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Media Bias: A Systematic Literature Review On Media Bias Taxonomy

Master's Thesis

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Declaration

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In Prague on July 30, 2024.   Martin Spirit

References

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Abstract

The topic of this thesis is a comprehensive set of definitions of media bias in news articles. The research questions aim to analyze the theoretical framework of media bias and identify the causes of conceptual fragmentation in the field. The thesis discusses in detail the types and categorization of this phenomenon through the results of a systematic literature review. In the first section, the thesis examines media bias within broader media theory, exploring its prevalence and implications. The author then summarizes the findings of related systematic reviews in this field and identifies gaps in existing research. The paper draws on an existing media bias taxonomy that includes four main categories: linguistic bias, text-level context bias, reporting-level bias, and cognitive bias. Using the data obtained in the systematic review, the author attempts to anchor these categories in a theoretical framework, reduce their overlaps, and suggest improvements to the existing taxonomy. The paper also discusses the methodological challenges in integrating different theoretical approaches to complete definitions into a unified taxonomic structure. Finally, the thesis concludes with recommendations for future research and applications in media studies to enhance understanding of media bias and its impact on society.

Abstrakt

Tématem této diplomové práce je ucelený soubor definic mediálního zkreslení (media bias) ve zpravodajských článcích. Výzkumné otázky cílí na analýzu teoretického rámce mediálního zkreslení a identifikace příčin konceptuální fragmentace v tomto oboru. Práce podrobně rozebírá typy a kategorizaci tohoto fenoménu prostřednictvím výsledků systematické rešerše literatury. V první části se práce věnuje mediálnímu zkreslení v rámci širší mediální teorie, zkoumá jeho výskyt i dopady. Autor následně shrnuje poznatky předchozích systematických rešerší v tomto oboru a identifikuje nedostatky v dosavadním výzkumu. Práce se opírá o existující taxonomii, která zahrnuje čtyři hlavní kategorie: lingvistické zkreslení, zkreslení v kontextu úrovně textu, zkreslení na úrovni reportovaného obsahu a kognitivní zkreslení. Pomocí dat získaných při systematické rešerši se autor snaží tyto kategorie ukotvit v teoretickém rámci, redukovat jejich vzájemné prolínání a navrhnout zlepšení stávající taxonomie. Práce rovněž diskutuje metodologické výzvy při integraci různých teoretických přístupů ke kompletaci definic do jednotné taxonomické struktury. Závěrem práce jsou formulována doporučení pro budoucí výzkum a aplikace v oblasti mediálních studií, s cílem posílit porozumění mediálnímu zkreslení a jeho dopadům na společnost.

Keywords

media bias, systematic literature review, taxonomy, framing, agenda-setting, misinformation, online news, news articles, conceptual frameworks

Klíčová slova

media bias, systematický přehled literatury, rešerše, taxonomie, framing, agenda-setting, misinformace, online zpravodajství, zpravodajské články, konceptuální rámce

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Media Bias: A Systematic Literature Review On Media Bias Taxonomy

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Introduction

This thesis focuses on media bias and the research of its various forms and types through a systematic literature review of existing definitions. A deeper interest in multidisciplinary research on this phenomenon has begun in recent years. Thus, similar literature reviews on this topic are still rare (Spinde et al., 2023). It is clear that given the role of media bias and the increasing political polarization worldwide (Schedler, 2023), more research in this field is needed. In this regard, this work aims to expand knowledge about media bias and research methodology on the definitions of similar newly studied phenomena in media studies.

Despite the growing scientific interest in media bias, a significant research gap exists in the systematic categorization and definition of its various forms. Current literature often provides fragmented insights, lacking a coherent and comprehensive framework. This gap hinders the development of effective tools for detecting and possibly mitigating the effects of media bias on society. Therefore, this thesis addresses the need for a more structured approach to media bias taxonomy, aiming to improve a unified framework that can be utilized for both academic research and practical applications in media analysis.

A total of 2498 articles were reviewed, and 133 definitions of media bias and related concepts were extracted based on the relevancy and criteria described in **Section 3.2.1**. The existing media bias taxonomy was evaluated by the manual classification of two news articles. Based on the literature review and the taxonomy evaluation, the author proposes a set of recommendations for improvements in the existing taxonomy as well as the addition of new concepts to the structure.

Addressing media bias requires an interdisciplinary approach. Media literacy programs can equip individuals with the skills to critically evaluate news sources and recognize bias (Mihailidis, 2009). Additionally, promoting transparency in journalism and encouraging diverse perspectives in news coverage can help mitigate the effects of bias (Christians et al., 2009). Efforts to develop automated tools for detecting media bias represent a promising avenue for enhancing the objectivity of news reporting. By leveraging technology to identify biased content, it is possible to improve the accuracy and reliability of the information the public relies on (Baly et al., 2020). **Section 1** of this thesis is dedicated to the exploration of the role of media and the impact of media bias on society.

The essential source for this thesis is the article *The Media Bias Taxonomy: A Systematic Literature Review on the Forms and Automated Detection of Media Bias* by Spinde et al. (2023), which proposes a consistent definition and taxonomy of media bias. Like the above-mentioned taxonomy, this thesis will focus only on media bias related to textual content, specifically in online news articles. Therefore, the research aims to improve the understanding of concepts like misinformation, framing, phrasing, hate speech, and agenda-setting (reporting-level) biases, as well as better clarify interrelationships between them. Attention is also paid to the intentionality dimension of media bias, which is inconsistently discussed in related literature reviews. The definition of media bias and the detailed overview of the existing theoretical framework in the field are discussed in **Section 2**.

Conducting a systematic literature review is crucial for several reasons. First, it allows for consolidating existing research, providing a holistic understanding of the current state of knowledge. Second, it identifies gaps and inconsistencies in the literature, guiding future research directions. Finally, the results of the literature review can be further analyzed in order to facilitate the development of standardized definitions.

A comprehensive and coherent media bias taxonomy is needed in the research for following purposes: It provides a structured framework for analyzing media content, facilitating the identification and categorization of bias forms. Second, it supports the development of automated detection tools, which are increasingly necessary given the volume of media content produced daily. Third, a standardized taxonomy enhances the comparability of research findings, contributing to the cumulative advancement of knowledge in media studies (Spinde et al., 2023). Without a stable overview of definitions and a unified framework, efforts to understand and mitigate conceptual fragmentation are ineffective.

The methodology of this thesis involves a systematic literature review following established guidelines (Kitchenham & Charters, 2007). The process began with scraping academic papers from the database Semantic Scholar, which meets the criteria for being a reliable and suitable source for literature review. (Brereton et al., 2007) Using a comprehensive set of keywords related to media bias. These papers were then filtered based on criteria such as citation count to ensure relevance and quality. A random selection was applied to narrow the number of papers to establish a manageable workload for the

research. The resulting articles were manually reviewed to identify the most relevant studies. The manual definition extraction for a subsequent meta-analysis was conducted to facilitate propositions for improvements in the existing theoretical framework. The methodology, including a description of developed guidelines for manual definition extraction from selected papers, is discussed in **Section 3**.

In **Section 4**, this thesis proposes improvements to the existing taxonomy based on the meta-analysis of results. In the final part, the author discusses the research's limitations and suggests future improvements for related work. It explores the limits of systematic literature review in social sciences and describes subsequent analysis regarding consolidating and unifying the part of the ever-growing number of definitions of terms related to media studies.

By synthesizing existing research and proposing standardized definitions, this thesis seeks to enhance the understanding of media bias and contribute to developing effective tools for its detection and analysis. The author of this work believes that the research findings could provide valuable insights for both academic researchers and practitioners in the field of media studies and will contribute with its piece to the slowly assembling mosaic of media bias.

1. Media Bias in News Articles

Media bias has been a part of journalism since the 19th century and the origins of printed newspapers. Newspapers in this period were often explicitly linked to political parties and specific economic interests. This tradition continued through the "yellow journalism" era in the late 19th century, when sensationalism and partisanship were rampant. (Thornton, 2013)

It is natural for people to project their worldviews and opinions intentionally or unintentionally in written words. Despite the constant efforts of professional journalists to achieve relative objectivity, opinions and judgments are present in the news of all forms, creating a space for biased interpretations of reality by media consumers. (McQuail, 2010)

Public opinion has been shaped by the media for centuries. (Lippmann, 1922) An author's subjective perceptions of the world can be unintentionally presented in news articles through superlatives, hate speech, or other words.

Motivations for consuming media are consumers' interest in current political and social events and the desire to form their own opinions. This desire meets the range of topics and agendas presented in newspapers, which successfully set and thus influence social discussion, which is what McCombs and Shaw call the "agenda-setting function of mass media." (McCombs & Shaw, 1972)

Often quoted statement by American political scientist Bernard C. Cohen about the relationship between media content and the opinion-making of consumers says: "The media may not be successful much of the time in telling people what to think, but is stunningly successful in telling its readers what to think about." (Cohen, 1963) In his article on Framing Bias, Robert M. Entman challenges this statement and implies that if media successfully manipulate people to "what to think about," they must also strongly influence the decision "what to think." (Entman, 2007)

In the world of digital media, it is crucial to acknowledge that a significant share of online content is not produced by professional journalists. In democratic countries, anybody with internet access can freely share his opinion without reflecting on objectivity and journalistic or academic writing standards. (Hermida. 2010)

Herein lies the importance of distinguishing between what is still a professional news article and what is a post on a personal blog or social media profile. Where should

consumers look for information to maintain their own media literacy? How do we verify that this information is true and objectively interpreted?

There is a growing number of studies on automated independent fact-checking to prevent the spread of misinformation and fake news in recent times. (Graves & Cherubini, 2016) In addition to fact-checking, however, it is important to remember that even truthful information can be presented misleadingly. While we might classify misinformation under the media bias domain, we find subtle forms of media bias even in articles whose authors try to inform the public truthfully. (Gentzkow & Shapiro, 2006) This implies that on the way to achieving news presenting reality more truthfully, it would be advisable to develop automated detection of these major and minor deviations from objectivity, i.e., media bias.

Examples of well-known popular projects dealing with media bias are news monitoring organizations such as All Sides, Ad Fontes Media, or Media Bias Fact Check. For example, the popular news aggregator website Ground News draws on the ratings of these projects to categorize news media purely by their tilt to the right or left on the political spectrum. (Ground News, 2024) The methodology of these projects varies, does not rely on algorithms, and is mainly based on peer reviews and data from third-party companies. (AllSides, 2024)

Media bias can manifest in various ways, including selective framing of issues, choice of sources, and the language used to describe events or individuals. The author of this thesis will discuss the taxonomy and types of bias in the following parts.

For the purpose of showing an example of general media bias, let us have a look at citations from two news articles regarding the same event.[1] The first example comes from a CNN article from June 30th, 2024, discussing United States President Joe Biden's performance in a presidential candidate debate against Donald Trump and its perceptions of NATO allies.

The article, discussing US's allies concerns about Biden's performance in the debate, also states: "The common view among US allies is that Biden is a sensible man

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[1] The media outlets CNN and Fox News were selected by the author as examples of articles containing media bias as representing ideological counterpoints based on an analysis of *AllSides Technologies Inc.* and their Media Bias Chart. (AllSides, 2024) Both articles report on the same event within a day of each other and in the same context, i.e., the view of U.S. foreign allies on Joe Biden's performance in the presidential candidates' debate. The articles were also used for the detailed media bias analysis and evaluation of the media bias taxonomy in Spinde et al. (2023). This analysis is discussed in **Section 4.1**. The annotations of the texts of articles are attached in **Appendices**.

who surrounds himself with sensible people, and whatever happens, they will continue to make rational, reasonable decisions" (CNN, 2024). This statement contains a potential bias through the use of positive descriptors like "sensible" and "rational." By framing the "common view" of US allies on Biden and his administration in a uniformly positive light, the article may influence readers to adopt a favorable view of him, regardless of the context of the discussed debate.

Another example of media bias can be found in the opposite ideological side of the US media landscape. A Fox News article published on June 29th, 2024, also discusses a presidential debate and pinpoints a social media post by a Polish official comparing President Joe Biden to the fictitious infamous Roman emperor from the movie Gladiator (2000). The article quotes Radek Sikorski, who wrote on platform X, "Marcus Aurelius was a great emperor, but he screwed up his succession by passing the baton to his feckless son Commodus (He, from the Gladiator) whose disastrous rule started Rome's decline)," and adds, "It's important to manage one's ride into the sunset" (Fox News, 2024). Fox News criticizes Biden's performance by focusing on this negative comparison. Unlike CNN, which, next to concerns, also provided a generally positive view of NATO allies regarding Biden, Fox News highlights a singular, critical perspective. This selective framing underscores Fox News' tendency to portray Biden negatively in this case.

Whether news, free of all judgments and subjective evaluations, would be attractive to consumers is far away from the matter of the following research.[2] However, questions may arise from the preceding text. What if the narrative that bias creates benefits society? This thesis does not attempt to prove that the media landscape should be free of all personal opinions and unique points of view because its main task is to define media bias and its types. However, before defining the broad concept, we can briefly review generally accepted academic interpretations of the role of the media in society to justify the motivation and need to recognize and pay critical attention to media bias.

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[2] A study in *Frontiers in Psychology* explored consumer preferences for news media and found that while some consumers prefer objective and fact-based reporting, others are drawn to news that aligns with their preexisting beliefs and offers interpretative or opinionated content. This indicates that a completely judgment-free and subjective-evaluation-free news model might not attract all consumers equally. (Wang et al., 2022)

Figure 1. AllSides Media Bias Chart [3]

1.1 The Role of Media in Society

Media fulfills various essential functions such as informing the public, shaping opinions, providing entertainment, and acting as a "watchdog" for democratic processes. However, the effectiveness of these roles, particularly the informative function, can be compromised when media are biased. This chapter explores the multifaceted role of media, emphasizing the necessity for unbiased information dissemination. Drawing on key theoretical frameworks and historical contexts, the focus lies on the critical functions of media and the implications of media bias on these functions.

One of the primary functions of media is to inform the public. According to Denis McQuail, the media serves as a crucial conduit for information, enabling individuals to stay informed about current events and developments locally and globally (McQuail, 2010). The informative role of media is vital for the functioning of a democratic society, as it empowers citizens with the knowledge required to make informed decisions. In his most

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influential book, "Public Opinion," Walter Lippmann highlighted the media's role in shaping public perceptions and the importance of accurate information for a healthy democracy (Lippmann, 1922).

The informative function is jeopardized when media content is biased. Bias can manifest in various forms, including selective reporting, framing of issues, and language use. This is evident in the contrasting examples of media coverage of the same event by CNN and Fox News, as discussed above. These biases can distort the audience's perception of reality, leading to misinformed or polarized public opinion.

The impact of media on society is well illustrated in the historical context. The 20th century witnessed significant advancements with the advent of radio and television. These new forms of media brought about unprecedented reach and immediacy, further amplifying their influence on public opinion. During both world wars, especially in the Second World War, media was used as a powerful tool for propaganda, demonstrating its potential for informing and manipulating public opinion (Hallin, 1989). Within the Frankfurt School, the works of Adorno and Horkheimer introduced the concept of the "culture industry," criticizing the media's role in supporting capitalist ideologies and maintaining societal power structures (Adorno & Horkheimer, 1944). They argued that media, as part of the culture industry, standardizes content to create passive consumers who are less likely to question the status quo.

The American tradition of media studies, represented by scholars like Paul F. Lazarsfeld and Robert K. Merton, focused on the empirical effects of media on audiences. Lazarsfeld's two-step flow model suggested that media effects are mediated by opinion leaders, emphasizing the indirect influence of media on public opinion (Lazarsfeld et al., 1944). This model underscored the complexity of media influence, challenging the notion of direct and uniform media effects. Marshall McLuhan's theory of technological determinism says that the medium, rather than the content, significantly influences society. His famous aphorism, "The medium is the message," suggests that media technologies shape human experiences and societal structures (McLuhan, 1964). This perspective highlights the transformative power of media technologies, from the printing press to the internet and smartphones, in reshaping communication patterns and social interactions.

Critical media studies, particularly those from the Birmingham School, emphasize the active role of audiences in interpreting media texts. Stuart Hall's encoding/decoding

model posits that media messages are encoded with specific meanings by producers but can be decoded in various ways by audiences based on their cultural contexts and individual experiences (Hall, 1980). This approach highlights the agency of audiences and challenges the idea of media as a monolithic force imposing uniform meanings.

Media bias undermines the informative function of media by presenting information in a skewed manner. Bias can take many forms, including selective framing, choice of sources, and the language used to describe events or individuals. The role of media in society is undeniably significant, serving as a source of information and as a platform for public discourse. However, media bias poses a critical challenge to these functions, particularly the informative role. As this thesis further explores media bias, it is crucial to recognize the historical, theoretical, and practical dimensions of media's role in society.

1.2 The Impact of Media Bias

The biased media's selective framing of issues and events can contribute to social polarization. When media outlets present news that aligns with specific ideological perspectives, they reinforce existing beliefs among their audiences, creating echo chambers (Sunstein, 2001; Stroud, 2010). This phenomenon, where people are exposed primarily to information that confirms their preconceptions, can deepen societal divisions and reduce mutual understanding.

In the Czech Republic, research by the STEM Institute (Středisko empirických výzkumů) and the Academy of Sciences of the Czech Republic has revealed similar trends in media polarization. The study found that Czech audiences increasingly consume news that aligns with their political beliefs, creating ideological media bubbles[4]. These media bubbles contribute to the polarization of public opinion and reduce the potential for cross-ideological dialogue (STEM, 2018). This trend is particularly noticeable in online news and social media consumption, where algorithms tend to reinforce users' existing

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[4] Media bubbles and echo chambers, while often used interchangeably, have distinct definitions in academic literature. Media bubbles, also known as filter bubbles or information bubbles, refer to the selective exposure to information sources that align with one's pre-existing beliefs, often due to algorithmic filtering and personal choice. This creates an environment where individuals are not exposed to differing viewpoints, leading to informational omission (Nguyen, 2020, Pariser, 2011). Echo chambers actively discredit opposing perspectives and manipulate trust, creating a more insulated and self-reinforcing belief system (Sunstein, 2001; Jamieson & Cappella, 2008).

preferences, further entrenching polarization (Hájek & Carpentier, 2015).

A study by the Reuters Institute for the Study of Journalism at the University of Oxford found that media polarization is increasingly prevalent across several European countries, including the United Kingdom, France, and Germany. The study highlights that audiences tend to choose news outlets that reflect their pre-existing political orientations, contributing to fragmented media environments (Nielsen et al., 2018). This polarization is further exacerbated by the rise of digital and social media platforms, which often amplify partisan content and create echo chambers similar to those observed in the United States.

Another study conducted by the Pew Research Center found that polarized media consumption is linked to increased political polarization in the United States, with individuals gravitating towards news sources that align with their political beliefs (Pew Research Center, 2014). This segmentation of media audiences contributes to the fragmentation of the public sphere, where different groups have divergent understandings of reality based on their media consumption (Bennett & Iyengar, 2008).

Media bias can erode public trust in the media. When audiences perceive news coverage as biased or agenda-driven, their confidence in media institutions diminishes. This erosion of trust is particularly problematic in democratic societies, where a free and independent press is essential for holding power to account and informing the citizenry (Ladd, 2012).

The Edelman Trust Barometer, an annual survey measuring trust in institutions globally, has consistently shown declining trust in the media over the past decade (Edelman, 2020). This decline can be partly attributed to perceptions of media bias and the increasing prevalence of misinformation and fake news (Tsfati & Cappella, 2003).

Biased media can undermine democratic processes by skewing the information environment. An informed citizenry is crucial for the functioning of democracy, as it enables voters to make decisions based on accurate and comprehensive information. However, when media coverage is biased, it can mislead voters and distort electoral outcomes (Delli Carpini & Keeter, 1996).

A notable example is the role of biased media coverage in the 2016 United States presidential election, where partisan media outlets played a significant role in shaping public perceptions of the candidates (Patterson, 2016). Studies have shown that exposure to biased news can influence voter behavior and electoral results, highlighting the critical

impact of media bias on democratic governance (Arceneaux, Johnson, & Murphy, 2012; Prior, 2013).

Addressing media bias requires a multifaceted approach. Media literacy programs can equip individuals with the skills to critically evaluate news sources and recognize bias (Mihailidis, 2009). Additionally, promoting transparency in journalism and encouraging diverse perspectives in news coverage can help mitigate the effects of bias.

Efforts to develop automated tools for detecting media bias represent a promising avenue for enhancing the objectivity of news reporting. By leveraging technology to identify biased content, it is possible to improve the accuracy and reliability of the information the public relies on (Baly et al., 2020). While eliminating bias in news is impossible, drawing attention to it and informing the audience about its presence can foster an informed society capable of more rational decision-making. (Spinde et al., 2023)

1.3 Research Questions and Aims of the Thesis

This thesis aims to analyze and consolidate various definitions and conceptual frameworks of media bias as presented in academic literature. By conducting a systematic literature review, this research intends to identify the key categories and subcategories of media bias and highlight the methodological challenges associated with integrating different theoretical approaches into a unified taxonomic structure. The overarching goal is to identify limits of the existing media bias taxonomy and propose improvements, facilitating a more comprehensive and nuanced understanding of media bias in online news articles.

Based on the stated aim of the thesis, the following three research questions were formed:

RQ1: In what ways do the conceptual frameworks and definitions of categories and subcategories of media bias vary in published academic studies?

RQ2: What are the key methodological challenges in integrating different theoretical approaches to media bias into a unified taxonomic structure?

RQ3: What are the basic principles of the structure that an existing unified taxonomy of

media bias contains, derived from the analyses conducted in response to the first two research questions?

The research questions are designed to address the complexities of categorizing media bias systematically. Examining the variations in conceptual frameworks (RQ1) will uncover diverse perspectives on studying media bias. This is crucial for understanding how different forms of bias are identified and categorized.

The investigation of the methodological challenges (RQ2) will focus on integrating and merging different definitions of the same concepts and bias categories. This will include an exploration of the limitations of current methodologies and the potential for developing more integrative approaches.

Finally, by analyzing the basic principles and limits of the proposed unified taxonomy (RQ3), the study proposes improvements to the existing taxonomy – a coherent structure that can accommodate the complexity of media bias observed in online news articles. This taxonomy should be a part of the theoretical framework for future research and practical applications in developing automated detection and analysis of media bias.

2. Theoretical Framework

This chapter delineates the theoretical foundation essential for understanding and analyzing media bias. It encompasses the problem with the definition of media bias, a summary of the findings of related literature reviews, and a discussion of additional pertinent literature. This framework is instrumental for contextualizing the systematic literature review.

2.1 The Definition of Media Bias

What is media bias? The introduction to this thesis shows that we are discussing a very broad concept, and it can be difficult to discern what to include. The lack of a precise concept definition has contributed to conceptual fragmentation in the field (Spinde et al., 2021). Below, the author lists several definitions of media bias and discusses their acceptability in terms of academic requirements for a proper definition.[5]

In the study on television news bias published in 1975, Alden Williams states that media bias must be intentional (reflect a conscious act or choice) and sustained (represent a systematic tendency rather than an isolated incident). (Williams, 1975) This definition offers a discussion of what to call media bias that is unintentional, i.e., to what extent we can perceive the subjective perception of the consumer with his opinion background itself as media bias, and it also opens up the question of whether media bias must be some kind of permanent activity of a given media outlet.[6]

Gentzkow and Shapiro define media bias as "the tendency of media outlets to present information in a way that systematically favors one side of a political or ideological spectrum." (Gentzkow & Shapiro, 2006) This definition highlights the media's role in shaping political and ideological narratives. A somewhat broader definition can be found in the work of Martha Lazaridou et al., which defines media bias as "news reporting that leans towards or against a certain person or opinion by making one-sided, misleading, or unfair judgments." (Lazaridou et al., 2023) This definition no longer places media bias solely in a political or ideological context. However, the defined concept still refers only to bias influencing "a certain person or opinion".

In interpretations of Mass Communication Theory, Denis McQuail implicitly

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[5] The academic requirements for a proper definition are discussed in the **Section 3.2.1.**
[6] The intentional media bias is also sometimes referred to as *media manipulation*.

defines concepts related to media bias as consistent patterns in the selection and presentation of news stories that reflect the preferences or prejudices of the media organization. Therefore, in his understanding, McQuail considers only media organizations as the origin of media bias, which is not entirely accurate in the age of networked media and a large amount of unprofessional journalism.

Lee et al. (2023) define media bias as "reporting in a prejudiced manner or with a slanted viewpoint." This straightforward definition focuses on bias in news coverage without specifying the originators. A similar definition can be found in the article on which this thesis is based. Spinde et al. (2023) define media bias as "slanted news coverage or internal bias reflected in news articles." This definition highlights the subjective nature that influences news stories' reporting and perception. As this single definition is based on the systematic literature search already carried out, and as it represents the taxonomy of media bias and respects the academic requirements for a comprehensive and clear definition, the author of this paper considers this definition to be sufficiently effective to capture the concept in its entirety. The definition anchors the concept firmly in newspaper articles, but this can be easily modified in the context of, for example, media bias contained in a television broadcast without significantly changing the definition's meaning.
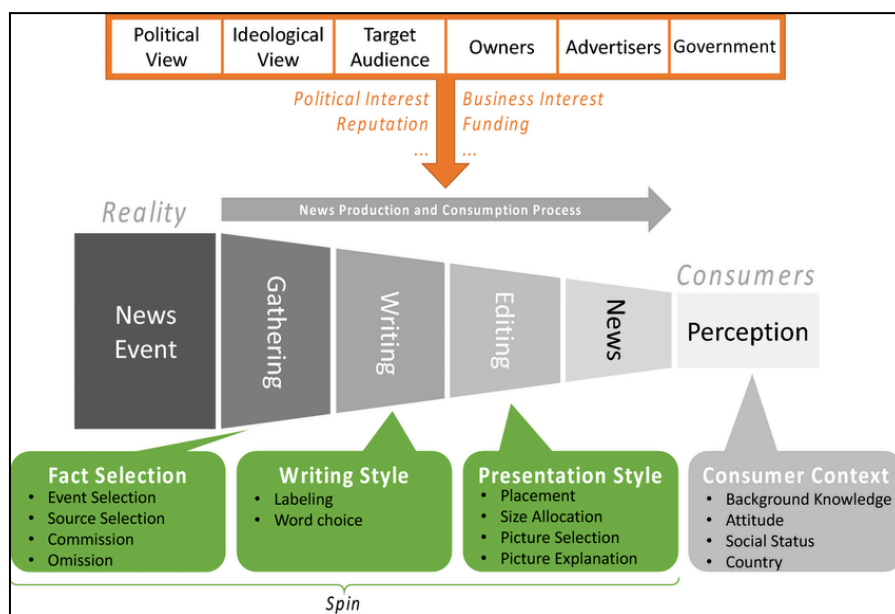

Figure 2. Motives underlying media bias and forms of media bias introduced in the news production process.[7]

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[7] Introduced in Hamborg et al. (2019) and adapted from Park et al. (2009)

2.2 Related Literature Reviews on Media Bias

This section examines existing systematic literature reviews on media bias to situate current research within a broader academic discourse. As already mentioned, similar studies within the field are scarce. Therefore, the author of this thesis has examined all three reviews in detail, compared their methodologies, and assessed the results of their analysis.

The following chapter will then directly discuss the media bias taxonomies that emerged from these researches and were included in the articles. The author focuses on three key titles: *Automated Identification of Media Bias In News Articles: An Interdisciplinary Literature Review published* by Hamborg et al. (2018), *A Systematic Review On Media Bias Detection: What Is Media Bias, How It Is Expressed, And How To Detect It* published by Rodrigo-Ginés et al. (2023), and *The Media Bias Taxonomy: A Systematic Literature Review on the Forms and Automated Detection of Media Bias* published by Spinde et al. (2023). Each review uses different methodologies and proposes different taxonomies of media bias, providing a comprehensive understanding of the field and highlighting areas for further investigation.

2.2.1 Interdisciplinary Approach to Methodology, Hamborg et al. (2018)

The article by Hamborg et al. (2019) aims to develop an interdisciplinary framework for the automated identification of media bias in news articles. The review integrates social sciences and computer science methodologies to create a comprehensive approach to detecting media bias.

In the introduction, the authors distinguish media bias as intentional and unintentional, arguing that unintentional bias can be produced by news values or by the subjective perception of consumers with different backgrounds. Therefore, the research should focus on intentional bias, made consciously by journalists and editors, to influence the final appearance and meaning of the report's content.

In the section dedicated to defining media bias, Hamborg et al. mentions Mullainathan and Shleifer's high-level classification of media bias, proposing two subtypes of intentional media bias: *ideological bias* and *spin bias*. Ideological bias occurs when an outlet biases articles to promote a specific opinion on a topic, while spin bias occurs when

the outlet attempts to create a memorable story (Mullainathan & Shleifer, 2002). Other commonly used subtypes of intentional media bias include coverage, gatekeeping (also referred to as selection bias or agenda bias), and statement bias (also referred to as presentation bias) (D'Alessio & Allen, 2000). However, the authors highlight the challenge of defining "spin bias" due to its vagueness and the lack of standardized criteria for its identification. Further, Hamborg et al. explore various mechanisms of media bias, such as commission and omission of information, labeling and word choice, placement and size allocation, and picture selection.

Hamborg et al. adopt a mixed-methods approach, combining qualitative and quantitative analyses to explore the automated identification of media bias. The article identifies significant gaps and potential in the field of media bias detection. They note that most computer science approaches to analyzing media bias are simplistic and overlook comprehensive models developed in social sciences. Conversely, social scientists often rely on labor-intensive manual content analysis, which hampers progress due to its time-consuming nature. They emphasize the potential for interdisciplinary research, where advanced NLP (natural language processing) techniques from computer science can enhance the efficiency and effectiveness of media bias detection, while social science models can provide the necessary theoretical grounding for these automated methods.

Hamborg et al. propose several areas for further research, including developing more diverse and comprehensive datasets, improving NLP techniques to handle the complexity of media bias, fostering interdisciplinary collaboration, and incorporating user perception variables to gain a deeper understanding of media bias.

2.2.2 A Systematic Literature Review by Rodrigo-Ginés et al. (2023)

The systematic literature review by Rodrigo-Ginés et al. (2023) aims to comprehensively synthesize existing studies on media bias, characterizing and classifying different types of media bias, and exploring state-of-the-art automatic media bias detection systems. The review aims to distinguish between information, misinformation, and disinformation within a theoretical framework and study the latest techniques and datasets used for automatic media bias detection. The article proposes its media bias taxonomy and defines a number of types and subtypes of media bias.

The article employs a systematic review methodology adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. A literature search is conducted through Google Scholar, Scopus, and ACL Anthology databases using keywords related to media bias. The review then includes studies that address media bias detection, particularly those using natural language processing (NLP) techniques. Exclusion criteria were applied to filter out irrelevant studies. Screening the selected studies based on abstracts and full texts were conducted to ensure that selected articles applied to the criteria, following a structured PRISMA flowchart to maintain transparency and replicability.

The review classifies media bias into two types, grouped by *the author's intention* and *the context*.[8] This taxonomy builds upon previous classifications, such as those by Hamborg et al. (2019), highlighting connections and distinctions among various biases. However, in many cases, there is a large overlap between them.

The review also discusses both non-deep learning methods (e.g., linguistic-based methods) and deep learning methods (e.g., RNNs and transformers), highlighting the infancy of current methods and their potential for improvement.

The review thoroughly synthesizes existing literature on media bias and its automatic detection. The review lays a solid foundation for future research and development in this field by categorizing media bias types and reviewing current detection methods. The identified research gaps and proposed future directions offer valuable insights for advancing the accuracy and robustness of media bias detection systems.

2.2.3 A Systematic Literature Review by Spinde et al. (2023)

The article by Spinde et al. (2023) aims to create a comprehensive taxonomy of media bias and evaluate automated methods for detecting these biases. The review seeks to bridge the gap between traditional media bias research and modern computational approaches, offering a unified framework for understanding and identifying media bias in news articles.

Spinde et al. employ a systematic literature review methodology, adhering to established best practices. The methodology includes an automated, keyword-based literature retrieval from academic databases such as DBLP and Semantic Scholar. Search

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[8] Definitions of types and subtypes of media bias proposed by Rodrigo-Ginés et al. (2023) are further discussed in the **Section 2.3.**

terms included combinations of keywords related to media bias and natural language processing (NLP). The review focuses on papers published between January 2019 and May 2022 that address media bias detection using computer science methods. Candidate documents were manually screened to ensure they met the criteria, aiming to mitigate common risks associated with literature reviews, such as incomplete data and selection biases.

The review identifies and categorizes various computer science methods used for media bias detection, providing a detailed taxonomy and reviewing state-of-the-art techniques. They propose a unified taxonomy for the media bias domain, integrating media bias-related concepts from non-technical disciplines such as framing effects, hate speech, and racial bias, addressing ambiguities around various concepts and terminologies used in prior work.[9]

An overview of available datasets for media bias detection is provided in the article, highlighting their characteristics and limitations. It notes the predominance of English language datasets and a heavy focus on political content from the USA. Spinde et al. recognize several types of media bias, categorized primarily based on the detection methods used: selection bias (gatekeeping bias), coverage bias, statement bias (presentation bias), framing bias, ideological bias, corporate bias, geographic bias, spin bias.

Spinde et al.'s review make several significant contributions to the field of media bias detection. Firstly, the proposed unified taxonomy helps mitigate ambiguities around media bias concepts and enhances clarity in future research. By classifying and summarizing computer science contributions to media bias detection, the review provides a valuable resource for researchers and practitioners. Additionally, the review identifies key gaps in current research, such as the need for more diverse datasets and the integration of user and perception-related variables to improve detection accuracy.

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[9] Definitions of types and subtypes of media bias proposed by Spinde et al. (2023) are further discussed in the **Section 2.3.** The table with media bias taxonomy is attached in **Appendices.**

2.3 Media Bias Taxonomy

The answer to the first research question of this thesis lies in finding differences in existing proposed theoretical frameworks and, in this case, in existing taxonomies of media bias. In the study of media bias, taxonomy serves as an essential tool for classifying and understanding the various forms and types of bias. In the two above-mentioned articles (Rodrigo-Ginés et al., 2023; Spinde et al., 2023), taxonomies of media bias have been proposed, including definitions of the concepts involved. The author will now discuss both theoretical propositions in the context of the purpose of coherent taxonomy. The main criterion for evaluating these taxonomies is their utility in the detection and classification of media bias, which requires clear and distinct categories with minimal overlap.

2.3.1 The Media Bias Taxonomy in Rodrigo-Ginés et al. (2023)

The taxonomy by Rodrigo-Ginés et al. (2023) classifies media bias into two primary dimensions. On the one hand, using Mullainathan and Shleifer's definitions as a classification according to the author's intention and, on the other hand, recalls the classification by D'Alessio and Allen and calls it context-based classification. Within these dimensions, they identify various specific types of bias.

Bias According to the Author's Intention

In the intentional dimension, Rodrigo-Ginés et al. distinguish two basic categories of media bias within this taxonomy. Spin bias and ideology bias. Spin bias includes unsubstantiated claims, sensationalism, mind reading, picture explanation, subjective qualifying adjectives, bias by labeling and word choice, flawed logic, omission bias, and commission bias. Ideology bias encompasses similar biases such as unsubstantiated claims, opinion statements presented as facts, sensationalism, ad hominem attacks, mind reading, slant bias, picture selection, subjective qualifying adjectives, bias by labeling and word choice, flawed logic, omission bias, commission bias, bias by placement, size allocation, source selection, and omission of source attribution.

Bias According to the Context

Distinguishing media bias by context, there are three bias categories: coverage bias, gatekeeping (in related literature, also referred to as selection bias), and statement bias (sometimes referred to as presentation bias). Coverage Bias covers picture selection, omission bias, commission bias, bias by placement, size allocation, source selection, and omission of source attribution. Gatekeeping Bias includes source selection and omission of source attribution. Statement Bias comprises unsubstantiated claims, opinion statements presented as facts, sensationalism, ad hominem attacks, mind reading, slant bias, picture explanation, subjective qualifying adjectives, bias by labeling and word choice, and flawed logic.

A significant issue with this taxonomy is the above-mentioned overlap between categories. For instance, if we look at a classification in detail according to the context, source selection appears in both coverage and gatekeeping biases. These categories share many overlapping characteristics and do not offer two clearly distinguishable types of bias. Similarly, unsubstantiated claims, omission bias, and commission bias are listed under multiple categories, blurring the lines between distinct types of bias.

Such overlaps can create confusion and make it challenging to apply the taxonomy consistently, particularly in automated detection systems that require clear, distinct categories to function effectively. The redundancy within the taxonomy diminishes its utility for classification purposes, as it becomes difficult to determine which category a particular instance of bias belongs to.

2.3.2 The Media Bias Taxonomy in Spinde et al. (2023)

Spinde et al. (2023) propose a detailed and comprehensive taxonomy of media bias, categorizing it into four primary types based on their form and conditions of occurrence: Linguistic Bias, Text-Level Context Bias, Cognitive Bias, and Reporting-Level Bias. Additionally, related concepts are included to elucidate the dimensions of media bias further. Below is a precise definition of each main category, along with the types of biases they include. The full taxonomy and all detailed definitions are provided in the appendices.

Linguistic Bias

Linguistic bias refers to biases embedded in the language used within media content. This includes biases that arise from word choice, connotations, and semantic properties, which can influence how information is perceived and interpreted by the audience. Concepts included in the category of linguistic bias are connotation bias, epistemological bias, framing bias, linguistic intergroup bias, and semantic properties. These biases affect the interpretation of information by embedding subtle prejudices within the language itself.

Text-Level Context Bias

Text-level context bias pertains to biases evident at the narrative structure level of media content. This includes biases that arise from the way information is presented within the text, shaping the overall context and narrative of the article. Concepts of text-level context bias include phrasing bias, spin bias, and statement bias. These biases influence the reader's perception by altering how information is framed and highlighted.

Cognitive Bias

Cognitive bias involves biases that affect how individuals process and interpret information. This type of bias is related to the audience's cognitive processes, often reinforcing pre-existing beliefs and attitudes. The category of cognitive bias includes partisan bias and selective exposure. Cognitive biases influence the consumption and interpretation of media content, reinforcing existing viewpoints and creating echo chambers.

Reporting-Level Bias

Reporting-level bias includes biases related to media outlets' selection and presentation of news stories. This category encompasses biases such as coverage bias, proximity bias, and selection bias/gatekeeping. These biases affect which stories are reported and how much prominence they receive, thus shaping the audience's perception of what is important and newsworthy.

Related Concepts

In addition to the primary categories, Spinde et al. (2023) also discuss several related concepts that further elucidate the dimensions of media bias. These include framing effects, hate speech, group bias, and sentiment analysis. These concepts provide additional dimensions to understand the broader impacts of media bias and how it can manifest in various forms.

The taxonomy by Spinde et al. (2023) is comprehensive and includes a wide range of linguistic, contextual, cognitive, and reporting-level biases. However, even this taxonomy is not entirely free from overlaps. Concepts like framing and spin bias can sometimes intersect, as both involve presenting information to promote a particular interpretation.

The media bias taxonomy by Spinde et al. (2023) offers a structured and more distinct categorization in comparison with the taxonomy presented in Rodrigo-Ginés et al. (2023), making it suitable for classification. For this reason, the second-mentioned taxonomy forms the basis for this thesis, which will be discussed in the practical part. The results of the systematic literature search will be used to suggest improvements.
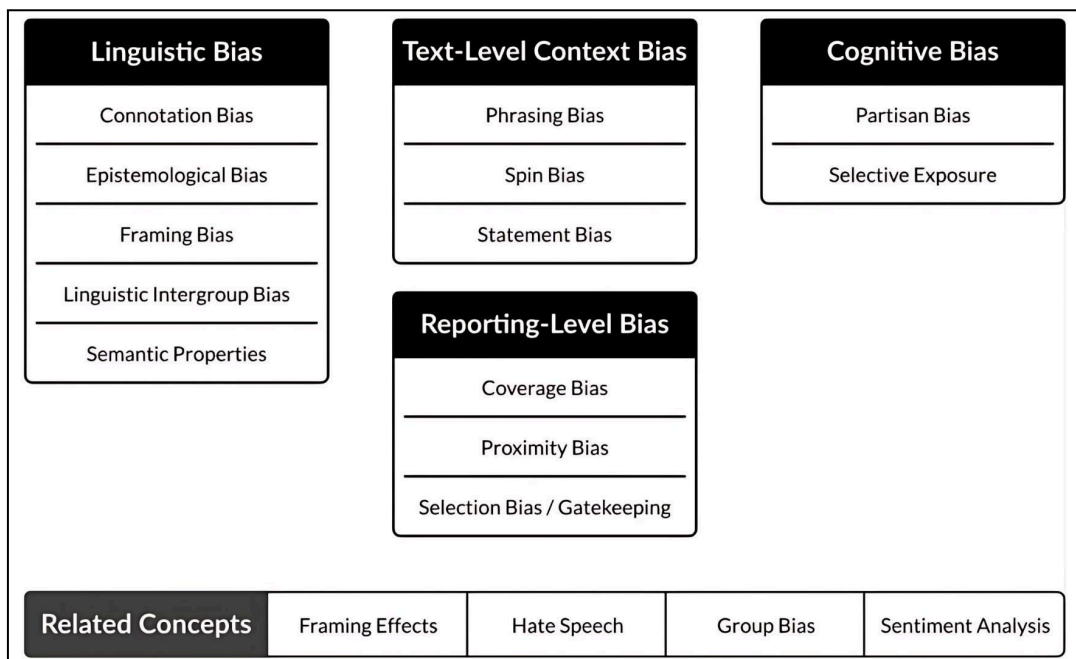
Figure 3. The media bias taxonomy proposed in Spinde et al. (2023).

2.4 Additional Literature

For a comprehensive understanding of media bias, the author of this paper suggests additional literature, ranging from foundational works that examine the role of media in society's cognitive bias to advanced methodologies for detecting media bias. The ideas and concepts mentioned in these titles have served to better understand the whole issue of media bias and offer suggestions for further research in this area.

Herman and Chomsky's (1988) Manufacturing Consent: The Political Economy of the Mass Media provides a critical analysis of media systems and the structural influences that lead to systemic bias. The propaganda model mentioned in the book highlights how media ownership, advertising, and sourcing can influence public opinion.

Denis McQuail's (2010) *Mass Communication Theory* offers an extensive overview of mass communication and its impact on public opinion. An essential and one of the foundational books for media studies, Walter Lippmann's (1922) *Public Opinion* examines how media shapes public perceptions, emphasizing the role of stereotypes and simplification in media content. His concept of "pictures in our heads" is fundamental for understanding how media bias can distort reality and influence discourse.

On the cognitive front, Daniel Kahneman's (2011) *Thinking, Fast and Slow*, along with Tversky and Kahneman's (1974) paper, "*Judgment under Uncertainty: Heuristics and Biases,*" delve into cognitive biases affecting perception and decision-making. Cognitive bias definitely belongs in the context of the taxonomy of media bias, at least in terms of the media consumer's perception and decoding of the content received. It is the set of types of different cognitive biases that is very broad and contributes in no small part to the field of media studies. These works collectively enrich the understanding of media bias from various perspectives.

3. Methodology

3.1 Systematic Literature Review

The methodology employed in this research involved a systematic literature review for the extraction of definitions and subsequent analysis to develop propositions for improvements to the taxonomy of media bias. Systematic literature reviews are a rigorous method for synthesizing research evidence, enabling a structured approach to collecting, evaluating, and integrating findings from multiple studies (Kitchenham et al., 2009; Moher et al., 2009). This section details the steps taken in conducting the literature review, including keyword generation, reference and data collection, and candidate article selection.

3.1.1 Initial Research and Generation of Keywords

The initial steps involved research on the basis of related literature reviews mentioned in **Section 2.2**. As part of this step, a list of keywords contained in the media bias taxonomy by Spinde et al. (2023) was compiled. This process began with the core term "media bias" and expanded to include semantically related terms to ensure broad coverage of the concept and its various dimensions. Keywords were grouped under the following parent categories: linguistic bias, cognitive bias, text-level context bias, reporting-level bias, and related concepts. All subordinate keywords were later included in the base to search for academic references. To expand the list of these keywords, a comprehensive list of concepts related to media bias was generated using ChatGPT.[10]

Utilizing ChatGPT, a list of 200 distinct concepts or phrases was generated for each subordinate keyword. The expansion included terms across several dimensions of media bias, such as political ideology, framing effects, hate speech, group bias, sentiment analysis, cognitive bias, partisan bias, selective exposure, text-level context bias, phrasing bias, spin bias, statement bias, linguistic bias, linguistic intergroup bias, connotation bias,

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[10] ChatGPT streamlines the systematic literature review process by automating tasks such as generating keywords, enhancing accuracy and efficiency. Its proficiency in natural language processing saves time and effort while ensuring reliable outcomes through consistent methodology. Additionally, ChatGPT improves reproducibility by allowing the same procedure to be replicated multiple times with consistent results. The flexibility and reliability of ChatGPT, with human expert reviews, make it a valuable tool across various research domains. (Alshami et al., 2023)

epistemological bias, framing bias, semantic properties, reporting-level bias, coverage bias, proximity bias, and selection bias/gatekeeping.

After the generated list was consolidated, duplicates were eliminated to maintain a set of 3507 keywords. This list was manually scanned; each keyword was individually assessed and then marked by the reviewer as relevant, related, and suitable for possible future exploration or completely irrelevant. The entire process of manually reviewing the keyword list was recorded and stored online. The final number of keywords retained for the next step of the search was 1096.

3.1.2 Generation of References and Data Collection

The subsequent phase in our research methodology involved the generation of references and systematic data collection. This multi-step process was designed to ensure the inclusion of high-quality academic sources and to lay a robust foundation for our literature review.

To begin, we developed a refined prompt for ChatGPT to generate references for each key term related to our study. This prompt included specific fields such as the concept, author, year, title, and a brief summary of the reference. This approach ensured that each concept within our research was linked to a scholarly source, thereby providing a comprehensive and scholarly foundation for our review. Previous studies have highlighted the importance of detailed and structured prompts in enhancing the accuracy and relevance of automated reference generation (Brown et al., 2020).

We selected Semantic Scholar as the primary database for our literature review. Semantic Scholar is a reputable and reliable source widely recognized for its extensive collection of peer-reviewed academic literature (Brereton et al., 2007). This choice was informed by its comprehensive coverage and robust search functionalities, which are crucial for conducting systematic literature reviews. The efficacy of Semantic Scholar in retrieving high-quality academic articles has been validated in various studies (Ammar et al., 2018).

To further ensure the relevance and impact of the selected studies, we set a citation threshold, discarding papers with fewer than 10 citations. This practice, commonly employed in academic research, ensures the inclusion of impactful and widely recognized

studies (Van Eck & Waltman, 2014). Citation analysis is a recognized method for assessing the influence and quality of academic work (Garfield, 2006).

Based on the generated references, 75,151 papers were initially identified. The downloaded papers were categorized across 19 distinct fields of study. From each field, we selected the 700 most cited papers, culminating in a total of 13,300 papers. This selection process was guided by citation counts, a common metric for assessing the influence and relevance of academic papers. Ultimately, 10,200 papers were chosen based on citation count, with approximately 80% having accessible URLs, resulting in a final collection of 8,218 articles. The process of leveraging citation counts to select high-impact papers is supported by extensive literature (Bornmann & Daniel, 2008; Waltman, Van Eck, & Noyons, 2010).

3.1.3 Candidate Articles Selection

To capture relevant literature comprehensively, we employed systematic search strategies as outlined by established methodologies (Petticrew & Roberts, 2006). Searches were conducted using generated keywords, ensuring a broad yet focused retrieval of pertinent studies. Titles and abstracts were screened to exclude irrelevant studies, following a structured screening process based on predefined inclusion and exclusion criteria (Higgins & Green, 2011).

To maintain the quality and credibility of our sources, we established stringent inclusion and exclusion criteria. Only peer-reviewed articles and publications were considered. Inclusion criteria were defined to select papers that focused on media bias, its various forms, and detection methods, as well as explicit definitions or taxonomies of media bias and methodologies applicable to automated media bias detection.

Conversely, papers were excluded if they did not provide substantial information on media bias, were not peer-reviewed, and were deemed irrelevant based on title and abstract screening. The importance of using peer-reviewed sources is well-documented in ensuring the reliability and validity of academic research (Björk & Solomon, 2013).

To manage the extensive literature volume, articles were distributed among six reviewers using a Python script. This script ensured proportional representation of all disciplines and citation levels, a method that aligns with established practices for

maintaining diversity and balance in systematic reviews (Liberati et al., 2009). The articles were divided into five categories based on the number of citations, ensuring that each category was proportionally represented among the reviewers. This stratified distribution approach is supported by literature indicating that citation levels often correlate with the impact and quality of research (Bornmann & Daniel, 2008).

The manual review process was essential for ensuring each selected article's methodological rigor, relevance, and contribution. Instead of automated filtering, manual review allows for a nuanced evaluation of each study's methodology and findings (Gough, Oliver, & Thomas, 2017).

A random sample was selected during the research to reduce the workload. After the initial automated filtering, distribution, and random selection, the final number for manual review of articles was 2498.

Of the 2498 articles reviewed, only 118 were marked as relevant. This rigorous screening ensured that only the most pertinent studies were included in the final analysis. From these 118 articles, 169 explicit or implicit definitions of media bias and related concepts were manually extracted. After the peer review, a set of 133 definitions was selected for further analysis. This detailed extraction process was crucial for a comprehensive understanding of the concept under study (Popay et al., 2006).

The definitions were systematically extracted from the selected articles. The extracted data formed the basis for subsequent analysis and the development of the proposed taxonomy. Systematic data extraction and synthesis are well-established practices in literature reviews to ensure that all relevant information is captured and analyzed (Thomas & Harden, 2008). A detailed description of the definition of extraction itself is described in the following section.

3.2 Definition Extraction

The guidelines for manual definition extraction have been crafted to guide reviewers through identifying relevant definitions across the searched studies.[11] According to Moher et al. (2009), well-defined extraction guidelines are crucial in systematic literature reviews to ensure consistency, reliability, and comprehensiveness in the data collection process.

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[11] The established guidelines for manual definition extraction are described in **Section 3.2.3**.

Our guidelines outlined a structured approach to extracting definitions of types of media bias and related concepts from the academic literature. The goal was to assemble a list of definitions used in the selected papers.

3.2.1 The Definition Criteria

The definition should be written in simple, direct, and specific language that accurately focuses on facts, evidence, and logical reasoning. It should avoid vague, complex, or ambiguous language that may confuse or mislead readers. However, definitions like this are not always used in existing literature. Therefore, from case to case, researchers were required to extract the definition indirectly or *implicitly*, using their own words.

The Cambridge Dictionary defines a definition as "a statement or rule that establishes the meaning of a concept and sets the boundaries for what does and does not belong to that concept".

Since there are many definitions of the definition itself, and they are often very broadly interpretable explanations, it is necessary to look at the properties and characteristics of a precise definition. The research incorporated four main criteria for a proper definition: comprehensiveness, precision/accuracy, consistency, and circularity (Wong et al., 2014). This ensured that the definition could be easily understood by a wide range of readers, from experts in the field to novices seeking foundational knowledge.

These criteria, based on rules generally accepted by the academic community, are appointed in the article *A Framework for Defining Scientific Concepts in Science Education* by Wong et al. (2020), which looks specifically at the essential characteristics of definitions and the creation of definitions across different scientific disciplines.

1. **Comprehensiveness**

A comprehensive definition must include all necessary features that collectively describe the full scope of a scientific concept. It should encapsulate sufficient elements to afford a complete understanding while being flexible enough to incorporate standard features relevant to the concept. The attributes within this definition should be atomic, meaning they cannot be further subdivided.

2. **Precision**

The terms and descriptions used are specific and unambiguous, limiting the potential for multiple interpretations. The definition defines only one term and uses only already defined terms (e.g., generic terms). The generic terms are as specific as possible, and the attributes do not extend the generic term.

3. Consistency

Consistency in definitions is crucial for maintaining uniformity within and across various contexts where the concept is applied. A consistent definition aligns with other related definitions within the field, preventing conflicts and confusion and ensuring the concept is uniformly understood across different studies and applications. Consistency is achieved by using standardized terminology and concepts, adhering to widely accepted criteria, and ensuring the definition does not deviate from established norms in the field.

4. Circularity

A definition should rigorously avoid circular reasoning; it must not use the defined term or rely on its close synonyms within the explanation. This ensures the definition is self-contained, providing a clear and standalone explanation without presupposing prior knowledge. By avoiding references to itself or its direct derivatives, the definition stands independently, facilitating a better understanding and preventing logical fallacies.

3.2.2 Examples of Extracted Definitions

Here are three examples of bias definitions evaluated according to the abovementioned criteria. These examples were part of the manual definition extraction instructions and served as a representative case for the reviewers. The concepts were randomly selected from the list of keywords related to media bias. The first two examples represent a case of extracted explicit definition of *content bias*. The first example illustrates the failure to meet two of the criteria (1 and 2). The second example represents extracted definitions that met all four required criteria to be included in the final list of definitions. The third example represents an extracted implicit definition of *negativity bias* that meets all criteria.

Example 1

Explicit definition of *content bias*: „Consistent patterns in the framing of mediated

communication that promote the influence of one side in conflicts over the use of government power." (Entman, 2007)

1. The definition considers content bias only in the context of political competition.

2. The definition uses the term "framing," which might require further clarification.

3. The definition is consistent.

4. The definition is non-circular.

The problem with this definition lies in the failure to meet criteria 1 and 2. The term "framing" cannot be considered a generic term and should be replaced. The definition also focuses purely on the media's view of the competition between political parties for governmental power, and it leaves out other situations where content bias may play a role. Content bias, however, by its very nature, can be reduced to bias in any content form. However, our study will also focus on more complex concepts. The first example suggests that we need to focus on studies dealing with concepts more broadly.

Example 2

Explicit definition of *content bias*: „The introduction of one-sided rather than two-sided information." (List et al., 2022)

1. The definition is comprehensive.

2. The definition is precise.

3. The definition is consistent.

4. The definition is non-circular.

Although very brief, this definition of content bias is simple, uses as few attributes as possible, and meets all the criteria.

Example 3

Implicit definition of *negativity bias*: "A psychological phenomenon where negative stimuli disproportionately affect an individual's emotional and cognitive responses compared to positive or neutral stimuli of similar intensity." (Baumeister et al., 2001)

The implicit definition was extracted from the following paragraph: „A motivational account of the differential effects of bad versus good has been proposed by Cacioppo and colleagues (...). They proposed a negativity bias in the model of evaluative space, such that comparable degrees of activation have greater effects on the negative, as opposed to the positive, motivational system. Accordingly, there is a steeper slope for the relationship between the activation and motivational response to negative stimuli. Several investigations have confirmed this negativity bias.“

1. The definition is comprehensive.

2. The definition is precise.

3. The definition is consistent.

4. The definition is non-circular.

Extracting implicit definitions from scientific articles is challenging due to their nuanced, context-specific nature and inherent subjectivity. Bazerman (1988) notes that scientific discourse demands advanced interpretation skills, leading to ambiguities without sufficient background knowledge. Swales (1990) adds that definitions often embedded in broader rhetorical structures complicate their extraction, resulting in worse replicability due to inconsistent terminology. We have taken note of these facts when recording our progress. Each extracted definition was therefore marked as either "explicit" or "implicit" so that their possible inaccurate formulation could be taken into account when analyzing the results of the literature review

3.2.3 Manual Definition Extraction Guidelines

This section outlines the systematic approach adopted for the manual extraction of definitions from the selected academic literature. The guidelines were developed to ensure that the process was consistent, transparent, and replicable, which are crucial aspects of a robust systematic literature review (Kitchenham & Charters, 2007). By maintaining a log of decisions and adhering to a structured methodology, we ensured that the process remained justifiable and auditable.

Step 1: Title and Abstract Review

The first step involved screening the articles based on their titles and abstracts. Researchers were tasked with understanding the type of media bias targeted in each paper. This initial screening was crucial in filtering out irrelevant studies, thereby focusing only on pertinent articles that addressed concepts related to media bias. If an article did not appear relevant after this screening, it was marked as non-relevant, and the researcher moved on to the next one. This process was rigorously documented to maintain a comprehensive audit trail, as recommended by Moher et al. (2009). Recording the inclusion and exclusion of papers ensured transparency and facilitated any future reviews or audits of the selection process.

Step 2: Full-Text Review

Once the relevant articles were identified through the title and abstract review, researchers proceeded to a detailed full-text review. This step required a meticulous search for keywords within the text and an examination of the context in which these keywords were mentioned. Special attention was given to critical sections of the text, such as the introduction and theoretical framework chapters, where definitions are often logically situated to provide the reader with foundational knowledge of the research topic. This practice was based on the observation that definitions tend to cluster in specific sections of scientific discourse, making these areas particularly fruitful for definition extraction. (Flowerdew, 1992)

Step 3: Definition Identification

After identifying the relevant sections, the next step was the identification of definitions. Researchers were instructed to look for explicit definitions first. An explicit definition was defined as a clear and direct statement that establishes the meaning of a concept. If an explicit definition was found, researchers also checked the paper for any other related definitions to ensure comprehensiveness.

In cases where explicit definitions were absent, researchers inferred implicit definitions from the context. This required summarizing the concept in their own words while ensuring alignment with academic criteria for good definitions derived from Wong et al. (2014) and mentioned in **Section 3.2.1**.

Each extracted definition was then evaluated using a checklist to ensure that it met all aspects of an acceptable definition. The checklist included the following questions:

- Does the definition encapsulate all essential elements and variations of the concept?
- Are the terms used specific, well-defined, and unambiguous?
- Does the definition align with established definitions in the field?
- Is the definition independent of the term being defined and its synonyms?
- Is the definition straightforward and free from unnecessary terms?

Step 4: Documentation

Once the definitions were identified and evaluated, they were meticulously documented in a provided spreadsheet. This documentation process included listing each definition alongside the title of the paper, the authors, and the year of publication. Proper documentation is critical for ensuring that the definitions can be referenced accurately in future research and analyses. This step also aligns with practices in systematic reviews, which emphasize the importance of accurate record-keeping (Liberati et al., 2009).

Step 5: Peer Review

The final step in the extraction process was a peer review of the extracted definitions. This review was essential to verify the accuracy and adherence to the initial extraction guidelines. Peer reviewers used the above-mentioned checklist to critically evaluate each definition, ensuring that all aspects were covered and identifying areas for improvement. This step was crucial for maintaining the integrity and reliability of the definitions, as peer review is a well-established method for enhancing the quality and credibility of academic research (Gough, Oliver, & Thomas, 2012).

The manual extraction of definitions from academic literature on media bias was a critical step toward developing a comprehensive and unified taxonomy. By following these structured guidelines, the research ensured that the extracted definitions were precise, consistent, and comprehensive, providing a solid foundation for subsequent analysis and the proposition of improvements to existing theoretical frameworks.

1. Preliminary Research

Review of relevant work and extraction of keywords. Utilizing ChatGPT, a list of keywords was expanded to a list 3507 keywords.

2. Keyword List Review

After a manual review, the list of keywords was narrowed to a number of 1096 keywords.

3. Reference Generation

To each of 1096 keywords, an academic reference was searched using ChatGPT.

4. Crawl

Based on the generated references, 75,151 papers were initially identified. on Semantic Scholar database.

5. Filter by Citation Count

The papers were categorized across 19 distinct fields of study.
From each field, the 700 most cited papers were selected, culminating in a total of 10 200 papers.

6. Accessibility and Workload Reduction

8218 papers had accessible URLs. The number was reduced to 2498 papers by random selection considering the workload for reviewers.

7. Candidate Article Selection

The set of 2498 papers was reviewed by 6 reviewers, who marked 118 papers as relevant to the media bias research.

8. Definition Extraction

After the definition extraction and peer-review of results, the list of 133 relevant definitions was completed.

10. Analysis of Results

The list of definitions was analyzed together with the results of taxonomy evaluation.

9. Media Bias Taxonomy Evaluation

The existing media bias taxonomy was evaluated on the basis of manual classification of two news articles.

11. The Proposition of Improvements

Based on the results of the analysis, improvements and suggestions for the addition of concepts to existing taxonomy were proposed.
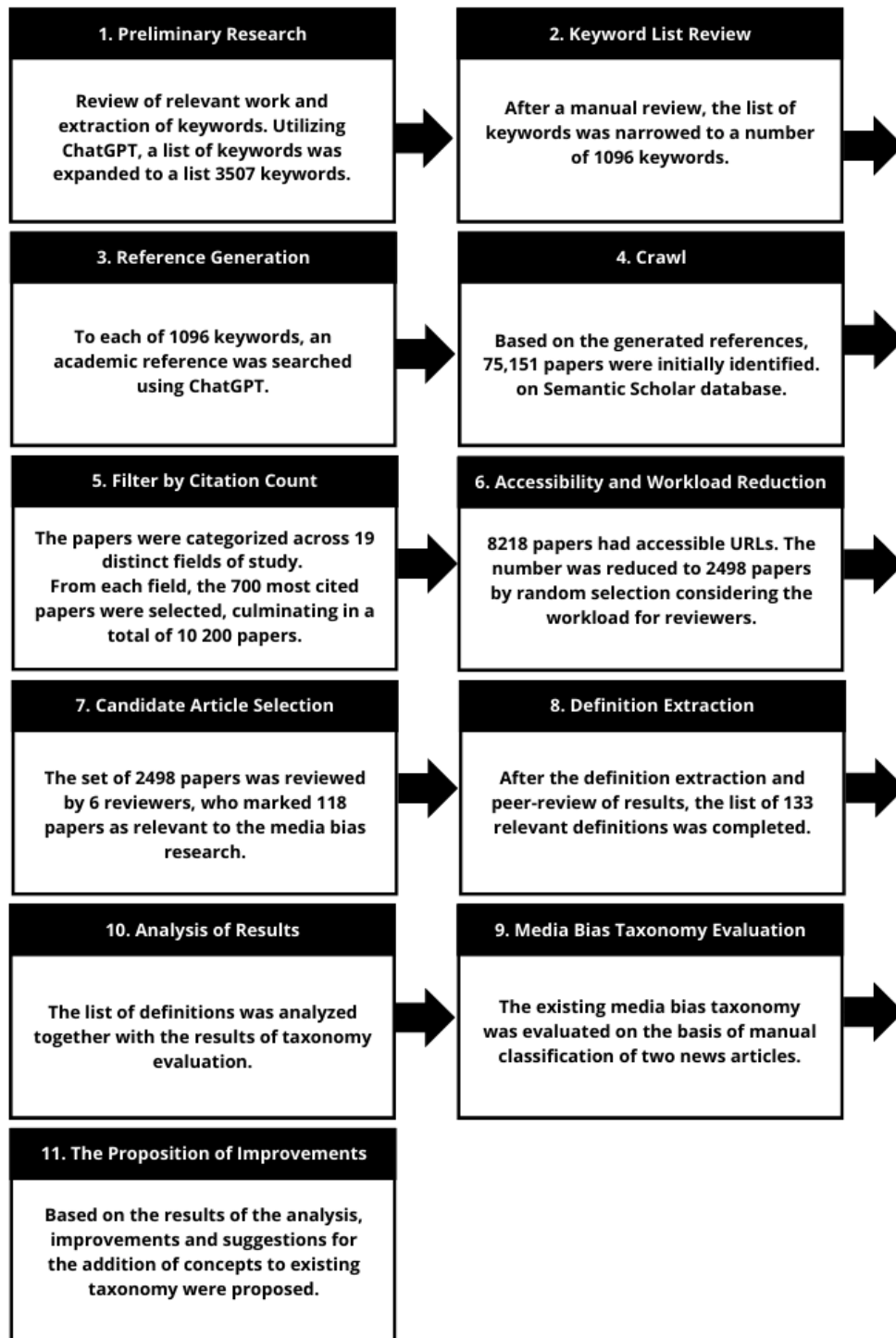
Figure 4. The figure shows the steps of the systematic literature review and subsequent analysis of the results, including the evaluation of the existing media bias taxonomy.

4. Analysis and Interpretation of Results

4.1 The Evaluation of Media Bias Taxonomy by Spinde et al. (2023)

Before the author proceeds to the interpretation of findings from the literature review, the evaluation of Media Bias Taxonomy by Spinde et al. (2023) is crucial for understanding its applicability and limitations. By manually classifying news articles, the author identifies areas where the taxonomy excels and falls short. This evaluation provides insights into the comprehensiveness of the existing definitions, the presence of nuanced details, and the potential overlaps and differentiations within the taxonomy. The classification was done manually on only two short news articles and, therefore, may show signs of subjectivity, which on the other hand, may have shown clear ambivalence and overlapping of some concepts from the point of view of the media consumers. Also, the annotated articles did not include all the media bias types listed in the taxonomy, and thus the classification mainly focused on the categories of linguistic and text-level context bias.

The evaluation was conducted by applying its classification to two selected articles: "*NATO Allies' View of Biden's Debate Performance Seen as Alarming*" from CNN.com and "*Polish Official Compares Biden to Commodus, the 'Gladiator' Emperor*" from FoxNews.com. This analysis aimed to identify the limitations of the taxonomy in detecting and classifying various types of media bias and propose necessary improvements based on empirical evidence.[12]

Both articles demonstrated several types of media biases that aligned with the categories in Spinde et al.'s taxonomy. However, the classification process highlighted several limitations in the taxonomy. The distinctions between various biases are not always clear-cut, leading to overlaps. The major limitation of the taxonomy concerns categories of linguistic bias and text-level context bias. The subjective language used in framing bias can also be seen as epistemological or connotation bias while having an influence on the final tone of the statement, potentially creating a spin bias in the whole text-level context. These overlaps complicate the manual classification process and may result in ambiguous and subjective results. Biases such as selection bias and coverage bias are also interrelated, making it difficult to categorize certain instances strictly under one type. Within the

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[12] The two media bias text-analyses that aimed to classify media bias in articles according to the media bias taxonomy of Spinde et al. (2023) are attached in **Appendices**.

reporting-level bias category, the decision on what to report (selection bias) directly influences how much attention different sides of an issue receive (coverage bias). Cognitive biases like selective exposure and partisan bias are more about the reader's behavior than the content itself, making them unfit for manual classification within one news article. Yet, they are essential for understanding the impact of media bias comprehensively. The author has no objection to this category regarding the manual classification, but the category of cognitive bias could be expanded to include several other concepts.

The taxonomy includes fine-grained categories that are challenging for subjective manual annotation. Separating framing bias from connotation bias, for instance, requires nuanced judgments. This granularity increases the complexity of bias detection and classification. While the taxonomy is comprehensive, detecting and categorizing biases manually can be challenging, especially given the overlaps and subtle differences. Automated systems may also struggle with the nuanced distinctions between different bias types.

Spinde et al. (2023) acknowledge several limitations in their literature review and taxonomy. They note that they excluded work from areas other than media bias due to the high number of publications involved, potentially leaving out valuable contributions. Additionally, they only included literature from 2019 to 2022 for computer science methods, excluding valuable earlier research. Spinde et al. also recognized in their discussion that, although they distinguish several categories within their taxonomy, the concepts related to media bias still overlap and appear concurrently.

4.2 Analysis of Extracted Definitions

As mentioned in **Section 3.1.3**, 169 definitions of media bias and related concepts were extracted from the systematic literature review. These definitions were peer-reviewed and categorized. After further refinement, the set of 133 definitions was included in the final analysis. This careful selection process ensured that the definitions used in this study were both comprehensive and relevant. The rigorous screening and selection processes are essential to ensure the validity and reliability of systematic reviews (Gough, Oliver, and Thomas, 2017). Although the final number of definitions included in our analysis is 133,

several concepts were defined multiple times. For example, the concept of "frame" had multiple acceptable definitions emphasizing different elements such as linguistic choices, narrative structures, and contextual framing. In total, the resulting list contains 108 unique defined concepts.

To systematically analyze the extracted definitions, the author categorized them into four main groups: Conceptual Framework/Related Concepts, Text-Level Media Bias, Reporting-Level Media Bias, and Audience and Reception/Cognitive Bias. This categorization is instrumental in organizing the definitions for analysis and is not intended as a final proposition for changing the existing media bias taxonomy. It serves as a framework to facilitate a deeper understanding of how different types of biases manifest and interact within media content.

The instrumental categories used in this analysis are based on the main categories in the media bias taxonomy proposed by Spinde et al. (2023). Their taxonomy, among other classifications, distinguishes between Linguistic Bias and Text-Level Context bias. For the purpose of this study, the author merged linguistic bias and text-level context bias into a single category called "Text-Level Bias." This decision was made to simplify the analysis and focus on the most relevant aspects of media bias in the context of our research.

The criteria for selecting the most pertinent definitions for the final analysis were guided by the need to fill gaps in the existing taxonomy proposed by Spinde et al. (2023). Specifically, the author focused on definitions that had the potential to enhance the comprehensiveness and applicability of the current taxonomy. This selection was informed by the literature review conducted by Spinde et al. and aimed at addressing areas where existing definitions were either lacking or insufficiently detailed or their mutual differentiation was complicated by too much overlap.

The selection process prioritized definitions that could provide more detailed insights into areas that were underrepresented in the existing taxonomy. For example, Spinde et al. (2023) highlighted the need for more nuanced definitions of cognitive biases and their impact on media consumption. Therefore, the author included definitions that offered a deeper understanding of these biases and their manifestations in media contexts.

Another key criterion was the applicability of definitions to empirical research and practical analysis. The author selected definitions that were not only theoretically robust

but also practically useful for identifying and categorizing media biases. This involved choosing definitions that were clear, specific, and operationalizable in research settings. Definitions that provided concrete examples or mechanisms of bias were particularly valued for their practical utility.

After applying these criteria, the author categorized the final count of definitions in each category as follows:

1. **Conceptual Framework/Related Concepts**: 51 definitions
2. **Text-Level Media Bias**: 30 definitions
3. **Reporting-Level Media Bias**: 23 definitions
4. **Audience and Reception/Cognitive Bias**: 29 definitions

The first step in our analysis was to examine each definition within its created category. This involved a detailed review of the terms, contexts, and examples provided in the definitions. The author aimed to identify patterns, similarities, and differences among the definitions to understand how they contribute to our overall understanding of media bias.

Given the number of extracted definitions, the author focuses only on a representative selection of definitions within each category to provide a thorough and manageable overview in the following paragraphs. Such a strategy is justified in qualitative research as it enables in-depth analysis and understanding of core concepts while maintaining clarity and focus (Miles, Huberman, & Saldana, 2014). The selection approach is also supported by Tranfield, Denyer, and Smart (2003), who emphasize the importance of prioritizing the most relevant and impactful data in systematic reviews to maintain clarity and focus in the analysis.

1. **Conceptual Framework/Related Concepts**

This category encompasses broad theoretical constructs and overarching ideas that form the foundation of media bias studies. These concepts provide essential context and a deeper understanding of the mechanisms and implications of media bias. Definitions often focus on overarching ideas and theories that are related to media bias. These included

concepts such as disinformation, propaganda, misinformation, public opinion polarization, and systematic bias.

By analyzing these definitions, we could see patterns of the description and explanation of bias in the media. For instance, **disinformation** refers to misleading information deliberately aimed at deceiving others (Giglietto, Iannelli, Valeriani, & Rossi, 2018). This concept is critical in understanding media bias, especially in the context of political communication and social media, where intentional efforts to mislead can have significant implications for public opinion and democratic processes. **Misinformation** is false or inaccurate information spread without malicious intent, as highlighted by Giglietto et al. (2018). **Propaganda**, defined as information, especially of a biased or misleading nature, used to promote a political cause or point of view, plays a significant role in shaping public perception and behavior (Herman & Chomsky, 1988). **Public opinion polarization**, discussed by Baldassarri and Gelman (2008), refers to the divergence of public attitudes towards opposite extremes, illustrating the impact of media bias on societal divisions. **Systematic bias**, referring to consistent and repeatable errors introduced by external factors, is another critical concept that underpins our understanding of media bias. These concepts collectively underscore the theoretical basis, broad applicability, and foundational nature of definitions in this category, serving as the bedrock for more specific biases.

2. Text-Level Media Bias

This group of media bias types focuses on biases that occur within the texts, such as news articles or reports. These biases are embedded in the language and structure of the text, influencing how information is presented and perceived. The Text-Level Media Bias category included definitions that highlighted specific linguistic and contextual elements. The analysis revealed common themes such as word choice, tone, and the framing of stories.

For example, one of the definitions of **framing** refers to the way information and events are presented to influence audience perception (Stokes & Warshaw, 2017). This concept is crucial in media studies, as it dictates the perspective from which a story is told. Understanding framing helps identify subtle biases that shape public understanding.

Another example is **stance**, which refers to the position or attitude of the writer towards the subject matter (Johnstone, 2009). Stance can reveal the underlying biases of the author and the media outlet, making it essential for understanding how subjective viewpoints are conveyed in ostensibly objective reports. The category also includes **labels**, which involve the use of specific terms to describe people, events, or issues in a biased manner (Pescosolido & Martin, 2015); **gossip**, referring to informal and often speculative communication about others (Martin, Borah, & Palmatier, 2017); and **hate speech**, defined as language that disparages a person or a group based on a characteristic such as race or religion (Davidson, Warmsley, Macy, & Weber, 2017). These elements are crucial in shaping audience perceptions and can subtly influence the interpretation of news. The linguistic features, contextual presentation, and immediate impact of these definitions highlight the importance of text-level biases in influencing how the audience receives and understands information.

This category should be the most represented within the classification of media bias in news articles as it directly addresses the content itself. Unfortunately, the results of the literature review did not offer a satisfactory number of definitions in this category and thus did not cover the full scope of definitions needed to achieve a representative overview.

3. Reporting-Level Media Bias

Biases related to the processes and decisions made during news reporting and production were included in this category. These include biases in story selection and agenda-setting, which affect the overall presentation of news content. Definitions focused on the practices and decisions made by journalists and media organizations. This category included biases related to source selection, story prominence, and editorial choices.

Gatekeeping, for instance, refers to the process by which journalists and editors select which news stories to cover and which to omit (Shoemaker & Vos, 2009). Gatekeeping highlights the power of media professionals in shaping the news agenda, making it critical to understand which issues gain public attention and why. **Agenda setting**, defined as the ability of the media to influence the importance placed on the topics of the public agenda, is another fundamental concept. McCombs and Shaw (1972) illustrate how media attention influences public perception of what is important. Both

definitions (gatekeeping and agenda setting) can be interchangeable and are an example of conceptual fragmentation in the literature.

Additional examples include **coverage bias**, which involves the disproportionate emphasis on certain stories or issues (Quail et al., 2012), and **selection bias**, referring to the selection of stories that align with the outlet's editorial stance or audience preferences (Smith, McCarthy, McPhail, & Augustyn, 2001). These definitions collectively emphasize the editorial decisions, institutional influence, and long-term impact of reporting-level biases, highlighting how media organizations can systematically influence public perception through their choices.

4. Audience and Reception/Cognitive Bias

The last recognized category encompassed definitions that dealt with how audiences receive and process media content. This included cognitive biases such as confirmation bias, echo chamber, selective exposure, illusory correlation, and ingroup bias. **Confirmation bias** refers to the tendency to seek or interpret evidence in ways that are partial to existing beliefs (Nickerson, 1998). This bias is crucial for understanding how audiences interact with media, as it explains why individuals may prefer media that aligns with their viewpoints, leading to polarized opinions. The **echo chamber**, defined as an environment where individuals are exposed only to information that reinforces their pre-existing beliefs, further amplifies this bias by limiting exposure to diverse perspectives. Nguyen (2018) examines how echo chambers in social media create polarized communities. **Selective exposure** involves the tendency to favor information that reinforces existing views while avoiding contradictory information (Borgesius et al., 2016). **Illusory correlation** refers to the perception of a relationship between two variables when no such relationship exists (Hamilton & Gifford, 1976). **Ingroup bias**, defined as favoring members of one's own group over those in other groups, highlights how social identity influences media reception. Jost, Banaji, and Nosek (2004) provide insights into how ingroup bias affects intergroup relations and media perception. The psychological processes, perceptual filters, and behavioral outcomes associated with these biases demonstrate how cognitive biases shape individual processing of information and reinforcement of pre-existing beliefs and attitudes.

4.3 The Interpretation of Results

This section addresses the research questions posed at the outset of this study by interpreting the results of the systematic literature review and the subsequent evaluation of Spinde et al.'s (2023) Media Bias Taxonomy. The author aims to identify the variation in definitions across studies, the methodological challenges in integrating different theoretical approaches, and the principles underlying a unified media bias taxonomy. The author highlights key findings and discrepancies that inform our proposed improvements by comparing the definitions extracted from the literature with those in Spinde et al.'s taxonomy.

RQ1: The systematic literature review revealed significant variation in definitions of media bias and conceptual frameworks across different studies. This diversity reflects the complexity of media bias as a phenomenon influenced by various cultural, political, and methodological contexts. For example, while some studies emphasize linguistic features and framing (Entman, 1993), others focus on cognitive biases and audience reception (Nickerson, 1998). The differences in emphasis and scope among these definitions indicate that media bias is a multi-faceted issue requiring a comprehensive and nuanced taxonomy (Entman, 2007).

RQ2: Integrating different theoretical approaches to media bias into a unified taxonomic structure poses several methodological challenges. One primary challenge is the overlap between categories, such as framing bias and connotation bias, which often complicates the classification process (Spinde et al., 2023). Additionally, the granularity of categories in existing taxonomies, like Spinde et al.'s, can lead to subjective judgments in distinguishing bias. The interrelated nature of cognitive biases, such as selective exposure and partisan bias, further complicates the integration, as these biases are more about reader behavior than the content itself (Shoemaker & Reese, 1996).

RQ3: Based on the analysis, a unified media bias taxonomy should adhere to several principles:

1. **Comprehensiveness:** The taxonomy must contend the full scope of media biases.

2. **Distinctiveness:** Categories should be clearly defined with minimal overlap to reduce ambiguity in classification.

3. **Context Sensitivity:** The taxonomy should account for contextual influences, such as information sources, information bias, and factuality.

4. **Practical Utility:** The taxonomy should apply to theoretical research and practical applications, providing clear guidelines for identifying and categorizing biases.

The comparison of the extracted definitions with those in Spinde et al.'s taxonomy highlights several key findings and discrepancies. While Spinde et al.'s taxonomy provides a structured approach to identifying media biases, our analysis revealed areas where the taxonomy could be improved.

The current taxonomy exhibits significant overlap between various types of biases, such as framing bias and connotation bias. This overlap complicates the classification process and makes it challenging to distinguish between different types of biases accurately. Certain biases, particularly connotation bias or selection bias, require more detailed subcategories to capture their nuances effectively. The existing taxonomy does not fully account for the factual and informational contexts on media bias, which is crucial for a comprehensive understanding.

The analysis indicates that while Spinde et al.'s taxonomy is an unprecedented and valuable tool for systematic media bias analysis, it requires enhancements. Specifically, reducing the overlap between categories, increasing the granularity, and incorporating contextual dependencies would improve the taxonomy's clarity and applicability.

4.4 Proposition of Improvements to the Media Bias Taxonomy

A coherent and comprehensive taxonomy is crucial for effectively classifying and detecting media bias, especially in automated systems. (Spinde et al., 2023) Clear distinctions between categories ensure that biases can be accurately identified and classified, reducing the risk of misclassification.

Overlapping concepts can lead to ambiguity, making it difficult to develop automated detection systems and algorithms that can consistently and accurately detect bias. For example, if omission bias is classified under multiple categories, an automated system might struggle to determine which category an instance of omission bias belongs

to. Classification of bias is then highly context-specific, and one type may imply multiple outcomes. On the other hand, some degree of interchangeability of terms is inevitable when trying to achieve a comprehensive taxonomy. Whether it is classification at the level of the context of the whole text or at the level of individual selected words and phrases. The choice of words will always have an impact on the tone of the whole sentence, which further affects the tone of the whole paragraph and so on. Thus, the newly proposed taxonomy should not attempt to eliminate these overlaps altogether but to minimize them to a distinguishable level that is justifiable in the context. The author compiled the following suggestions not only on the basis of the results of a systematic search, which did not cover the full range of necessary definitions but also on the basis of deeper knowledge gained through the study of related literature.

1. Text-level Bias

The categories most concerned with the problem of overlapping definitions are text-level context bias and lexical (linguistic) bias. The author kept this fact in mind when making the following suggestions. Therefore, he focused on nuances in the existing taxonomy where the overlap of definitions is redundant.

The author proposes to treat the categories of text-level context bias and lexical bias as one coherent category of **text-level bias** with multiple levels. To define these levels, the author proposes to use individual articles of syntax: words, phrases, clauses, sentences, paragraphs, and finally, the text as a whole. Breaking the text down into these individual blocks then makes it easier to relate the different types of media bias to them and to make clear where the types overlap and how they relate to each other. The approach the author proposes is thus as follows: mapping the sequential relationships of the lowest links of the text syntax structure to those above them and then doing the same on the level above.

Logically, then, there should be most types at the lowest level. Here the author recommends distinguishing connotation bias when it deals with emotionally colored words implying **negative** or **positive** emotions, with a focus on adjectives. The next level should then be phrases within sentences and their framing. On this level, the author suggests the identification of **the level of persuasion** in the text, i.e. phrases that are explicitly trying to change the audience's opinion or viewpoint by their sound.

Regarding the level of the context of the whole text, the author recommends adding the concept of **informational bias**, which would allow the classification of the whole text within the completeness of its factuality, regarding the relevancy of information within the context, possible omission of information, or presenting misinformation, or disinformation. This concept is already mentioned in Spinde et al. (2023) and listed as a possible sub-concept in the Text-Level Context category. However, in the context of bias detection, this concept would be more challenging to classify because it would require a reliable fact-checking system.

2. Reporting-level Bias

As for the reporting-level bias category, the author sees no major flaws in the taxonomy of Spinde et al. here. However, the category could be understood more as a description of a process and its individual concepts as a part of it. The classification of the individual phenomena would then place these phenomena on the timeline of the gatekeeping process and reveal at what point in time the bias was created. Thus, the author proposes to design the information flow model. An example of such a model follows based on the definitions obtained and the literature reviewed:

A real event occurs → Information about the event is picked up by news agencies from local journalists. → Staff journalists take over the information from news agencies → Information is finalized by editors. → Information reaches the audience.

Within this model, and with access to the possible first interpretation of the real event, we can further classify where particular information was omitted (omission bias), where facts that were mentioned in the text were missing in the original report (informational bias), and when and what view of the event was highlighted (coverage bias, spin bias). Within this process, the author proposes the inclusion of the concept of **inter-media agenda setting**, which emphasizes at what level (i.e. already at the level of the reception of information by a medium from another medium) the bias occurs. However, there may be several variations of models of information flow, depending on the origin of the information and, especially in the context of social media, on its virality.

The model of information flow from an event to the final consumer is well-supported by key theories in media studies. Robert M. Entman's concepts of agenda setting, framing, and priming explain how media shapes public perception by determining which issues are highlighted, how they are presented, and what aspects are made more salient in people's minds. Shaw and McCombs' agenda-setting theory further emphasizes the media's role in influencing public priorities. McQuail's Mass Communication Theory provides a comprehensive framework, noting that media not only inform but also shape audience understanding through these processes.

Adding to this, Lazarsfeld's two-step flow model suggests that information first reaches opinion leaders, who then interpret and disseminate it to their networks, highlighting the mediating role of influential individuals. Shoemaker and Vos' gatekeeping theory explains how journalists and editors filter information, deciding what is newsworthy and shaping its presentation. These theories collectively illustrate the journey of information from its source to the audience, emphasizing the role of media in framing public discourse and influencing the agenda-setting process. In these fundamental works, the information flow model could be improved.

3. Cognitive Bias

Within the category of cognitive bias, the systematic review does not yield many new results. It is undeniable that one of the biggest biases today in terms of perception is selective exposure, which in the context of networked media is mainly due to the algorithmization of content. Thus, the author agrees with the inclusion of the concept of "selective exposure" in the final taxonomy, as well as the "partisan bias", which can be a manifestation of users' activity on social networks when sharing and commenting on content. However, the topic of content perception and media bias impact is much deeper. Nowadays, psychological research is advancing in this regard, building on the fundamental works by Kahneman and Tversky, and a taxonomy of media bias from the perspective of psychologists could expand its cognitive perception category to include a whole range of other concepts. However, because this paper has focused primarily on media bias in the texts of newspaper articles and not their perception, the author leaves room for further research by authors who focus more on psychological phenomena and the impact of media on audiences from this perspective.

Text-Level Bias		
Choice of Words	**Phrases and Sentences**	**Context Bias**
Epistemological Bias	Phrasing Bias	Framing Bias
Linguistic Intergroup Bias	Statement Bias	Spin Bias
Semantic Properties	The Level of Persuasion	Informational Bias
Connotation Bias		
Positive Emotion		
Negative Emotion		

Reporting-Level Bias
Coverage Bias
Proximity Bias
Selection Bias
Gatekeeping
Intermedia-Gatekeeping

Bias in Perception (Cognitive Bias)
Partisan Bias
Selective Exposure

Figure 5. The proposition of media bias taxonomy with new additional concepts.

5. Discussion

The systematic literature review and the evaluation of the media bias taxonomy by Spinde et al. (2023) have revealed significant insights into the nature and categorization of media bias. This variation underscores the complexity of media bias as a phenomenon influenced by linguistic choices, contextual factors, and cognitive processes.

The literature review revealed considerable variation in how media bias is defined and conceptualized across different studies. Some definitions focus on linguistic features and framing, while others emphasize cognitive biases and audience reception. This diversity reflects the multi-dimensional nature of media bias and the need for a comprehensive taxonomy that can accommodate different theoretical perspectives.

By categorizing 133 definitions into distinct groups and evaluating their applicability to real-world news articles, we have identified both strengths and limitations in the existing taxonomy. The manual text analysis of CNN and FOX News articles provided concrete examples of how different types of media bias manifest in journalistic practices. This evaluation of existing taxonomy by Spinde et al. (2023) has also highlighted the need for a more nuanced and context-sensitive taxonomy to effectively capture the multi-faceted nature of media bias.

Integrating various theoretical approaches into a unified taxonomy presents several challenges. The primary challenge is the overlap between different types of biases, such as framing bias and connotation bias, which complicates the classification process. Additionally, the granularity of existing categories can lead to subjective judgments, making it difficult to achieve consistent and reliable manual classifications.

The principles for a unified media bias taxonomy should include comprehensiveness, clarity, context sensitivity, and practical utility. A robust taxonomy should encompass all relevant types of media bias, provide clear and distinct definitions, account for contextual influences, and be applicable in both theoretical and practical analyses. The proposed improvements to Spinde et al.'s taxonomy aim to address these principles by enhancing clarity, increasing granularity, and incorporating contextual factors.

Media bias is a pervasive issue that significantly influences public perception and discourse. The findings from this study underscore the importance of developing a

comprehensive and nuanced understanding of media bias. By recognizing the various ways in which bias can manifest, scholars and practitioners can better identify and address these biases in media content. The proposed improvements to the media bias taxonomy provide a foundation for more effective analysis and detection of bias, ultimately contributing to more transparent and balanced media practices.

5.1 Research Limitations

While this study has provided insights into media bias and proposed improvements to the existing taxonomy, it is important to acknowledge its limitations.

The literature review was limited to articles available in specific databases (Semantic Scholar), potentially excluding relevant studies from other sources. This limitation may result in a partial understanding of the media bias landscape as it relies on the accessibility and comprehensiveness of the chosen databases. A more extensive review covering a wider range of databases could provide a more holistic view of media bias. The author of this thesis must state that the results of the literature review failed to capture the full scope of the definitions.

The selection criteria for the literature review, while rigorous, might have introduced selection bias. Articles that met specific inclusion criteria were selected, potentially overlooking relevant studies that did not conform to these criteria but could have offered valuable insights into media bias. Although the extraction of definitions was peer-reviewed, due to the large volume of articles, there was no peer-review of the manual selection from the candidate papers.

The manual classification of news articles was subject to the author's interpretations of bias types. While efforts were made to ensure objectivity, the subjective nature of bias detection means that results could vary with different reviewers. Additionally, the manual process is time-consuming and may not be feasible for larger datasets, highlighting the need for automated classification tools.

The evaluation of the taxonomy was based on two specific news articles. While these provided concrete examples, a larger sample size would have offered a more comprehensive evaluation of the taxonomy's applicability across different contexts and media outlets. Future studies should include a more extensive range of articles from

various sources to validate the taxonomy's effectiveness and robustness. The detailed categories within the taxonomy increased the complexity of the analysis. This granularity, while valuable for nuanced understanding, made the classification process more challenging and time-consuming. The intricate nature of some biases requires a deep understanding and careful interpretation, which can be subjective and lead to inconsistencies.

The proposed improvements to the taxonomy are based on theoretical analysis and manual classification. There is a need for empirical testing to validate these improvements and assess their practical applicability. Future research should involve empirical studies that apply the refined taxonomy to a wide range of media content to test its robustness and reliability.

Automated tools for bias detection were not utilized in this study, which could have enhanced the accuracy and efficiency of the analysis. The development and implementation of machine learning models trained on annotated datasets could address some of the challenges associated with manual classification and offer more scalable solutions for bias detection. This use is also suggested for future research for existing LLMs such as ChatGPT.

The study primarily focused on English-language articles from U.S.-based media outlets. This limitation may not account for the nuances of media bias in different cultural and geographic contexts. Future research should explore media bias across diverse cultures and regions to develop a more universally applicable taxonomy.

English is not the native language of the author of this thesis. Although the author believes his level of English is on a professional level, it is possible that the subtle nuances in the definitions that a native speaker would recognize have been missed by the author.

5.2 Future Research Suggestions

Expanding the literature review to include a wider range of sources and older studies would provide a more comprehensive understanding of media bias. This could help identify additional types of bias and theoretical approaches that were not covered in this study. Furthermore, developing and testing automated systems for bias detection could enhance the consistency and scalability of media bias analysis. Machine learning models

trained on annotated datasets could help address the challenges of subjective interpretation and improve the efficiency of the classification process.

Future research should also focus on analyzing different types of media content, such as visual and multimedia content. For instance, exploring how images and videos contribute to media bias could provide a more holistic understanding of the phenomenon (Boomgaarden et al., 2016).

Investigating media bias in different cultural and geographic contexts would help identify context-specific biases and enhance the taxonomy's applicability across diverse settings. This could involve comparative studies of media coverage in different countries or regions.

The author also suggests that future research should focus on the information flow models, recognizing the selection bias and agenda-setting chokepoints of the media landscape, together with the implementation of fact-checking systems into the media bias analysis. Conducting longitudinal studies to examine how media bias evolves over time would provide insights into the dynamics of bias and its impact on public perception. This approach could reveal trends and patterns that are not apparent in cross-sectional analyses. Additional avenues of research may also be directed toward the classification of text complexity, writing styles, and general tonality.

Conclusion

This thesis set out to explore and analyze the multifaceted concept of media bias through a systematic literature review, empirical evaluations, and the development of an improved taxonomy. The research aimed to bridge gaps in existing studies and offer a comprehensive framework that enhances our understanding and detection of media bias in news articles.

Building on the findings from the literature review and empirical analysis, the thesis proposed several improvements to the existing taxonomy. These improvements aimed to address identified limitations such as overlapping definitions in the tex-level context bias category and linguistic category, resulting in the unified category. The proposed taxonomy offers additional concepts, such as positive and negative distinctions between connotations, the level of persuasion in the text, and the expansion of the classification of selection bias.

The literature review was comprehensive but not exhaustive. The selection criteria and databases used, while rigorous, may have excluded some relevant studies, particularly those published in non-English languages. The manual classification of biases in the news articles involved a degree of subjectivity, which could affect the consistency and reliability of the findings. Future research could incorporate automated tools and multiple reviewers to enhance objectivity.

The author believes that further research in the area of media bias and its classification is necessary. This need arises from the context of today's world, plagued by several ongoing war conflicts and polarized societies destabilizing the internal politics of the stats of western civilization. This thesis focused exclusively on textual content in news articles. However, media bias is prevalent in other media forms, such as visual imagery, audio, and video, which were not covered in this study, but represent the majority of content consumed by today's audience on social media. Future research should explore these dimensions to provide a holistic understanding of media bias.

As has been demonstrated in the theoretical part of the thesis, based on several fundamental and contemporary studies in the field, the clue to the causes of this division of opinion is the commercialization and deprofessionalization of traditional media outlets, the presence of propaganda made by totalitarian states and the ongoing spread of disinformation in addition to media bias.

The need for research in this area also stems from technological advances in the contemporary world and the opportunities they offer. Advances in machine learning and the development of LLMs (Large Language Models) now allow us to analyze textual data in huge volumes. Applications available to the wider public, such as annotation aggregators of online news articles using advanced text analysis to classify the level of media bias, are already part of today's digital marketplace and Euro-American media landscape. A more precise classification of concepts into a structured taxonomy, which formed the core and purpose of this thesis, has the potential to improve the functionality of these tools and give rise to other projects focusing on media bias, for example, in the educational field and media literacy.

Závěr

Tato diplomová práce vznikla za účelem prozkoumat a analyzovat koncept mediálního zkreslení prostřednictvím systematického přehledu literatury, empirických vyhodnocení stávající taxonomie a návrhů na její zlepšení. Cílem bylo doplnit mezery ve stávajícím výzkumu a nabídnout komplexní teoretický rámec, který by přinesl větší vhled do fenoménu mediálního zkreslení ve zpravodajských článcích.

Na základě zjištění rešerše a empirické analýzy autor navrhl několik úprav stávající taxonomie. Tyto úpravy řeší zjištěné nedostatky, jako je vzájemné prolínání definic v kategorii zkreslení na úrovni textového kontextu a v lingvistické kategorii, což vedlo k vytvoření jednotné kategorie. Navržené úpravy taxonomie nabízejí další pojmy, jako je pozitivní a negativní rozlišení konotací, úroveň persvaze v textu a rozšíření klasifikace selekčního zkreslení (agenda-settingu).

Přehled literatury byl ve svém provedení komplexní, avšak pro zdokumentování celého spektra konceptů nedostačující. Přestože byla kritéria výběru a použité databáze akademicky podloženy, mohlo dojít k vyloučení některých relevantních studií, zejména těch, které byly publikovány v jiném než anglickém jazyce. Manuální klasifikace biasu ve zpravodajských článcích zahrnovala určitou míru subjektivity, což mohlo ovlivnit konzistenci a spolehlivost zjištění. Budoucí výzkum by tak mohl zahrnout automatizované nástroje a více recenzentů pro zvýšení objektivity.

Autor se domnívá, že další výzkum v oblasti mediálních předsudků a jejich klasifikace je nezbytný. Tato potřeba vyplývá z kontextu dnešního světa, který je sužován probíhajícími válečnými konflikty a polarizovanými společnostmi destabilizujícími vnitřní politiku statutů západní civilizace. Tato práce se zaměřila výhradně na textový obsah zpravodajských článků. Mediální zkreslení však převládá i v jiných mediálních formách, jako jsou vizuální obrazy, audio a video, které nebyly v této studii zahrnuty, ale představují většinu obsahu konzumovaného dnešním publikem na sociálních sítích. Budoucí výzkum by se tak měl zabývat i těmito mediálními formami.

Jak bylo v teoretické části práce na několika fundamentálních i současných studiích z oboru dokázáno, vodítkem k příčinám názorové polarizace je vedle komercializace a deprofesionalizace tradičních mediálních domů a propagandy ze strany totalitních států a šíření dezinformací, právě mediální zkreslení.

Potřeba výzkumu v této oblasti vychází také z technologických pokroků v současném světě a příležiostí, které nabízejí. Pokrok ve vývoji strojového učení a takzvaných LLM (Large Language Models) nám v současnosti umožňuje analýzu textových dat v obrovských objemech. Širší veřejnosti přístupné aplikace, jako anotační agregátory zpravodajských online článků využívajcí pokročilou analýzu textu ke klasifikaci úrovně mediálního zkreslení, jsou již součástí dnešního digitálního trhu a euroamerické mediální krajiny. Přesnější klasifikace pojmů do strukturované taxonomie, která tvořila jádro a smysl této práce, má potenciál funkce těchto nástrojů zdokonalit a dát možnost vzniknout dalším projektům soustředících se na media bias, například v oblasti školství, osvěty a mediální gramotnosti.

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Appendix no. 2: ChatGPT prompt for reference generation (prompt)

Appendix no. 3: Media Bias Text-Analysis of the News Article from CNN.com (text)

Appendix no. 4: Media Bias Text-Analysis of the News Article from FoxNews.com (text)

App. 1: Media Bias Taxonomy Adapted from Spinde et al. (2023)

Media bias type/subtype		Definition
Linguistic Bias		
	Connotation Bias	Using words with certain connotations to influence perception. For example, referring to a protest as a "riot" versus a "demonstration."
	Epistemological Bias	Presenting information in a way that reflects certain knowledge assumptions. This might involve implying certain facts are universally accepted when they are not.
	Framing Bias	Framing information to promote a particular interpretation. For instance, highlighting certain aspects of a story while downplaying others to shape the audience's understanding.
	Linguistic Intergroup Bias	Using language that favors one group over another. This can be seen in the choice of descriptors for different social or ethnic groups.
	Semantic Properties	Choosing words with specific meanings to influence perception. This can involve subtle shifts in language that carry significant interpretive weight.
Text-Level Context Bias		
	Phrasing Bias	Phrasing statements in a way that influences interpretation. This could be through the use of leading questions or loaded terms.
	Spin Bias	Presenting information with a particular spin to influence audience perception. For example, emphasizing the positive aspects of a policy while ignoring potential drawbacks.
	Statement Bias	Bias in the statements made within the text. This involves the explicit assertions or claims made by the media source.
Cognitive Bias		
	Partisan Bias	Favoring one political party over others. This could manifest in selective reporting on political events that favor one party.
	Selective Exposure	Preferring information that aligns with pre-existing beliefs. This bias highlights the tendency of audiences to consume media that reinforces their viewpoints.

Reporting-Level Bias		
	Coverage Bias	Giving disproportionate coverage to certain events or issues. For example, consistently covering crimes committed by one group while ignoring similar crimes by another.
	Proximity Bias	Favoring news that is geographically or culturally closer to the audience. This can result in over-reporting of local events and under-reporting of distant ones.
	Selection Bias	Selecting certain stories to report while ignoring others. This bias is evident when media outlets prioritize some topics over others based on subjective criteria.
Related Concepts		
	Framing Effects	How the framing of information affects audience interpretation and understanding.
	Hate Speech	Language that incites hatred against particular groups, often reflecting underlying biases.
	Group Bias	Favoring certain groups over others in media reporting.
	Sentiment Analysis	Using computational methods to analyze the sentiment expressed in text which can reveal underlying biases.

App. 2: ChatGPT Prompt for Reference Generation

Take this list of concepts, and for every concept, print me in one table the following columns: Concept, Author, Year, Title, Summary. Please look up one reference of your training data that deals with each concept. Add it to the list. Example: [Commercial Bias, Boyd, J. P., & Ellison, N. B. (2007). Social network sites: Definition, history, and scholarship. Journal of Computer-Mediated Communication, 13(1), 210-230. 2007 Social network sites: Definition, history, and scholarship. Boyd and Ellison explore the phenomenon of commercial bias in social network sites (SNSs) and its implications for user behavior and experiences. The article provides a comprehensive overview of SNSs, examining their definition, history, and scholarly research. By analyzing the commercial interests and design features of SNS platforms, the authors discuss how commercial bias influences user interactions, content distribution, and privacy practices. The findings contribute to understanding the socio-technical dynamics of SNSs and their impact on social connectivity, digital culture, and online communities.] Print out the final table here. Use only real academic sources.

App. 3: Media Bias Text-Analysis of the News Article from CNN.com

Title: "The reason why NATO and Europe found Biden's debate performance so alarming"

Joe Biden's performance at the CNN presidential debate against Donald Trump has raised concerns with US allies - particularly within NATO and Europe.

Annotation

Statement Bias (Implying widespread concern): 'raised concerns with US allies' implies a broad consensus without specifying which allies or providing direct quotes, potentially overstating the concerns.
Selection Bias (Focus on specific groups): Emphasizing NATO and Europe selectively highlights certain reactions, ignoring any positive or neutral perspectives. In the context of the topic of the article, however, the focus on this group is understandable.

Those concerns, to be clear, are not about whether or not Biden is fit to make decisions. They are not worried that he will implement dangerous policies or take dramatic actions internationally – always a factor when talking about the person in charge of the world's most powerful armed forces, a nuclear arsenal, and largest economy.

Annotation

Epistemological Bias (Certainty in allies' concerns): 'to be clear', 'they are not worried' and 'always a factor' use definitive language to assert the nature of the concerns, presenting them as established facts rather than opinions.

The common view among US allies is that Biden is a sensible man who surrounds himself with sensible people, and whatever happens, they will continue to make rational, reasonable decisions.

Annotation

Epistemological Bias (Asserting credibility through factive verbs): Phrases like 'the common view' and 'is a sensible man' use factive verbs to assert credibility and present subjective opinions as objective truth.
Phrasing Bias (Positive connotation): Describing Biden as 'sensible' and his decisions as 'rational' and 'reasonable' carries a positive connotation.

Nor is the concern that Biden's stumbling at times incomprehensible performance has ensured a second Trump term. The prospect of a Trump return is a concern, but it has already been baked into allied thinking.

Annotation

Framing Bias (Negative implication of performance): 'stumbling at times incomprehensible performance' frames Biden's performance negatively.
Statement Bias (Overstating concerns): Suggesting that a Trump return is a significant concern without providing balanced viewpoints from other sources.

Europe, in particular, has never really moved on from Trump 1.0 and has held the view since 2020: that if it could happen once it could happen again. That has been at the heart of European strategic thinking since Trump took office in 2016 and has continued through Biden's presidency.

Annotation

Selection Bias (Selective historical context): The statement selectively focuses on a historical context, potentially ignoring other relevant factors or viewpoints.
Statement Bias: The phrase "has been at the heart of European strategic thinking" asserts a strong, definitive statement about European strategic priorities without providing evidence or acknowledging that this might be an opinion rather than a fact.

The concerns that America's allies have are that the most powerful country on earth cannot provide the one thing they most want: stability.

Annotation

Statement Bias (Mind reading): The statement implies that the thing that US's allies want the most is its internal political stability.

Removing a candidate this late in the electoral cycle diplomats fear could undermine the whole process. It could allow adversaries like China and Russia to lash out at the US democratic system making it look weak in comparison to their autocracies where strongmen grip power tight.

Annotation

Framing Bias (Negative implication of removal of the candidate): Emphasizing the potential negative consequences of removing a candidate, framing it as a threat to the democratic process.
Selection Bias (Selective examples): Citing China and Russia selectively highlights specific adversaries, ignoring other global reactions or perspectives.

This may sound trivial but diplomacy at this level is often seen in zero-sum terms: something bad or embarrassing for the West particularly the mighty US is good for its enemies.

Annotation

Framing Bias (Zero-sum framing): Framing diplomacy in zero-sum terms suggests a simplistic view of international relations, potentially ignoring more nuanced perspectives.

These small shows of supposed weakness create openings for adversaries to spread propaganda sow divisions in the US and the West itself through disinformation.

Annotation

Framing Bias (Negative implication): Describing them as 'shows of supposed weakness' frames actions negatively, suggesting vulnerability.
Selection Bias (Focus on adversaries): Emphasizing adversaries spreading propaganda without balancing with any positive diplomatic efforts or countermeasures.

These risks would be bad enough in removing a candidate but imagine if these conversations are taking place once Biden had secured a second term. Constant speculation about his ability to govern at home and abroad might be unfounded at a policy level but it would doubtless create division distrust and panic throughout his second term.

Annotation

Framing Bias (Negative implication of speculation): Framing speculation leads to division, distrust, and panic, emphasizing potential negative outcomes.
Spin Bias (Speculative language): Using speculative language like 'might be unfounded' and 'would doubtless create' implies negative development of events if Biden is re-elected as president.

What might that materially mean? Would Biden be able to push things like aid for Ukraine through the House? Would he have the political capital to take potentially unpopular action in the Middle East or Indo-Pacific if those regions further destabilise? And would a question mark over the White House's power embolden America's global adversaries in to act more aggressively in their own backyards? Meeting all of these challenges effectively requires stability.

Annotation

Framing Bias/Spin Bias (Negative hypothetical scenarios, speculative language): Posing hypothetical negative scenarios frames Biden's potential actions and outcomes negatively, emphasizing instability.

That brings us back to Thursday night. The world saw an old man struggling to speak eloquently or coherently. Whether you are a supporter or opponent, that performance raises legitimate questions about whether or not he is simply too old for the job he wants to keep doing.

Annotation

Framing Bias (Negative implication of age): Describing Biden as 'an old man struggling to speak eloquently or coherently' frames his performance and capability negatively.
Statement Bias (Legitimizing concerns): Stating that it 'raises legitimate questions' legitimizes concerns about his age and capability without providing balanced viewpoints.

Stability means more than political stability or consistency. If the noise and questions about Biden's ability to govern continue allies fear that he will be unable – fairly or unfairly – to provide the stability the West desperately needs at an uncertain time.

Annotation

Framing Bias (Negative implication of governance): Framing the ongoing questions and concerns as a threat to stability, emphasizing potential negative outcomes.

App. 4: Media Bias Text-Analysis of the News Article from FoxNews.com

Title: "European official appears to liken Biden to failed Roman emperor after disastrous debate performance"

A top Polish official recently appeared to draw an unflattering comparison between President Biden's Thursday debate performance and the decline of ancient Rome.

Annotation

Framing Bias (Unflattering comparison): 'Unflattering comparison' frames the Polish official's comments negatively.

Polish Foreign Minister Radosław Sikorski made the comment in an X post Friday. The statement was posted in English which hinted it was intended for English-speaking audiences because Sikorski usually posts in Polish.

Annotation

Selection Bias (Highlighting language choice): Highlighting the fact that the language choice of the post implies a specific intent to target an English-speaking audience. In this context, however, the statement cannot be entirely regarded as bias, because the implication seems justified.

In the X post Sikorski took aim at Marcus Aurelius's son Commodus whose reign marked the end of Pax Romana an era of peace and prosperity in ancient Rome.

Annotation

Framing Bias (Negative historical comparison): Citation of comparison of Biden to Commodus, a negative historical figure, frames Biden negatively.

"Marcus Aurelius was a great emperor but he screwed up his succession by passing the baton to his feckless son Commodus (He from the Gladiator)" Sikorski wrote. "Whose disastrous rule started Rome's decline.

Annotation

Connotation Bias (Strong negative connotations): Words like 'feckless' and 'disastrous' carry strong negative connotations, influencing readers' perceptions of both Commodus and by extension, Biden.

Framing Bias (Negative comparison): The statement frames Biden's potential leadership negatively by associating him with a negative fictional figure representing a tyrant.

"It's important to manage one's ride into the sunset."

Annotation

Connotation Bias (Implied incompetence): The phrase implies that Biden, like Commodus, needs to manage his exit carefully, suggesting incompetence or decline.

Biden's recent debate performance has sparked commentary across the world prompting increased concern about his advanced age and declining cognitive abilities.

Annotation

Framing Bias (Negative implication of age and ability): Highlighting 'advanced age and declining cognitive abilities' frames Biden negatively, emphasizing potential weaknesses.
Statement Bias/Spin Bias (Global concern): The statement implies a widespread global concern without providing balanced viewpoints or specific examples. The word 'prompting' implies that a focus of world attention on events in the US worsens concerns about president's competency.

Media publications in Russia China Iran and other countries all covered the debate and used it as an opportunity to criticize the U.S.

Annotation

Selection Bias (Selective focus on adversarial countries): Mentioning Russia, China, and Iran selectively highlights adversarial countries' negative reactions, potentially ignoring neutral or positive coverage elsewhere.

Rebekah Koffler a strategic military intelligence analyst and author of "Putin's Playbook" told Fox News Digital most foreign publications "are derogatory of both candidates and mocking America."

Annotation

Statement Bias (Critical source): Including a quote from a critical source frames the situation negatively without balancing it with other perspectives.

Selection Bias (Selective quoting): Quoting a source that emphasizes derogatory views selectively highlights negative opinions without providing balanced coverage.

"Bottom line Moscow feels confident that the societal crisis that has engulfed the U.S. is good for Russia" Koffler said.

Annotation

Statement Bias (Critical conclusion): The statement frames the situation as beneficial for Russia, emphasizing a negative view of the USA.

Institute of Communication Studies and Journalism
Faculty of Social Sciences, Charles University
Master thesis

THIS SECTION IS FILLED IN BY THE STUDENT:	
Surname and name of the graduate: Spirit Martin	**Stamp of the mailroom:** Univerzita Karlova Fakulta sociálních věd Došlo dne: **1 5 -03- 2024** -1- Čj: **89** Příloh: Přiděleno:
The matriculation year of the graduate student: 2021	
Faculty e-mail of the graduate student: 18676417@fsv.cuni.cz	
Study program/form of study: Media Studies / full-time	

Title of the thesis in Czech:
Media bias: Systematický přehled literatury a taxonomie mediálního zkreslení

Title of the thesis in English:
Media Bias: A Systematic Literature Review On Media Bias Taxonomy

Expected completion date (semester, academic year)
(The thesis may be defended no earlier than six months after the thesis is approved):
Summer semester, 2023/2024

Characteristics of the topic and its treatment so far (max. 1800 characters):
The thesis deals with a complex analysis and categorization of various forms of distortion of media content. Media bias, as a factor influencing the presentation and perception of information towards the public, has a significant impact on the public perception of events and also on the political behavior of individuals. In the context of the growing influence of digital media and social networks on the formation of public opinion, this topic is increasingly relevant and the author considers its thorough analysis necessary.

The existing treatment of media bias in academic literature is characterized by a diversity of approaches and definitions. Published studies focus on specific aspects such as political, commercial, or ideological distortions, often lacking a unified theoretical and methodological framework. The problem addressed in this thesis stems from the diversity and inconsistency in the definitions and conceptions of media bias in the current academic literature. This heterogeneity makes the unified application of theoretical concepts and categories to practical analyses of media content difficult and it creates a significant barrier to a comprehensive understanding of the phenomenon of media bias.

Several theoretical and empirical approaches have been put forward within media studies, sociology, political science, and computer science to identify and analyze media bias. Furthermore, there is already an individual attempt to establish a unified media bias taxonomy. However, there needs to be more systematic reviews that integrate these diverse approaches and provide a comprehensive view of the issue.

Expected aim of the thesis, or formulation of the problem, research question, or hypothesis (max. 1800 characters):
The main objective of this thesis is to improve a unified taxonomy of media bias based on a thorough systematic review of the existing literature and subsequent analysis of its relevant findings. The following analysis seeks to identify and categorize different forms of media bias and related concepts. The thesis aims to provide a structured review, which has been lacking so far, to reveal the differences between existing approaches to defining categories and subcategories of media bias and to offer a comprehensive framework for understanding this phenomenon. Among the intentions of the thesis is to contribute to the development of automated detection of media bias in media content, thus expanding

the theoretical basis for the work of researchers and developers in the field of machine learning and artificial intelligence.

Based on the stated aim of the thesis, the following three research questions can be formed:
Q1: In what ways do the conceptual frameworks and definitions of categories and subcategories of media bias vary in published academic studies?
Q2: What are the key methodological challenges in integrating different theoretical approaches to media bias into a unified taxonomic structure?
Q3: What are the basic principles of the structure that an existing unified taxonomy of media bias contains, derived from the analyses conducted in response to the first two research questions?

Considering the topic, the author decided to write the thesis in English for the sake of more accurate citations of sources without the need for translation and wider accessibility to an international audience.

Expected structure of the thesis (division into individual chapters and subchapters with a brief description of their content):
1. Introduction (General definition of media bias, its role in media and society. Description of the aims of the thesis and a brief outline of the methodology.)
2. Theoretical framework (Presentation of existing research on the media bias taxonomy.)
3. Methodology (A description of the process of conducting a systematic literature review on media bias and the subsequent analysis of the results.)
4. Analysis and interpretation of results (Analysis of the relationships and differences between the various definitions of categories and subcategories of media bias. Analysis and discussion of relevant findings).
5. Conclusion (Proposal for improved media bias taxonomy. Research limitations and possible directions for further research in this area.)

Definition of the background material (e.g. title of the periodical and period analysed):
The systematic literature review will include as many scholarly publications searchable online in the Google Scholar and Semantic Scholar databases related to media bias and similar concepts as possible.

Methods (techniques) of material processing:
Systematic literature review and analysis. Multiple automation tools, such as Generative Pre-trained Transformer 4 (GPT-4), will be used to sort scientific publications based on relevant keywords.

Basic literature (at least 5 most important titles on the topic and its method; for all titles a brief annotation of 2-5 lines is required):
1. Spinde, T., Hinterreiter, S., Haak, F., Ruas, T., Giese, H., Meuschke, N., & Gipp, B. (2023). The Media Bias Taxonomy: A Systematic Literature Review on the Forms and Automated Detection of Media Bias.

This paper offers a detailed review and taxonomy of media bias forms and their automated detection, bridging computer and social sciences to enhance understanding and methodologies in identifying media bias.

2. Kitchenham, B. (2004). Procedures for performing systematic reviews. Keele, UK, Keele University, 33(2004), 1-26.

This foundational text by Kitchenham outlines the procedures for conducting systematic reviews in software engineering, providing a structured approach that has been influential across various fields, including the study of media bias.

3. Hamborg, F., et al. (2019). Automated identification of media bias in news articles: An interdisciplinary literature review. International Journal on Digital Libraries, 20, 391–415.

Hamborg et al.'s work provides an interdisciplinary overview of automated methods for identifying media bias, directly relating to the paper's focus on automated detection techniques and the categorization of media bias forms.

4. Herman, E.S. and Chomsky, N. (1988). Manufacturing Consent: The Political Economy of the Mass Media. New York: Pantheon Books.

In this book Chomsky introduces the Propaganda Model of media, exploring how economic structures and ownership impact news content, effectively categorizing media biases influenced by political and commercial pressures.

5. Pritchard, D. (2000). Media Bias: A Comparative Study. Journal of Communication, 50(4), pp.102-119.

This study provides a comparative analysis of media bias across different countries and media systems, offering a foundation for discussing the impact of political, commercial, and ideological biases on media content.

Master's theses and dissertations on the topic (list of bachelor's, master's, and doctoral theses that have been defended on the topic at Charles University or other faculties or universities close to the topic in the last five years):
Wessel, M. (2023). Improving Media Bias Detection with State-of-the-Art Transformers. Master's Thesis. Universität Konstanz, Faculty of Politics, Law, and Economics, Department of Politics and Public Administration.

Date / Signature of student
15.3.2024. ██████████ ....

THIS SECTION IS FILLED IN BY THE TEACHER/EDUCATOR:
Recommendations on the topic, structure, and technique of the material: Nothing to be added here, we meet weekly and I will supervise Mr. Spirit closely. I have published 23 peer-reviewed articles, submitted my doctoral thesis, and coordinated the research network. https://media-bias-research.org/
Possible recommendation of other titles of literature prescribed for the topic: Will be sent to Mr. Spirit directly in the the process of the thesis.
I confirm that I have consulted the author(s) of the above thesis and that the topic corresponds to my field of specialization and area of professional work. **I agree to be the supervisor of this thesis.**

██████████████	████████
Timo Spinde	8.3.2024 ....
Surname and name of the teacher	**Date / Signature of the teacher**

THESES MUST BE SUBMITTED **PRINTED, SIGNED, AND IN DUPLICATE** BY THE DEADLINE SPECIFIED IN THE INSTITUTE'S DIRECTOR'S DECREE, THROUGH THE OFFICE OF THE FSV UK· ACCEPTED THESES MUST BE **COLLECTED** FROM THE SECRETARIAT OF THE RELEVANT DEPARTMENT AND **BOUND INTO A COPY OF THE THESIS.**

THE THESES ARE APPROVED BY THE GUARANTOR OF THE RELEVANT STUDY PROGRAMME.