

•Coding: It is defined as a meaningful category/code creation from qualitative data. In the example, codes and categories were created from frequency words (Hsieh & Shannon, 2005; Poole & Folger, 1981)

•Theme analysis: It refers to combining codes under broader themes. In the example, themes were created from the codes and missing themes were identified (Vaismoradi et.al. 2016).

•Computer-assisted qualitative data analysis: It is the use of computer programs (voyanttools, GPT-4) in qualitative data analysis.

# 3. FINDINGS

## 3.1. Bibliometric Analysis Regarding Gender Perception in WoS in terms of categories

As a result of the bibliometric analysis, 557 publications were selected from WoS Core Collection in terms of the keyword “gender bias”.

**Table 1:** *The WoS categories in terms of “gender bias”*

| Web of Science Categories | Record Count | % of 557 |
|---|---|---|
| Education Educational Research | 414 | 74.327 |
| Education Scientific Disciplines | 186 | 33.393 |
| Health Care Sciences Services | 52 | 9.336 |
| Surgery | 26 | 4.668 |
| Engineering Multidisciplinary | 15 | 2.693 |
| Economics | 12 | 2.154 |
| Computer Science Interdisciplinary Applications | 11 | 1.975 |
| Linguistics | 11 | 1.975 |
| Psychology Educational | 11 | 1.975 |
| Language Linguistics | 10 | 1.795 |
| Management | 9 | 1.616 |
| Computer Science Artificial Intelligence | 6 | 1.077 |
| Computer Science Theory Methods | 6 | 1.077 |
| Emergency Medicine | 6 | 1.077 |
| Engineering Electrical Electronic | 6 | 1.077 |
| Psychology Social | 6 | 1.077 |

| | | |
|---|---|---|
| Social Sciences Interdisciplinary | 6 | 1.077 |
| Sociology | 6 | 1.077 |
| Women S Studies | 6 | 1.077 |
| Music | 5 | 0.898 |
| Psychology Multidisciplinary | 5 | 0.898 |
| Public Environmental Occupational Health | 5 | 0.898 |
| Psychiatry | 4 | 0.718 |
| Sport Sciences | 4 | 0.718 |
| Chemistry Multidisciplinary | 3 | 0.539 |
| Nursing | 3 | 0.539 |
| Physics Multidisciplinary | 3 | 0.539 |
| Psychology Applied | 3 | 0.539 |
| Psychology Developmental | 3 | 0.539 |
| Business | 2 | 0.359 |
| Communication | 2 | 0.359 |
| Cultural Studies | 2 | 0.359 |
| Environmental Studies | 2 | 0.359 |
| History Philosophy Of Science | 2 | 0.359 |
| Oncology | 2 | 0.359 |
| Pharmacology Pharmacy | 2 | 0.359 |
| Psychology Experimental | 2 | 0.359 |
| Veterinary Sciences | 2 | 0.359 |
| Computer Science Information Systems | 1 | 0.180 |
| Engineering Biomedical | 1 | 0.180 |
| Ethnic Studies | 1 | 0.180 |
| Geography | 1 | 0.180 |
| Geosciences Multidisciplinary | 1 | 0.180 |
| Hospitality Leisure Sport Tourism | 1 | 0.180 |
| Humanities Multidisciplinary | 1 | 0.180 |
| Imaging Science Photographic Technology | 1 | 0.180 |
| Law | 1 | 0.180 |
| Medicine Research Experimental | 1 | 0.180 |
| Philosophy | 1 | 0.180 |
| Psychology Mathematical | 1 | 0.180 |
| Religion | 1 | 0.180 |
| Social Issues | 1 | 0.180 |
| Urban Studies | 1 | 0.180 |

Table 1 shows the WoS categories in terms of “gender bias”. The largest category is "Education Educational Research" with 414 records, constituting 74.327% of the total publications on "gender bias." This is followed by "Education Scientific Disciplines" with 186 records (33.393%), and "Health Care Sciences Services" with 52 records (9.336%). Other categories such as "Surgery," "Engineering Multidisciplinary," and "Economics" also appear, with a smaller number of records.

This finding reveals a clear emphasis on research on gender bias in education and healthcare, while highlighting the need for more attention in other crucial fields like engineering, computer science, and business. Understanding these trends can inform future research efforts and promote a more comprehensive understanding of gender bias across all disciplines. These tendencies are in parrallel to the previous studies underlining that gender and education are the two phenomena bound to each other and some precautions regarding tackling against gender inequality must be taken (Bölükbaşı et al, 2016; EIGE, 2020; UN, 2015).

**Table 2:** *A different breakdown of records related to "gender bias" across various citation topics or meso-categories*

| Citation Topics Meso | Record Count | % of 557 |
|---|---|---|
| 6.11 Education & Educational Research | 156 | 28.007 |
| 1.14 Nursing | 111 | 19.928 |
| 6.178 Gender & Sexuality Studies | 84 | 15.081 |
| 6.73 Social Psychology | 40 | 7.181 |
| 6.24 Psychiatry & Psychology | 15 | 2.693 |
| 6.69 Language & Linguistics | 11 | 1.975 |
| 1.156 Healthcare Policy | 10 | 1.795 |
| 6.185 Communication | 10 | 1.795 |
| 6.3 Management | 10 | 1.795 |
| 1.21 Psychiatry | 6 | 1.077 |
| 10.240 Music | 6 | 1.077 |
| 6.238 Bibliometrics, Scientometrics & Research Integrity | 6 | 1.077 |
| 1.136 Autism & Development Disorders | 5 | 0.898 |
| 1.172 Sports Science | 4 | 0.718 |
| 1.7 Neuroscanning | 4 | 0.718 |
| 6.146 Anthropology | 4 | 0.718 |
| 6.223 Hospitality, Leisure, Sport & Tourism | 4 | 0.718 |
| 1.44 Nutrition & Dietetics | 3 | 0.539 |
| 10.99 Literary Theory | 3 | 0.539 |
| 4.48 Knowledge Engineering & Representation | 3 | 0.539 |
| 6.110 Law | 3 | 0.539 |
| 1.112 Palliative Care | 2 | 0.359 |
| 1.142 Urology | 2 | 0.359 |
| 3.232 Veterinary Sciences | 2 | 0.359 |
| 6.10 Economics | 2 | 0.359 |
| 6.263 Agricultural Policy | 2 | 0.359 |
| 6.269 Political Philosophy | 2 | 0.359 |
| 6.303 Sociology | 2 | 0.359 |
| 1.100 Substance Abuse | 1 | 0.180 |
| 1.155 Medical Ethics | 1 | 0.180 |
| 1.158 Dermatology - General | 1 | 0.180 |
| 1.23 Antibiotics & Antimicrobials | 1 | 0.180 |
| 1.252 Smoking Cessation | 1 | 0.180 |
| 1.34 Orthopedics | 1 | 0.180 |
| 10.144 Modern History | 1 | 0.180 |
| 10.268 History & Philosophy Of Science | 1 | 0.180 |
| 2.165 Nanofibers, Scaffolds & Fabrication | 1 | 0.180 |
| 3.85 Food Science & Technology | 1 | 0.180 |

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|---|---|---|
| 4.284 Human Computer Interaction | 1 | 0.180 |
| 4.47 Software Engineering | 1 | 0.180 |
| 6.27 Political Science | 1 | 0.180 |
| 6.277 Asian Studies | 1 | 0.180 |
| 6.86 Human Geography | 1 | 0.180 |
| 8.124 Environmental Sciences | 1 | 0.180 |
| 29 record(s) (5.206%) do not contain data in the field being analyzed | | |

Table 2 shows a different breakdown of records related to "gender bias" across various citation topics or meso-categories, as indexed by WoS. These categories are more specific and seem to be a further breakdown of the larger WoS categories listed in the first image. At the end of the table, there's a note that 29 records (5.206%) do not contain data in the field being analyzed, which indicates some publications might not have been categorized into any of the listed topics. This table provides insight into the interdisciplinary nature of "gender bias" research, showing its relevance across a wide range of academic fields (Kaplan and Greval, 2002; Mart, 2004; Wood and Ridgaway, 2010).

**Table 3:** *Micro-categories along with the record count and the corresponding percentage of the total 557 publications on "gender bias."*

| Citation Topics Micro | Record Count | % of 557 |
|---|---|---|
| 1.14.841 Academic Medicine | 90 | 16.158 |
| 6.178.443 Work-family Conflict | 75 | 13.465 |
| 6.11.1889 Student Evaluation Of Teaching | 51 | 9.156 |
| 6.11.295 Science Education | 26 | 4.668 |
| 6.73.447 Prejudice | 26 | 4.668 |
| 6.11.31 Self-regulated Learning | 22 | 3.950 |
| 6.11.345 School Leadership | 17 | 3.052 |
| 1.14.363 Nursing Education | 13 | 2.334 |
| 1.156.1502 Indigenous Education | 9 | 1.616 |
| 6.11.666 Intergenerational Mobility | 7 | 1.257 |
| 6.73.685 Item Response Theory | 7 | 1.257 |
| 10.240.657 Music Psychology | 6 | 1.077 |
| 6.11.1526 Computational Thinking | 6 | 1.077 |
| 6.178.516 Divorce | 6 | 1.077 |
| 6.69.342 Language Policy | 6 | 1.077 |
| 6.24.1058 Bullying | 5 | 0.898 |
| 6.24.15 Parenting | 5 | 0.898 |
| 1.14.724 Shared Decision Making | 4 | 0.718 |
| 6.11.1544 Academic Development | 4 | 0.718 |
| 6.11.190 Teacher Education | 4 | 0.718 |
| 6.238.166 Bibliometrics | 4 | 0.718 |
| 1.136.536 Disabilities | 3 | 0.539 |
| 1.14.265 Nursing | 3 | 0.539 |
| 1.172.1331 Sport Psychology | 3 | 0.539 |
| 1.44.103 Physical Activity | 3 | 0.539 |

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|---|---|---|
| 4.48.672 Natural Language Processing | 3 | 0.539 |
| 6.11.1859 Assurance Of Learning | 3 | 0.539 |
| 6.185.1004 Internet Addiction | 3 | 0.539 |
| 6.185.1390 Video Games | 3 | 0.539 |
| 6.185.1644 Privacy | 3 | 0.539 |
| 6.24.1528 Early Childhood Education | 3 | 0.539 |
| 6.3.368 Technology Acceptance Model | 3 | 0.539 |
| 6.3.726 Entrepreneurship | 3 | 0.539 |
| 6.69.218 Phonological Awareness | 3 | 0.539 |
| 6.73.1166 Personality | 3 | 0.539 |
| 1.112.1789 Ageism | 2 | 0.359 |
| 1.142.2404 Female Genital Mutilation | 2 | 0.359 |
| 1.21.1179 Mindfulness | 2 | 0.359 |
| 1.21.2270 Perfectionism | 2 | 0.359 |
| 1.7.1026 Intelligence | 2 | 0.359 |
| 10.99.2232 Children's Literature | 2 | 0.359 |
| 3.232.1375 Animal-assisted Therapy | 2 | 0.359 |
| 6.11.1094 Medical Education | 2 | 0.359 |
| 6.11.1248 Creativity | 2 | 0.359 |
| 6.11.1506 Engineering Education | 2 | 0.359 |
| 6.11.2101 Critical Thinking | 2 | 0.359 |
| 6.11.333 Digital Learning | 2 | 0.359 |
| 6.11.882 Critical Pedagogy | 2 | 0.359 |
| 6.110.45 Supreme Court | 2 | 0.359 |
| 6.223.961 Sport | 2 | 0.359 |
| 6.223.972 Place Attachment | 2 | 0.359 |
| 6.263.898 Farmers | 2 | 0.359 |
| 6.3.1388 Business Ethics | 2 | 0.359 |
| 6.303.2437 Educational Science | 2 | 0.359 |
| 6.69.610 Conversation Analysis | 2 | 0.359 |
| 6.73.1708 Career Development | 2 | 0.359 |
| 1.100.180 Methadone | 1 | 0.180 |
| 1.136.1070 School Psychology | 1 | 0.180 |
| 1.136.283 Autism | 1 | 0.180 |
| 1.14.849 Surgical Education | 1 | 0.180 |
| 1.155.2316 Pharmacovigilance | 1 | 0.180 |
| 1.156.436 Self-rated Health | 1 | 0.180 |
| 1.158.201 Melanoma | 1 | 0.180 |
| 1.172.648 Lactate Threshold | 1 | 0.180 |
| 1.21.35 Depression | 1 | 0.180 |
| 1.21.624 Psychopathy | 1 | 0.180 |
| 1.23.846 Heat And Moisture Exchangers | 1 | 0.180 |
| 1.252.74 Smoking Cessation | 1 | 0.180 |
| 1.34.440 Anterior Cruciate Ligament | 1 | 0.180 |
| 1.7.1311 Numerical Cognition | 1 | 0.180 |
| 1.7.1400 Mental Rotation | 1 | 0.180 |
| 10.144.1118 Anthropometric History | 1 | 0.180 |
| 10.268.2117 Eugenics | 1 | 0.180 |

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|---|---|---|
| 10.99.2261 Science Fiction | 1 | 0.180 |
| 2.165.679 Additive Manufacturing | 1 | 0.180 |
| 3.85.1711 Lathyrus Sativus | 1 | 0.180 |
| 4.284.1210 Public Displays | 1 | 0.180 |
| 4.47.410 Software Metrics | 1 | 0.180 |
| 6.10.590 Wages | 1 | 0.180 |
| 6.10.82 Economic Growth | 1 | 0.180 |
| 6.11.2145 Geography Education | 1 | 0.180 |
| 6.11.2221 History Education | 1 | 0.180 |
| 6.11.2298 Mixed Methods Research | 1 | 0.180 |
| 6.11.2312 Economic Education | 1 | 0.180 |
| 6.110.580 Crime | 1 | 0.180 |
| 6.146.1803 Kemalism | 1 | 0.180 |
| 6.146.2193 Modernity / Coloniality | 1 | 0.180 |
| 6.146.734 Anthropology | 1 | 0.180 |
| 6.146.955 Caste | 1 | 0.180 |
| 6.178.1183 Microfinance | 1 | 0.180 |
| 6.185.2293 Wikipedia | 1 | 0.180 |
| 6.238.1700 Physician-scientists | 1 | 0.180 |
| 6.238.1790 Plagiarism | 1 | 0.180 |
| 6.24.1084 Sexual Assault | 1 | 0.180 |
| 6.24.858 Intimate Partner Violence | 1 | 0.180 |
| 6.269.1694 Deleuze | 1 | 0.180 |
| 6.269.2443 Philosophy For Children | 1 | 0.180 |
| 6.27.1821 Social Capital | 1 | 0.180 |
| 6.277.722 China | 1 | 0.180 |
| Showing 100 out of 106 entries | | |
| 29 record(s) (5.206%) do not contain data in the field being analyzed | | |

Table 3 lists various micro-categories along with the record count and the corresponding percentage of the total 557 publications on "gender bias." For example, "Academic Medicine" has 90 records, which is 16.158% of the total, while "Work-family Conflict" has 75 records, making up 13.465% of the total. Similar to the previous tables, the note at the end indicates that 29 records (5.206%) do not contain data in the field being analyzed, which might suggest these records could not be classified under the provided micro-categories or perhaps are uncategorized within the dataset. This detailed breakdown highlights the complexity and interconnectivity of "gender bias" as a subject of study across various academic fields, being consistent with those of studies putting forwarding the same results (Bora, 2021; Smith, 2022).

### 3.2. Bibliometric Analysis Regarding Gender Perception in WoS in term of keywords in author keywords, keywords and abstracts


**Figure 1:** *Mandala for the most frequent words in the corpus for author keywords determined by voyant tools*

Figure 1 demonstrates the findings about the most frequent words in the corpus for author keywords determined by voyant tools. These are gender (25); bias (17); education (10); teaching (5); teacher (4); student (4); analysis (4); work (3); medical (3); learning (3); evaluation (3); discrimination (3); surgery (2); stem (2); roles (2); representation (2); peer (2); music (2); graduate (2); female (2); evaluations (2); equity (2); english (2); development (2); career (2); zagreb (1); women (1); vignette (1); vietnam (1); verbal (1); values (1); university (1); unconscious (1); traditional (1); thailand (1); textbooks (1); textbook (1); team (1); survey (1); surgical (1); surgeons (1); study (1); stereotypes (1); social (1); sexism (1); self (1); second (1); sciences (1); school (1); scholarship (1); review (1); residency (1); reproduction (1); regulation (1); reasoning (1); ratemyprofessors.com (1); psychometrics (1);programming (1); professors (1).

Analyzing the most frequent words in the author keywords provided, GPT-4 can identify severaloverarching categories and themes that are prominent in the corpus:

- **Gender Studies:** The most frequent keyword is "gender," indicating a strong focus on gender studies. This is further emphasized by related keywords like "bias," "discrimination," "sexism," "roles," "female," "equity," and "representation," which point to a concern with how gender differences and inequalities are perceived and enacted in various spheres.
- **Education:** With "education," "teaching," "teacher," "student," "learning," "evaluation," "medical," "stem," "english," "university," "textbooks," "school," and "scholarship" being prevalent, there is a clear focus on educational settings. This theme explores how gender bias

affects educational practices, evaluations, and opportunities, particularly in STEM (Science, Technology, Engineering, and Mathematics) and medical education.

- **Workplace and Career:** Keywords like "work," "career," "medical," "surgery," "graduate," "professors," and "residency" suggest an examination of gender bias in professional and academic career paths. The emphasis might be on how gender bias influences career development, professional evaluations, and the experiences of individuals in the workplace, especially in typically male-dominated fields like surgery.
- **Analysis and Evaluation:** The presence of "analysis," "evaluation," "peer," "zagreb," "vignette," "survey," "review," "regulation," "reasoning," "psychometrics," and "programming" indicates a methodological approach to studying gender bias. It suggests a range of techniques and tools used to measure, understand, and mitigate gender bias, from statistical analysis to peer evaluation and psychometric assessments.
- **Cultural and Social Context:** Words such as "vietnam," "verbal," "values," "traditional," "thailand," "textbook," "team," "social," "self," "second (language)," "sciences," and "sexism" point to the investigation of gender bias within different cultural and social contexts. This could involve analyzing gender roles in textbooks, the impact of traditional values on gender perceptions, and the manifestations of sexism in different cultural settings.
- **Personal and Unconscious Bias:** The keywords "unconscious," "self," and "stereotypes" suggest a focus on the psychological aspects of gender bias, including implicit or unconscious biases that individuals may hold and how these biases shape attitudes and behaviors towards different genders.
- **Specific Studies or Cases:** Some keywords reference specific tools, locations, or studies, such as "ratemyprofessors.com," "Zagreb," "Vietnam," and "Thailand," indicating case studies or research focused on particular regions or using specific datasets.

These categories and themes reflect a multifaceted approach to gender bias, encompassing a range of disciplines and methods. The corpus seems to be centered on the systemic nature of gender bias, its impact on educational and professional progression, and the various ways it can be analyzed and addressed. These results are consistent with those of Savoldi, et al. (2022), Shah et. al. (2020) and Matthews et. al. (2021).

The missing themes according to GPT-4 are “Mental Health Impacts, Legislative and Policy Implications, Intersectionality, Technological Bias, Economic Consequences, Historical Perspectives, Media Representation, Parenting and Domestic Roles, Leadership and Governance, Global vs. Local Perspectives, Bias in Non-Academic Professions, Role of Language, Healthcare Disparities, Activism and Social Movements, Gender Bias in Science and Research, Gender Diversity and Non-BinaryIdentities".

Figure 2 shows the most frequent words in the corpus for the keywords. They are women (9); bias (7); faculty (6); education (6); science (5); gender (5); discrimination (5); stereotypes (4); ratings (4); prejudice (4); performance (4); perceptions (4); impact (4); students (3); student (3); sexual (3); sexism (3); implicit (3); harassment (3); expectations (3); attitudes (3); achievement (3); teachers (2); teacher (2); surgery (2); stereotype (2); sex (2); self (2); school (2); promotion (2); professors (2); participation (2); medicine (2); knowledge (2); judgments (2); instructors (2); evaluations (2); diversity (2); consequences (2); college (2); beliefs (2); barriers (2); academic (2); ability (2); workshop (1); womens (1); wages (1); video (1); universities (1); threat (1); theory (1); thailand (1); textbooks (1); tests (1); technology (1); teams (1); teaching (1); susceptibility (1); success (1).

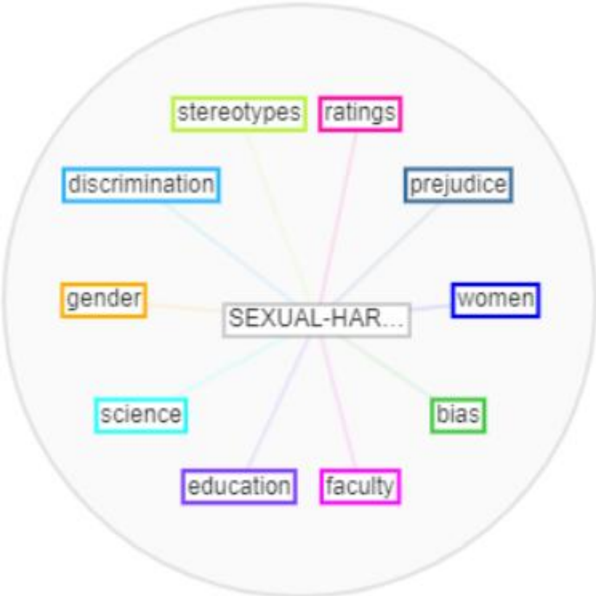


**Figure 2**: *Mandala for the most frequent words in the corpus for keywords determined by voyant tools*

The keywords from this corpus suggest several categories and themes focused on gender bias and its manifestations can be interpreted by GPT-4 as follows:

**Gender Dynamics in Academia and Science**: With "women," "faculty," "education," "science," "gender," "teachers," "professors," "academic," and "medicine" as frequent keywords, there is a clear emphasis on the study of gender dynamics within academic and scientific communities. This likely encompasses research on the representation and treatment of women in academia, including issues related to faculty positions, tenure, and promotion within educational and scientific institutions.

**Bias and Discrimination**: Keywords such as "bias," "discrimination," "stereotypes," "prejudice," "sexism," and "harassment" highlight the focus on different forms of gender bias. These terms suggest that the corpus deals with the attitudes and beliefs that contribute to discrimination against women, as well as the social and professional impacts of such biases.

**Evaluation and Performance**: The presence of "ratings," "performance," "evaluations," "achievement," "judgments," and "expectations" indicates an interest in how gender bias affects the assessment of individuals' work and capabilities. This theme might explore how stereotypes and prejudices influence the evaluation of women's performance in various contexts, from academia to the workplace.

**Societal Perceptions and Attitudes**: With "perceptions," "attitudes," "stereotype," "beliefs," and "knowledge," the corpus seems to address the broader societal understanding of gender roles and how these perceptions shape behavior and decision-making related to gender.

**Personal and Psychological Factors**: Words like "implicit," "self," "sex," and "susceptibility" imply a focus on the individual-level cognitive and psychological aspects of gender bias. This may include studies on implicit bias and self-perceptions of ability or susceptibility to bias.

**Educational Context**: "Students," "school," "textbooks," "teaching," and "college" suggest a concentration on the educational environment. This could involve research into how gender bias impacts students, teaching materials, and the overall school or college experience.

**Career and Professional Development**: "Promotion," "participation," "surgery," and "barriers" are keywords that point to the study of professional advancement and the challenges that women may face in their careers due to gender bias.

**Diversity and Inclusion**: "Diversity," "consequences," and "inclusion" indicate a consideration of the broader implications of gender bias for creating diverse and inclusive environments, particularly in education and the workplace.

**Cultural and Regional Studies**: The mention of "Thailand" and "technology" suggests that some of the research may be focused on specific cultural contexts or the intersection of gender with technology.

**Economic Aspects**: With keywords like "wages," the corpus may also be exploring the economic impacts of gender bias, such as wage gaps and economic inequality.

Overall, the themes and categories derived from these keywords depict a corpus deeply engaged with understanding, identifying, and addressing gender bias across various spheres, with particular attention to the academic and scientific fields, and the professional development. The keywords reinforce the initial analysis regarding the focus on gender and bias within education and broader social and psychological contexts. Additionally, they suggest emerging interests in sexual harassment and the role of technology in research. The studies of Rodríguez-Rodríguez and Heras-González (2020), Henrey, et al. (2015) and Machimbarrena et al. (2018) reported similar results.

The missing themes according to GPT-4 are “Mental Health Impacts, Intersectionality, Legislative and Policy Implications, Technological Bias Beyond Methodology, Historical Perspectives, Media Representation, Global vs. Local Perspectives, Parenting and Domestic Roles, Leadership and Governance, Activism and Social Movements, Gender Bias in Non-Academic Professions, Role of Language, Healthcare Disparities, Gender Diversity and Non-Binary Identities”.

As another finding, the most frequent words in the corpus for the abstracts are gender (184); bias (140); study (32); students (27); female (27); teachers (25); results (25); women (21); research (20); faculty (18); education (17); surgery (16); male (16); surgical (15); stem (15); teaching (14); student (14); beliefs (14); academic (14); training (13); men (13); higher (13); intervention (12); data (12); career (12); participants (11); females (11); evaluations (11); analysis (11); work (10); paper (10); word (9); used (9); textbooks (9); reported (9); medical (9); interventions (9); graduates (9); experience (9); differences (9); university (8); subtle (8); studies (8); residents (8); findings (8); evaluation (8); equity (8); efficacy (8); departments (8); compared (8); article (8); vs (7); using (7); show (7); set (7); residency (7); related (7); reduce (7); multiple (7).

The analysis by GPT-4 of the most frequent words in the abstracts of the corpus allows for theidentification of prominent categories and themes in the context of gender bias:

- **Gender Disparities:** Words like "gender," "bias," "female," "women," "male," "men," and "females" point towards a primary focus on gender disparities. The frequency of these terms indicates that the abstracts discuss differences, discrimination, or biases that are specifically related to gender.
- **Academic Research and Education:** With "study," "students," "teachers," "research," "faculty," "education," "teaching," "student," "academic," "training," "university," "textbooks," "graduates," "residents," and "residency," there's a significant emphasis on the educational environment. This theme might explore the manifestation of gender bias in academic settings, including the impact on students and educators, curriculum content, and the educational system at large.
- **Professional and Career Analysis:** The presence of "faculty," "surgery," "surgical," "stem," "career," "medical," "residents," "residency," and "departments" suggests a focus on professional fields, particularly in STEM and medicine. This indicates an examination of gender bias in professional training, career progression, and workplace dynamics.
- **Research Methodology and Analysis:** Terms like "study," "results," "research," "data," "analysis," "participants," "findings," "compared," and "multiple" point towards the methods

used in gender bias research. This includes the presentation of study results, comparative analyses, and the use of participant data to draw conclusions.

- **Cognitive and Social Psychology:** Keywords such as "beliefs," "subtle," "efficacy," and "intervention" reflect an interest in the cognitive and psychological aspects of gender bias. This could include the study of personal beliefs about gender roles, the effectiveness of interventions to combat bias, and the subtler forms of bias that can permeate social attitudes.
- **Impact Assessment:** With "effects," "impact," "interventions," and "reduce," the abstracts likely address the consequences of gender bias and the effectiveness of strategies to mitigate its effects. This theme considers both the impact of gender bias on individuals and the efforts made to address and reduce bias through various interventions.
- **Evaluation and Performance:** The recurrence of "evaluations," "performance," "efficacy," and "experience" indicates a concern with how gender bias affects the assessment of performance and the experiences of individuals in academic and professional contexts.
- **Workplace and Labor:** The mention of "work," "paper," "word," "reported," "experience," "differences," "equity," and "vs" suggests a discussion of gender bias in the context of the workplace, including issues of labor, equity, and workplace experiences reported in the literature.
- **Measurement and Tools:** The use of "word," "used," "show," "set," "using," and "measure" might reflect the specific tools and measurements used to quantify and demonstrate gender bias in various studies.

In summary, the abstracts seem to cover a broad spectrum of issues related to gender bias, ranging from its psychological underpinnings and social manifestations to its specific impacts on education, professional development, and workplace environments (Bhasin, 2003; EIGE, 2020).

The missing themes according to GPT-4 are “Legislative and Policy Implications, Intersectionality, Technological Bias Beyond Methodology, Economic Consequences, Historical Perspectives, Media Representation, Parenting and Domestic Roles, Leadership and Governance, Global vs. Local Perspectives, Activism and Social Movements, Gender Diversity and Non-Binary Identities, Role of Language, Healthcare Disparities, Gender Bias in Non-Academic Professions”.

### 3.3. Bibliometric Analysis Regarding Gender Perception in WoS in terms of full abstracts via Claude-AI and GPT-4

The key points about gender bias in education based on the studies analyzed by Claude-AI are as follows:

- Gender bias exists in various forms in educational settings, including textbooks, teacher interactions, evaluations, and recommendations. It can be explicit or implicit, intentional or unintentional.
- Gender bias impacts students of all genders. It can negatively impact girls' and women's interest and advancement in certain fields like STEM. It can also negatively impact boys in areas viewed as traditionally feminine.
- Interventions aimed at raising awareness of gender bias among educators show promise for reducing biased behaviors and improving gender equity. These include workshops, curricula, policy changes, and providing tools to address bias when witnessed.
- More research is still needed in many areas related to understanding and mitigating gender bias in education across cultural contexts, educational levels, and fields of study. Assessments to detect gender bias in materials, evaluations, etc. are also still in development.

In short, substantial evidence shows gender bias exists in educational systems globally. A multipronged approach across policies, curricula, assessments, training, and tools shows potential for meaningful progress toward gender equity in education (Bhasin, 2003; Bölükbaşı et al, 2016; EIGE, 2020).

The key points about gender bias in education based on the studies analyzed by GPT-4 can begiven below:

- **Clinical and Medical Education**: There are multiple studies focused on gender bias in clinical training and medical education, particularly looking at the experiences of residents and faculty within these settings. They often involve surveys, structured interviews, and longitudinal data to assess both the prevalence and evolution of gender bias, as well as the effectiveness of interventions like curricular changes and mentorship programs.
- **Performance Evaluation in Different Fields**: Several abstracts discuss the evaluation of performances in fields ranging from music to teaching, and how gender bias can affect these evaluations. The use of blind assessments and the study of extramusical or non-academic factors suggest that bias can manifest even when gender is not explicitly known, indicating deep-rooted stereotypes and prejudices.

- **Educational Bias and Stereotypes**: Bias in educational settings is a recurring theme, with studies exploring the impact of gender bias on both students and teachers. This includes biases in language classrooms, educational materials, and the recommendations teachers make for students' future studies.
- **Technological and Methodological Bias**: Some studies focus on the technological aspects of gender bias, such as the presence of bias in word embeddings used in natural language processing. This indicates a concern for the ways in which gender bias can be inadvertently encoded into and perpetuated by algorithms and tools that are becoming increasingly central to various fields.
- **Bias in Academic and Professional Advancement**: A number of abstracts address the impact of gender bias on the career advancement of women in academia, particularly within STEM fields. This includes the effects of biases on perceptions of legitimacy, the influences of academic leadership, and the underrepresentation of women in tenure-track positions.
- **Interventions and Training to Reduce Bias**: Several abstracts detail interventions designed to raise awareness of and mitigate gender bias, such as workshops, courses, and simulations. The outcomes of these interventions are measured in terms of changes in bias literacy, awareness, and motivation to address bias.
- **Gender Bias in Evaluation Tools**: There's a focus on the investigation of potential gender bias in tools used for assessment, such as student evaluations of teaching, peer assessment in team assignments, and publication peer review processes. The methodologies include both analysis of existing data and experimental studies to test for bias.
- **Cultural Context and Bias**: The intersection of culture and gender bias is explored in textbooks and educational materials, with a particular focus on how cultural values and narratives influence the representation and treatment of different genders.
- **Systemic Issues and Gender Regulation**: Some abstracts highlight the systemic nature of gender bias, addressing how universal regulations and prejudices can lead to discrimination and stereotype reinforcement within educational and social institutions.
- **Perception and Experience of Bias**: Many studies focus on the perception and experience of gender bias among different groups, such as students, faculty, and professionals, suggesting that recognition and dialogue are key steps toward addressing gender bias.

Shortly, the abstracts provide evidence of widespread and varied research into gender bias, highlighting its presence in educational settings, professional fields, technological tools, and cultural contexts. They also emphasize the importance of interventions and structural changes to address and reduce gender bias, suggesting a need for ongoing attention to and action against these biases in multiple spheres of society, in the same way the previous studies suggested (Lindgren and Holmström, 2020; Pathak et al, 2024; Shields, 2002).

The missing themes according to GPT-4 are "Mental Health Impacts, Intersectionality, Economic Consequences, Historical Perspectives, Media Representation, Parenting and Domestic Roles, Leadership and Governance, Global vs. Local Perspectives, Activism and Social Movements, GenderDiversity and Non-Binary Identities".

## 4.DISCUSSION

This study's AI-assisted bibliometric analysis reveals a complex landscape of gender bias research, highlighting both progress and significant gaps. While the dominance of education and healthcare research demonstrates a commendable focus on these crucial areas, the underrepresentation of other fields like engineering, computer science, and business is concerning. This skewed distribution suggests a potential blind spot in understanding how gender bias operates within these influential sectors.

The identification of missing themes through AI analysis is particularly thought to be insightful. The lack of research on mental health impacts of gender bias is a glaring omission, considering the well-established link between discrimination and mental well-being. Similarly, the scant attention to intersectionality overlooks the unique experiences of individuals facing multiple forms of discrimination based on gender, race, class, and other social categories.

The under-exploration of economic consequences and leadership and governance issues related to gender bias hinders our understanding of its broader societal impact. Furthermore, neglecting the role of media representation and parenting and domestic roles in shaping gender perceptions perpetuates harmful stereotypes and limits opportunities for change.

The study's findings point to a critical need to align academic research with the actual concerns of communities affected by gender bias. This necessitates incorporating diverse voices and perspectives into research agendas and methodologies. Engaging with community-based organizations, activists, and individuals with lived experiences of discrimination can enrich research and ensure its relevance to real world challenges.

Several avenues for future research emerge from this analysis:

Expanding the Scope: Exploring gender bias in under-researched fields like engineering, technology, and business is crucial to understand its diverse manifestations.

Intersectionality: Research should examine the experiences of individuals facing multiple forms of discrimination based on gender, race, class, and other social categories.

Mental Health: Investigating the psychological impacts of gender bias on individuals and communities is essential for developing effective support systems.

Economic Analysis: Assessing the economic costs of gender bias and its impact on individual and societal well-being is crucial for promoting equitable policies.

Media and Representation: Analyzing the role of media in perpetuating or challenging gender stereotypes can inform strategies for promoting positive change.

Policy and Advocacy: Research should inform the development of legislation and policies that promote gender equality and address discrimination.

This study's findings have significant implications for social change. By addressing the identified gaps in research, we can develop a more comprehensive understanding of gender bias and its multifaceted impacts. This knowledge can then inform the development of effective interventions, policies, and advocacy efforts aimed at promoting gender equality and creating a more just and equitable society.

In conclusion, this AI-assisted bibliometric analysis offers valuable insights into the current state of gender bias research. By acknowledging the limitations and addressing the missing themes, we can move towards a more inclusive and impactful research agenda that contributes to dismantling gender bias and fostering a more equitable future.

## 5. CONCLUSION

At first, the distribution of the 557 publications across various academic categories, citation topics, and micro-categories assigned by Web of Science were examined. The analysis reveal that the education field dominates, with 74.3% of publications categorized under "Education Educational Research" and 33.4% under "Education Scientific Disciplines." Healthcare also has notable representation at 9.3% of documents categorized under "Health Care Sciences Services." However, the fields like engineering, computer science, business, and economics have limited representation despite their societal influence. Moreover, there is an evidence of an interdisciplinary focus, with categories like "Social Sciences Interdisciplinary" and presence of wide-ranging citation topics. Another finding demonstrates that the most frequently cited micro-categories are "Academic Medicine," “Work-family Conflict,” and “Student Evaluation of Teaching,” among others related to higher education.

As to the analysis via, GPT-4, it was found out that the common frequent missing themes in the analyses of keywords and abstracts are as follows:

- Mental Health Impacts,
- Legislative and Policy Implications,
- Intersectionality,

- Technological Bias (Beyond Methodology mentioned in some versions),
- Economic Consequences,
- Historical Perspectives,
- Media Representation,
- Parenting and Domestic Roles,
- Leadership and Governance,
- Global vs. Local Perspectives,
- Activism and Social Movements,
- Gender Diversity and Non-Binary Identities,
- Role of Language,
- Healthcare Disparities,
- Gender Bias in Non-Academic Professions.

Last but not the least, the bibliometric analysis points out the lack of discussion on "Mental Health Impacts," "Intersectionality," "Economic Consequences," "Media Representation," "Parenting and Domestic Roles," "Leadership and Governance," "Activism and Social Movements," "Gender Diversity and Non-Binary Identities," "Role of Language," and "Gender Bias in Non-Academic Professions." These themes cover a wide range of critical areas from the psychological effects and economic impacts of gender bias to the importance of diverse gender identities and the role of language in perpetuating biases.

**Limitations of the Research and Further Works**

There are some limitations in this study. First of all, regarding the limitations is about the data analysis. While the use of AI (GPT-4) for identifying missing themes is innovative, the methodology's transparency regarding how AI interpreted data and determined missing themes could be better detailed. Secondly, it is about the scope of literature review, that is, the focus on Web of Science database might limit the scope, missing relevant studies in databases not covered. A more diverse database selection could provide a more comprehensive literature review. Moreover, abot addressing bias, the study itself, while analyzing gender bias, does not deeply discuss the potential biases within its own methodologies—such as AI biases in text analysis or bias in survey design. Finally, as to the practical implications, while the study suggests the need for more targeted research and inclusion, it could further elaborate on practical steps for academia, policy-makers, and technology developers to address identified gaps.

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