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TOWARDS AN ETHICS IN INTELLIGENT ALGORITHMS FOR FEMALE ENTREPRENEURSHIP: A SYSTEMATIC REVIEW OF THE PROPAGATION OF SOCIAL BIASES TO DIGITAL MEDIA

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Abstract: How do cognitive biases and social influence shape our decisions and perceptions, and how do they propagate through societal norms and digital ecosystems? How do these factors affect the perception and recognition of women in entrepreneurship and leadership? The novelty of this research lies in its valuable guidance for evaluating the literature and advancing the knowledge base on the conceptual and social structures, as well as the propagation mechanisms of biases, to later understand how these dynamics specifically manifest themselves in female entrepreneurship and business leadership. This study aims to conduct a systematic review of the literature to establish a research framework and identify future research directions regarding the existence and dissemination of biases in female leadership and entrepreneurship, both in society and in different internet media. Through the selection and analysis of 462 articles published between 2006 and 2024 in the Scopus and Web of Science databases, using a systematic review approach, the study focuses on research related to cognitive biases. Articles were selected based on their relevance to the existence, influence, impact, and persistence of these biases, particularly in decision-making and their transmission to society and digital ecosystems. A strategic classification framework was then built using machine learning tools and TCM approach to highlight the influence of biases in various societal contexts, including how they propagate into intelligent algorithms.

The presented framework not only provides an initial understanding of entrenched biases in society and their spread to digital media but also identifies gaps in existing research, highlighting opportunities and directions for future research. In addition, the study presents key insights for the development of algorithmic ethics, aimed at mitigating biases and promoting more equitable decisions in automated systems, considering that contemporary society bases its decisions on information provided by these intelligent algorithms available on the internet.

Keywords: ethics of algorithms; social biases; algorithmic biases: social transmission of biases; digital propagation of biases.

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1. INTRODUCTION AND JUSTIFICATION

Search engines, recommendation systems, social networks, and any digital context that uses intelligent algorithms is susceptible to reproducing biases and can have repercussions in areas including privacy; replicate or aggravate social, gender, and sexist biases regarding race, politics, etc.; or have direct cultural, social or institutional influences due to the technical limitations of its design (Mateos & Gómez, 2019). To understand the fundamentals of this research on women, entrepreneurship, equity, and algorithmic biases, we invite the reader to explore this topic by involving the search for the terms "CEO" (Chief Executive Officer, the highest-ranking executive in a company), "CTO" (Chief Technology Officer, responsible for overseeing a company's technological needs), and "beauty" in any conventional search engine. These keywords reflect critical intersections of gender representation, leadership roles, and societal perceptions in digital ecosystems.

- What kinds of images come up when searching for the word "CEO"?
- What if "CTO" is searched?
- And for the word "beauty"?

This experiment, inspired by the findings of Mateos & Gómez (2019), highlights that even in 2024, gender biases persist in the data presented by search engines. Datasets often contain significant gender biases, and predictive models trained on these datasets tend to amplify these biases. For example, when searching for the word "CEO," most images presented are overwhelmingly male, reinforcing stereotypical associations of leadership and business roles with men. A similar pattern emerges when searching for "CTO," where images depict men, further solidifying the perception of technological leadership as a male-dominated domain. In contrast, when searching for the word "beauty", nearly all the images are associated with women, and notably, with women portrayed as conventionally attractive.

These biases not only affect gender representation but also raise critical questions about how success in business or leadership are perceived, appreciated, and promoted in our society. This phenomenon underscores how societal perceptions, deeply ingrained with gender biases, shape the data used by algorithms.

In this sense, it is worth considering whether society values leadership or business success in the same way as do influential and recognized platforms, such as Google or LinkedIn, especially in terms of visibility, recognition, or the trust they convey. Additionally, it is relevant to explore how do these technological institutions address the existence of algorithmic biases caused by the partial use of data (Zhao, Zhaou, et al., 2018). According to different studies, technology acts in many cases as a catalyst for inequality (Mateos & Gómez, 2019).

It is imperative, therefore, to reflect on the role algorithms play in perpetuating these biases and how they affect our perceptions and evaluations of leadership or success in business. Understanding this interplay between societal biases and algorithmic outputs is precisely the foundation of this research, which aims to explore the origins, amplification, and implications of these biases to discern key patterns in the context of women, entrepreneurship, and equity (Vicente, Saiz, & Esteban, 2024).

This work clearly aims to create a research framework that allows for exploring the influence of biases in society and their spread to digital ecosystems, with special attention to intelligent algorithms, to understand key aspects of this construct. This paper provides a defining *context* of biases and explores their origins and various classifications for a deeper understanding of their impact and *influence* on people's decision-making and perceptions. Similarly, how these biases are *transmitted* in society and *spread* to algorithms is analysed, highlighting the interactions and repercussions in various areas.

This underscores both the justification and the opportunity for this study. While previous research has focused on areas such as decision-making, business, financial and strategic behaviour; and trust in the business sector, the absence of significant studies on keywords such as culture, semantics, influence, transmission, female entrepreneurship, or entrepreneurship role model, represents a critical gap in the literature (see Table 5, section 5.3). This gap, uncovered through a systematic review of the literature (SRL), the TCM classification methodology (Paul, Alhassan, Binsaif, & Singh, 2023), and machine learning (ML) approaches, provides the foundation to this paper's contribution.

This review aims to highlight the existence of biases, particularly gender biases, in the consideration of role models in the fields of entrepreneurship and business, as well as in the perception of leadership, and to analyse how these biases influence, impact, and exert motivational power on society and future generations. The use of the internet and the rise of artificial intelligence will constitute important parts of people's lives, in the learning process, in the influence of opinions, and in the decision-making of individuals across the world (Harris, 2020). Therefore, it is important to understand how these biases spread to society not only through culture but also through technology and digital ecosystems (Thomas, 2017) since they are the main axes driving the creation of new companies in the 21st century (Kraus, Roig-Tierno, & Bouncken, 2019) and essential tools for business networking, information gathering, and crowdfunding for entrepreneurs (Olanrewaju, Hossain, Whiteside, & Mercieca, 2020).

The following fundamental research questions guide this analysis: How do cognitive biases and social influence shape our decisions and perceptions, and how do they propagate through societal norms and digital ecosystems? How do these factors affect the perception and recognition of women in entrepreneurship and leadership?

In response to these questions, the study will contribute to building an agenda along different lines to advance future research. The literature review is presented in Section 2, while the entire classification process is covered in Section 3 of this paper. Section 4 outlines the main findings and provides a detailed description of the research framework central to this study. In Section 5, the results are discussed in detail, providing a critical analysis of the findings, and areas of opportunity across various themes. Finally, the main conclusions are given in Section 6: directions for future research are offered; and the study limitations are outlined.

2. LITERATURE REVIEW

The existing literature on biases and their impact on both society and digital systems is reviewed in this section. Firstly, algorithmic biases (2.1) are explored, highlighting patterns of distortion that emerge in automated systems. Then, attention is given to cognitive biases (2.2), which refer to the prejudices and errors in judgment that influence human decision-making. The role of social influence (2.3) in the transmission of these biases within society (2.4) is also examined, followed by an analysis of how these biases propagate through intelligent algorithms (2.5). This review offers a comprehensive framework for understanding the interaction between human biases and digital systems, and the mutual influence they exert on society (2.6).

2.1. ALGORITHMIC BIASES

An intelligent algorithm learns from the data it processes, generating new knowledge aimed at predicting patterns or identifying outputs and classes in a general way. When new knowledge, patterns or classes reflect information linked to the values or beliefs of the people who are behind the data processing (collection, selection, coding) by which these algorithms learn, algorithmic bias arises (Zwitter, 2014).

An example of algorithmic bias is related to the professional network LinkedIn, which in 2016 discovered a gender bias in its search engine, as shown in "How LinkedIn's Search Engine May Reflect a Gender Bias" (Day, 2016). According to Day (2016), in searches for female names, the search engine makes recommendations for male variations, but it does not recommend female variations in searches for male names. For example, in a search for "Andrea", the engine suggests the possibility of referring to "Andrew".

Other cases that highlight this problem are found in The White Book of Women in Technology by Sara Mateos Sillero and Clara Gómez Hernández (Mateos & Gómez, 2019). The book references several studies that highlight this issue, including research from the University of Cambridge revealing that women are less likely to receive high-paying job offers. Another study shows that Google's algorithms tend to display more prestigious and higher-paying jobs to men rather than to women (Datta, Tschantz, & Datta, 2015). Additionally, a separate case involving Amazon found that its intelligent algorithms for curriculum selection were biased against women (Arrabales, 2016).

Algorithmic bias is linked to cognitive biases, which are an ingrained part of the human decision-making process. ML algorithms, designed to mimic this decision-making process, rely on human judgment as training data. As a result, these algorithms inadvertently incorporate and propagate the same cognitive biases present in human decisions (Zook, et al., 2017).

Machine learning algorithms were designed to make decisions not only faster but also with greater precision and fairness; in other words, these algorithms are designed to eliminate or reduce cognitive biases. However, since human judgements typically serve as inputs to decision-making algorithms, these cognitive biases are integrated into the resulting algorithms, thus propagating the biases (Harris, 2020).

Interest in the identification, mitigation, and eradication of biases in ML algorithms has increased recently, with the aim of guaranteeing fairness in their operation and addressing issues such as discriminatory treatment towards certain social groups (Zwitter, 2014). These efforts align with the broader examination of how algorithms impact the exercise and protection of human rights (Council of Europe, 2018).

2.2. COGNITIVE BIASES

While algorithms can perpetuate biases due to limitations or errors in their design processes, cognitive biases, as introduced by Tversky and Kahneman (1974), are commonly framed as a lack of precision and impartiality and a form of systematic error in thinking, resulting from the limitations and characteristics of information processing. This perception contrasts with the idea that cognitive biases may be optimal in certain contexts, as they facilitate the optimization of cognitive effort and the reduction in complexity, although they entail the risk of yielding nonoptimal results (Marshall, Trimmer, Houston, & McNamara, 2013).

People use "shortcuts" based on heuristic strategies to make decisions and judgements. These heuristics often provoke cognitive biases, which are systematic and predictable errors in judgement that arise due to an excessive reliance on these heuristics (Kahneman, Slovic, & Tversky, 1982).

Cognitive biases inadvertently influence decision-making. Recent research has revealed that people are often unaware of their own cognitive biases. However, these biases are present and have significant repercussions on people's lives in a variety of contexts, from recruitment processes and advertising strategies to decisions related to criminal justice, personalized medicine and policy-making (Larrick, 2016). A wide range of contexts is affected by implicit biases in decision-making.

Biases, of which more than 60 types have been identified (Baron, 2008), are classified according to their processes of origin. The model of two processes is most commonly considered; this model distinguishes between system 1 (automatic, fast, effortless) and system 2 (deliberative, effortful, slow, and conscious) (Stanovich & West, 2000). However, to overcome the limitations of this model, Stanovich (2011) proposes a conception of three cognitive processes, which postulates that metacognitive processes of reflection are necessary to switch between the dual systems of fast and slow automatic processing (systems 1 and 2). In this context, thinking errors can be attributed to failures in the metacognitive monitoring of the internal dialogues of individuals rather than just automatic or motivated processes.

Despite their potential to contribute to decision-making failure, biases should not be considered inherently bad, as their psychological function reduces effort, complexity, and uncertainty in cognitively overwhelming situations (Hahn & Harris, 2014).

2.3. SOCIAL INFLUENCE

In addition to individual cognitive biases, research in the field of sociology has shown that decision-making and perceptions are also heavily influenced by social factors. Sociological studies have long argued that reality is socially constructed (Berger & Luckmann, 1966). Individual preferences are fundamentally shaped by the preferences of those around them, such that people with similar attitudes and beliefs tend to group together (Larrick, 2016).

The influence of context, or the social influence on an individual, can occur in two ways. Firstly, a social context can lead to better decisions than those an individual might make alone, depending on the contribution of the people involved. Secondly, the social context can change the decision-making process of individuals in such a way that they begin to think and behave differently in the future (Larrick, 2016).

The pure dynamic of social influence is traced through the exchange of information. On the one hand, indirectly, popular options tend to receive more attention, while unpopular options are ignored and rarely reconsidered. On the other hand, directly, people seek the judgement of others in the face of uncertainty, granting them an influence referred to as informative (Deutsch & Gerard, 1955).

The kind of influence known as "peer pressure," or normative influence, fosters momentary conformity and leads people to publicly follow others to avoid the social costs of disagreement. In contrast, informational influence results from a sincere attempt to understand a complex world and tends to generate lasting changes in beliefs and preferences (Larrick, 2016).

Owing to this persistent informative influence, individuals who coincide in time and in different tasks can come to converge in the way of thinking over time. This phenomenon is described in the forecasting literature as "shared error" (Armstrong, 2001) since individuals with similar mental models make similar errors due to their homogeneous thinking about a problem.

2.4. TRANSMISSION TO SOCIETY

Based on the above, any social context is susceptible of generating biases and expanding them if there is an exchange of information. This idea suggests that biases can spread in society in several ways (Mateos &

Gómez, 2019). Social learning, where people imitate the behaviours and beliefs in their environment, can contribute to the spread of biases. Cultural norms also play an important role since they can perpetuate certain biases by reinforcing discriminatory attitudes (Larrick, 2016).

The diffusion of biases in society through people is intrinsically linked to the exchange of information (Deutsch & Gerard, 1955), which suggests the importance of in-depth exploration of the process of communication and the narratives themselves. In each story we tell we choose a sequence of events and characters that shows a direction or course of action, influenced by a specific perspective. This means that narratives not only order events in a coherent way but also reflect particular points of view, affecting how people interpret reality (Sheldrake, 2016).

Furthermore, exploring the influence of semantics and culture on cognitive biases (Larrick, 2016) has shed light on how the perceptions and meanings attributed to certain concepts shape societal dynamics. Specifically, the interplay between language, semantics, and culture plays a crucial role in how cognitive biases influence the formation of opinions, attitudes, and behaviors (Shymko & Babadzhanova, 2020). This connection highlights the profound impact of cultural and linguistic frameworks on the ways individuals interpret and respond to information, ultimately affecting decision-making and social interactions.

In addition, the media can influence the spread of biases by representing groups in a stereotypical way. Social institutions, such as the educational system or the judicial system, can maintain biases through discriminatory policies. Finally, social media, both in person and online, can facilitate the spread of bias through peer influence (Gagliardi, 2023).

Together, these mechanisms can contribute to the persistence of biases in society, both analogically and digitally, highlighting the importance of addressing them in a comprehensive manner to promote justice and inclusion.

2.5. PROPAGATION INTO ALGORITHMS

To understand how biases are generated and perpetuated in artificial intelligence systems, it is crucial to analyse the environment and the learning techniques they use, from the perspective of both the programming teams and the external context (Mateos & Gómez, 2019). The growing demand for intelligent systems among companies is due to the large amount of data that they generate and store, which requires automated and advanced analysis, commonly known as big data (Zook, et al., 2017).

In the field of artificial intelligence (AI), there are various learning modalities, both supervised and unsupervised, that allow machines to perform specific tasks. One of the most prominent areas in recent years is natural language processing (NLP). Word2Vec and GloVe are among the most used software for this purpose; these programs can effectively create vector representations of words, although they are susceptible to the transmission of biases that can end in discriminatory results. To address this problem, initiatives aimed at developing gender-neutral libraries, such as GN-Glove, which eliminate gender information without compromising the functionalities of word embedding models, have emerged (Zhao, Zhou, Li, Wang, & Chang, 2018).

Research from Princeton University has shown that machines tend to associate female names with household and family tasks, while male names are associated with professional careers. Similarly, terms such as "woman" and "girl" are more frequently associated with the arts than with mathematics. Platforms such as the IBM Watson Developer Cloud, Amazon Machine Learning, and BigML have recognized these biases and their consequences and have launched initiatives to mitigate them, although without conclusive results (Puri, 2018).

In the field of deep learning, platforms such as Loop AI Labs can process millions of unstructured documents and generate structured representations autonomously. The presence of biases in AI underscores the need to address the lack of diversity in technology, especially in the AI sector. To develop algorithms free of gender biases, it is vital to intervene in processes via human participation and establish mechanisms that correct the reproduction of biases from the environment (Arrabales, 2016).

Other areas, such as fact-checking, in which human evaluators identify, evaluate, and review the veracity of informational elements, are subject to systematic errors, especially cognitive biases, which cause evaluations to deviate from an objective perception of the information. Although biases can minimize the cost of making mistakes, they are frequent and critical and can cause errors with great potential impact by spreading not only in the community but also in the datasets used to train automatic and semiautomatic machine learning models to combat misinformation (Soprano et al., 2024).

High-quality data, that is, bias-free data, are essential for changing the current trend in AI. In addition, the formation of more diverse and inclusive programming teams supports the identification and prevention of gender, age and race biases in the data used, thus reducing the probability of obtaining discriminatory results. Not only can team diversity reduce biases and promote a more equitable society, but it is also key to innovation and business productivity (Mateos & Gómez, 2019).

2.6. CONCLUSIONS OF THE LITERATURE REVIEW

The literature review has examined the multifaceted nature of biases, including algorithmic biases that may reflect and propagate existing societal disparities, cognitive biases that affect individual decision-making processes, and the significant role of social influence in shaping perceptions and behaviours.

This research focuses on understanding how specific mechanisms—such as the interaction between cognitive biases and social influence, the transmission of biases through cultural narratives and semantics, and their integration into intelligent systems—contribute to this phenomenon.

The study of algorithmic biases highlights the significant role intelligent systems play in the perpetuation of cognitive, semantic, and cultural biases. These biases, inherently present in human decision-making, are encoded into algorithms through the training data and the judgments of their designers. Algorithms not only reflect these biases but also amplify them, reinforcing societal inequalities and stereotypes.

Furthermore, as the internet serves as the predominant source of information for people in the 21st century, its reliance on intelligent systems to filter, process, and present data amplifies the importance of addressing these biases. The pervasive influence of digital platforms in shaping social perspectives makes it even more critical to ensure that the algorithms driving these systems are transparent and equitable.

With this foundation laid, the following section will outline the methodology employed in this study to investigate these issues more deeply and systematically.

3. METHODOLOGY

To carry out this study, a systematic review of the literature (SRL) is proposed using the Web of Science and Scopus databases to identify relevant studies related to the existence, influence, impact, evolution or inertia of cognitive biases in society in general and, more specifically, in decision-making and the transmission of these biases to society and digital ecosystems, with special attention to intelligent algorithms.

The methodology used in this SRL is described below (see Figure 1). It begins with a search strategy in the two specified electronic databases involving a combination of search keywords: ((“Cognit * bias *”) OR (“cultur * bias *”) OR (“semant * bias *”)) AND (soci * OR decision *) AND ((influ * OR impac * OR evolution * OR inertia *)) OR ((“Cognit * bias *”) OR (“cultur * bias *”) OR (“semant * bias *”)) AND (algorithm * “OR” artificial intelligence “OR” machine learning “OR” internet “OR” social network *) AND (transmis * OR propagat *)), adopting the Boolean operators “AND” and “OR”, in the fields related to “title”, “abstract” and “keywords”. The search yielded 2,154 documents from the Scopus database and 2,811 documents (with 1,696 documents in its Core Central) from the Web of Science (WOS) database without filtering by any time frame.

The exclusion criteria applied in the search for articles were intended to delineate broad subject areas that would provide a sufficiently complete framework reflecting society. In this sense, thematic areas such as business, administration, and accounting; arts and humanities, and decision sciences were included. In addition, research areas related to cognitive biases, such as business economics, education, educational research, social issues, communication, and sociology, were taken into account. These categories were selected to guarantee the relevance and pertinence of the selected articles in the context of the study of cognitive biases in society. Likewise, after a preliminary review of the titles, documents regarding biosanitary issues, psychopathies or specific niches, such as agriculture or aviation, were excluded (512 - Scopus; 391 - WOS).

The last filtering process focused on three main criteria: the type of document, the language, and the date of publication. It was decided to select journal articles and reviews written in English that were recent, with the purpose of addressing current research and ensuring a solid academic record to prevent the inclusion of outdated topics. Initially, a search for works published since January 2010 in both databases was established as a starting point. However, a preliminary review of the records obtained after the search query in the WOS database indicated that the relevant studies on entrepreneurship date from 2006. Consequently, the date ranges were adjusted to include studies from 2010 in Scopus and from

2006 in WOS, which yielded 256 documents from the first database and 283 from the second database. After the articles were identified and extracted from their corresponding databases, they were organized and cross-checked to eliminate duplicates.

For the final documents (462), the TCM methodology (Paul, Alhassan, Binsaif, & Singh, 2023), adapted based on the previous reviews by Paul and Rosado-Serrano (2019), and Mishra et al. (2021), was used. This methodology is used to classify the universe of studies (a set of documents) according to their theme (T), context (C), or place where the study is carried out, and methodology (M), and ensures the use of a structured and systematic approach in the analysis.

The implementation of systematic mapping began with the use of an unsupervised and strategic analytical approach (grouping based on clusters) that provided a detailed analysis of the various themes (or areas) addressed by the selected articles. This approach allowed us not only to analyse the fundamental aspects related to this research, namely, to understand the influence and evolution of biases in different areas, their transmission to society and their spread to intelligent algorithms, but also to identify the areas of greatest interest to researchers, saturated areas of study and areas of opportunity in this field of research. After obtaining the initial mapping of the articles via analysis of all the titles and keywords, we opted for a detailed and exhaustive review of the articles classified as "reviews" (35 in all). To identify additional relevant literature, the forward and backward reference search technique (Levy & Ellis, 2006) was subsequently implemented. The backward reference search involves reviewing the references of the articles identified in our initial keyword search, while the forward reference search entails examining additional articles that have cited these initial articles. Figure 1 provides a detailed description of the process used for the analysis, as well as the taxonomy applied to guide each decision made in this phase of the research.

To establish a broad and unbiased research framework, we decided not to initially limit the searches to the field of female entrepreneurship and leadership. This strategy allowed us to address the origin and propagation of biases that influence decision-making and world perception in a more global manner, providing a more comprehensive understanding of the phenomenon. Focusing solely on this niche would have narrowed the scope of findings and introduced bias into the information gathered, making it difficult to conduct the integral analysis required to contextualize female leadership and entrepreneurship. Moreover, in the literature

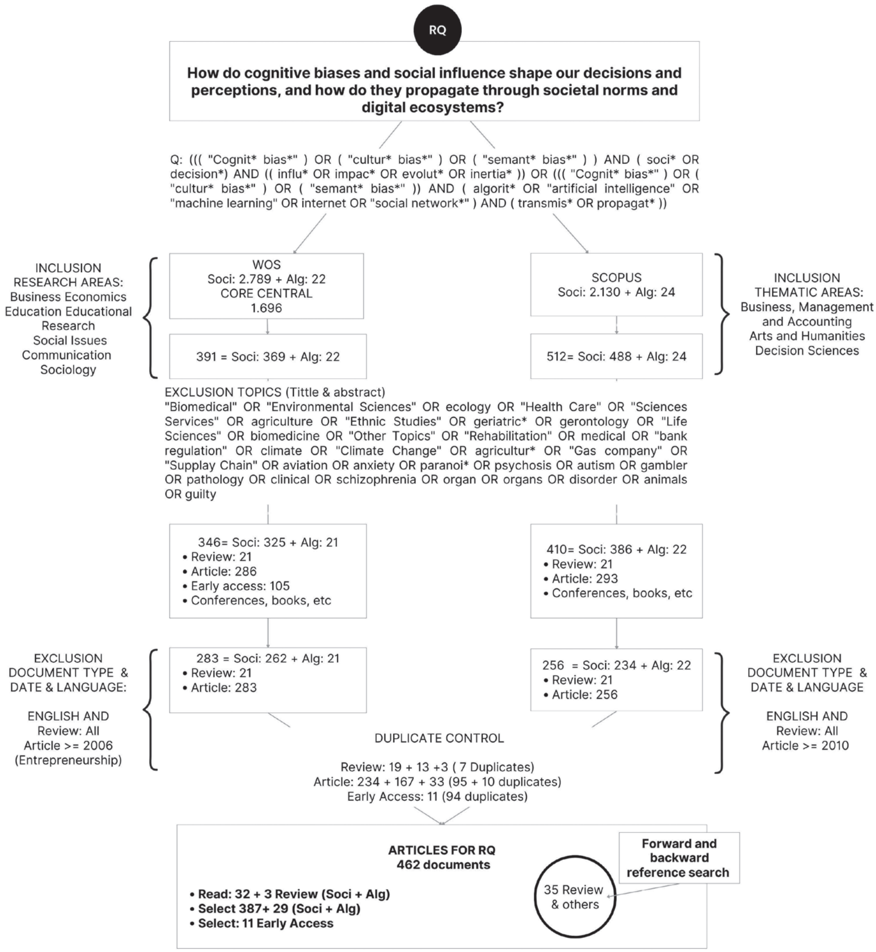

Figure 1. Methodology followed in the SRL

review we conducted, we identified the elimination of gender information as a common approach to mitigate bias, aligning with initiatives such as GN-Glove, which removes gender information without compromising the functionality of word embedding models (Zhao, Zhou, Li, Wang, & Chang, 2018).

The classification and subsequent sections discussed in this document will help us understand how cognitive biases and cultural and semantic factors influence our decisions and how they are transmitted to society and propagated to algorithms.

4. RESULTS OF THE CLASSIFICATION PROCESS VIA THE TCM

In this section, we explore the included studies and certain aspects of their contents according to the TCM methodology (Paul, Alhassan, Binsaif, & Singh, 2023). Below, we describe our findings regarding the themes (T, section 4.1), contexts (C, section 4.2), and methodologies (M, section 4.3) observed in the included studies. The objective is to obtain a useful framework of knowledge about the universe of studies, which will allow us to better understand the key elements and trends present in the relevant literature.

4.1. STRATEGIC MAPPING (T)

To extract thematic clusters from the titles provided, text analysis and grouping techniques were used via the Python tool and specialized libraries, such as nltk and sklearn, which facilitate the natural language processing (NLP) and the text clustering process as proposed by Vicente, Saiz and Esteban (2024).

The strategic mapping procedure began with the compilation of the original corpus of articles, consisting of 462 elements, each of which was accompanied by the associated original title. The data preprocessing stage was subsequently conducted; this stage included cleaning and normalizing the titles to eliminate special characters, standardizing letters to lowercase and discarding irrelevant or stop words. Finally, the term frequency-inverse document frequency (TF-IDF) method was used for the vectorization of the texts, thus ensuring an accurate and relevant representation of the keywords in the analysis.

Once the properly prepared data had been obtained, an unsupervised machine learning algorithm, specifically K-means, was applied to group the articles into clusters on the basis of the similarity of their titles. In this unsupervised approach, the algorithm needs no predefined labels but focuses on the identification of patterns and structures inherent in the data for the formation of clusters. The clustering algorithm computes the distance between the titles of the articles and assigns each of them to a cluster based on this distance. Articles with similar titles are grouped in the same cluster, while those with dissimilar titles are assigned to different clusters.

Once the clustering phase was concluded, the quality of the clusters formed was evaluated by applying metrics such as intracluster cohesion and intercluster separation. These metrics are used to determine the significance of the clusters and their ability to adequately represent the patterns present in the data.

The mapping or strategic clustering process produced a total of 20 different clusters, which were quickly reviewed and then assigned meaningful nomenclature. The distribution of the results of this stage is presented below (Table 1).

Table 1. Distribution of the dataset in the identified clusters

Strategic Clustering by Area of Study	Total articles	Percentage
Financial and Business Decision Making	85	18,40%
Decision Making and Entrepreneurship	54	11,69%
Organizational Change and Decision Making	43	9,31%
Social Media, AI, Technology, and Biases	40	8,66%
Business Context: Decision Making and Entrepreneurship	30	6,49%
Cognitive Research and Behavior	30	6,49%
Social Beliefs and Social Behavior	27	5,84%
Prejudices in Decision Making	26	5,63%
Marketing and Consumer Behavior	23	4,98%
Environment and Sustainability	23	4,98%
Education, Critical Thinking, and Decision Making	20	4,33%
Politics and Decision Making	12	2,60%
Linguistics and Communication	10	2,16%
Cultural Biases and Decision Making	9	1,95%
Gender, Bias, and Social Justice	7	1,52%
Religion and Spirituality	7	1,52%
Intelligence, Strategy, and Decisions	6	1,30%
Risk Perception and Decision Making	5	1,08%
Ethical and Moral Decision Making	3	0,65%
Legal Decision Making and Biases	2	0,43%
Total distribution	**462**	

4.1.1. Trends and evolution over time

Starting from the mapping obtained in the previous stage and considering the additional information on the year of publication, we explored how these themes evolved over time in the selected articles and years. An analysis of these data made it possible to identify some trends and patterns over the years, which are visualized and explored in detail below (Figure 2).

Figure 2. Trends and evolution of strategic areas over time

The temporal trends of the strategic areas analysed are detailed below:

1. Early exploration of biases in society: The initial focus on issues related to beliefs, critical thinking, and education in the early years of the period could reflect an incipient interest in understanding the cognitive and social biases that influence education beliefs and decision-making. These areas of study suggest a concern with understanding how people process information, evaluate evidence, and develop their perspectives, which in turn may be linked to the identification and understanding of biases present in society. Over time, these

areas may have been the subject of continuous research but to a lesser degree than other emerging themes.

2. Appearance of entrepreneurship topics: While studies related to entrepreneurship began to emerge in 2006, this topic attracted greater interest beginning in 2010. This suggests a growing interest in the study of entrepreneurship over the last decade.
3. Exploration of business areas and decision-making: Themes focused on business decision-making, as well as on organizational change, have been consistently addressed over time. However, there has been a significant increase in the number of articles related to these areas in recent years, which could reflect greater recognition of their importance in the current business context.
4. Focus on social media, AI, technology, and biases: Since 2019, there has been an increase in the number of articles that explore the relationships among social media, AI, technology, and cognitive biases. This change could reflect the increasing impact of technology on our lives and on how we make decisions.
5. Interest in cognitive and behavioural research: Interest in this subject is increasing. This suggests a growing interest in understanding mental processes and how they affect our decisions.
6. Diversification of topics: Over the years, the spectrum of topics addressed in the articles has diversified, ranging from marketing and consumer behaviour to environment and sustainability, education, politics, gender, and social justice, among others.

Next, we focused exclusively on analysing articles of the "review" type (35), with the aim of facilitating a detailed and efficient exploration of all the articles to outline hypotheses about saturated areas and areas of opportunity within the fields of study. Focusing our attention on these articles enabled us to delve into the content in an agile way to identify significant patterns and define lines of interest for future research.

The analysis of the relationships between keywords, the exhaustive review of the abstracts and the complete reading of the articles represent fundamental stages in the development of this research. This strategy made it possible to delve into the understanding of the issues addressed, identify significant connections between key concepts, and evaluate the scope and relevance of the papers reviewed.

4.1.2. Keyword analysis

To identify the most frequent topics or concepts studied in the articles included, we sought to explore the strongest relationships and associations between keywords, represented by a directed graph. This allowed us to identify the most frequent topics or concepts studied in the articles of the analysed dataset. In the process, Python and the NetworkX and Matplotlib libraries were used to build and visualize the graph.

Articles with the first four complete keywords were first selected. Some articles did not have this information well filled in, and some articles had null values, which limited the availability of data for a complete analysis (Table 2).

Table 2. List of keywords selected by article

Keyword1	Keyword2	Keyword3	Keyword4
Biological education	Cognitive biases	Educational assessment	Evolution
Christian spirituality	Definitions of spirituality	History	Politics of interpretations
behavioral decision theory	cognitive diversity	group decision making	heuristics and biases
Cultural dimension	E-payment	Hong Kong	Octopus
Die Mannschaft	Halo effect	Soccer	Social psychology
Management	Academic literature	Academic research	Business organizations
Behavioral economics	Behavioral operations	Bounded rationality	Cognitive biases and heuristics
Personal factors	Pro-environmental behaviour	Pro-environmental concern	Review
Green technology	Policy instruments	Technology diffusion	Technology transfer
Bias	Cognitive	Decision- making	Process
atheism	Cognitive Science of Religion	creeds	implicit theism
Corporate reputation	Corporate social responsibility	Customer engagement	Social exchange theory

(Cont.)

Table 2. List of keywords selected by article *(cont.)*

Keyword1	Keyword2	Keyword3	Keyword4
cognitive bias	empirical legal studies	judicial decision-making	legal psychology
Egocentrism	Perspective-taking	Social influence	Social judgment
From the Poets in the Kitchen	Learning from others	Paule Marshall	Reading relations
Character	Coronavirus	Covid-19	Discourse
Behavioral strategy	Capital allocation	Cognitive biases	Organizational repairs
Adam Smith	Behavioral psychology	Cognitive biases	Early modern philosophy
behavioral economics	cognitive biases	conspiracy theories	decision-making
Behavioural finance	Cognitive biases	Emotional biases	Heuristics
Behavioral finance	Behavioral biases	Investment decision-making	Heuristics
Trust	Distrust	Cognitive Bias	Dysfunctional Trust
Behavioural economics	Behavioural operations	Experimental economics	Inventory decision-making
Decision making	Entrepreneurial decision	Heuristic	Ecological rationality
cognitive biases	behavioral accounting	Cognitive Reflection Test	SUBJECTIVE-PROBABILITY
Cognitive biases	Decision making	Tourists	DESTINATION IMAGE
Social media	Stereotype	Online review	Attractiveness
Life satisfaction	Happiness	Children	Parenthood
multicultural education	African American students	self-esteem	academics
age	cultural biases	education	grid-group theory
FEMINIST CRITIQUE	THERAPY	PERSPECTIVE	Communication

With this information, a word cloud was generated to complement the analysis (Figure 3). A word cloud is a visual technique that allows the identification of the most frequently occurring words in a dataset. In the context of an SRL, this method can be applied to article titles, keywords, or abstracts. In this work, the aim was to provide an intuitive visual representation of the most relevant and recurrent concepts among the keywords, since, through visualization, it is possible to quickly and clearly identify the most prominent thematic areas in the reviewed literature, which facilitates the identification of important patterns and trends.

Figure 3. Cloud of selected keywords in articles

Subsequently, a list of keyword pairs, which represent the relationships between the concepts studied in the articles, was generated (Figure 4).

Finally, a directed graph was created, and all these relationships were incorporated. To improve the clarity and focus of the analysis, the graph was filtered to include only the edges connecting nodes with a degree greater than 1, which meant that the keywords were closely related to multiple keywords.

The resulting graph shows (Figure 5), where the nodes represent the keywords and the edges indicate the relationships between them. This approach provides a clear overview of the most important and significant connections between the concepts addressed in the articles included in this research. For example, there is a group of highly interconnected

```
[ ] import networkx as nx
    import matplotlib.pyplot as plt

    # Lista de pares de palabras clave
    pairs = [
        ("biological education", "cognitive biases"),
        ("biological education", "educational assessment"),
        ("biological education", "evolution"),
        ("christian spirituality", "definitions of spirituality"),
        ("christian spirituality", "history"),
        ("christian spirituality", "politics of interpretations"),
        ("behavioral decision theory", "cognitive diversity"),
        ("behavioral decision theory", "group decision making"),
        ("behavioral decision theory", "heuristics and biases"),
        ("cultural dimension", "e-payment"),
        ("cultural dimension", "hong kong"),
        ("cultural dimension", "octopus"),
        ("die mannschaft", "halo effect"),
        ("die mannschaft", "soccer"),
        ("die mannschaft", "social psychology"),
        ("management", "academic literature"),
        ("management", "academic research"),
        ("management", "business organizations"),
        ("behavioral economics", "behavioral operations"),
        ("behavioral economics", "bounded rationality"),
```

Figure 4. Example of relationships between keywords to create the graph

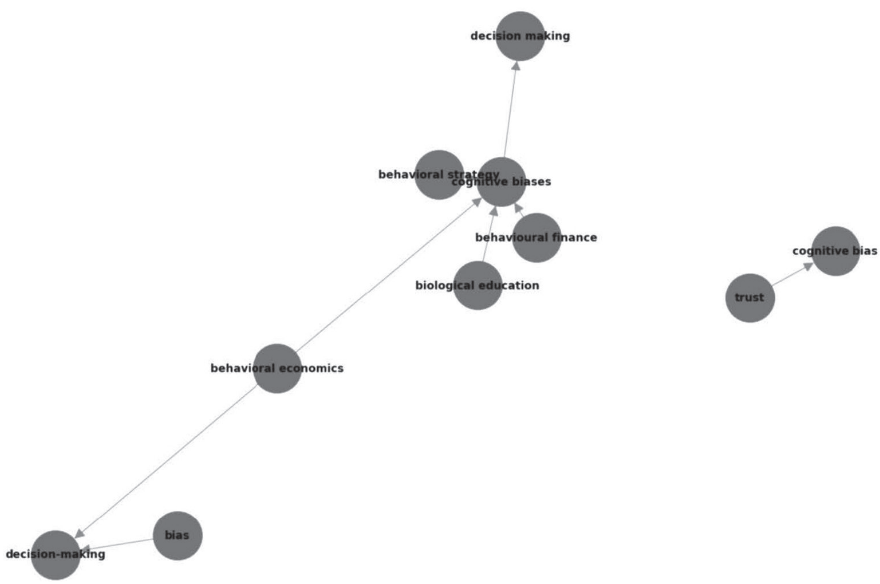

Figure 5. Directed graph between keywords with relevant relationships

keywords. The relationship between “behavioural strategy,” “cognitive biases,” “behavioural finance,” and “biological education” forms a dense network, where biological education and behavioural strategies are linked to cognitive biases and behavioural finance. This suggests a mutual influence between these fields, particularly in the context of financial decision-making and behaviour-based strategies.

Additionally, most of the connections in the graph are unidirectional, which suggests causal or influential relationships between the keywords. For instance, “biases” seem to influence “decision-making,” and “behavioural economics” plays a role in shaping how these decisions unfold. These directional relationships provide a clear view of how different disciplines and concepts are interconnected in the analysis.

4.2. AFFILIATION ANALYSIS (C)

According to the process of the methodology selected for the classification of the selected documents, the context dimension (C) was explored in the analysis. In this case, we focused on the main affiliations of the study authors to detect the geographical areas in which the researchers exploring the topics of interest to this study are located. This approach allowed us to identify regional patterns and determine whether trends or areas of opportunity are present in these geographic contexts.

The analysis of the affiliations of the reviewed studies (Figure 6), reveals the wide geographic distribution of the researchers. Affiliations are con-

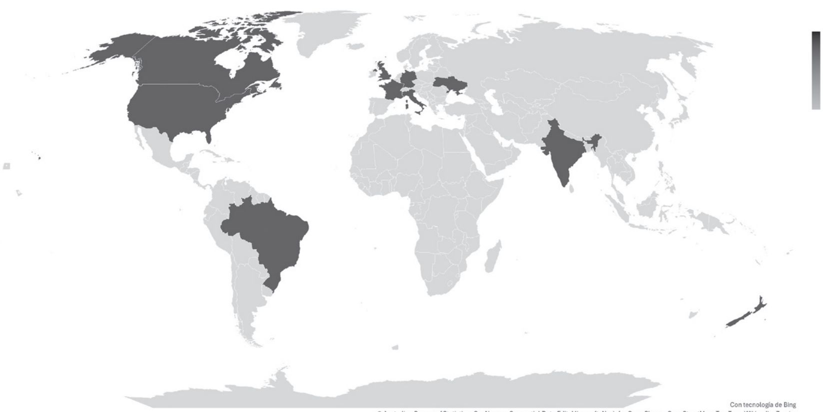

Figure 6. Distribution of affiliations by geographic area

centrated in countries such as the United States, with five studies, and to a lesser extent in countries such as India, Italy, Canada, and Ukraine, each with multiple studies. Countries such as Germany, New Zealand, Brazil, the Netherlands, France, and the United Kingdom contributed at least one study each. This geographic diversity suggests a broad international research base on the topics of interest to us, which can contribute a variety of perspectives and approaches to our analysis.

4.3. ANALYSIS OF METHODOLOGIES (M)

Finally, the methodological aspect (M) was comprehensively explored, with the consideration of quantitative, qualitative, and mixed approaches. By employing a structured and systematic approach in the analysis of the methodologies used in the studies, we sought to obtain a deep understanding of the techniques and approaches used and identify key elements and trends in the relevant literature to help us build a solid and consistent knowledge framework. The results of this analysis (Figure 7), show a predominant distribution of studies adopting qualitative methodologies in the study universe, representing 46% of the total. This method is followed by mixed methodologies, which combine qualitative and quantitative elements, with 38%. Experimental studies constitute 13% of the total, while quantitative methodologies represent the lowest percentage, with only 4%. These data indicate a preference for qualitative and mixed approaches in the analysed research, suggesting an emphasis on obtaining a detailed and contextual understanding of the phenomena studied.

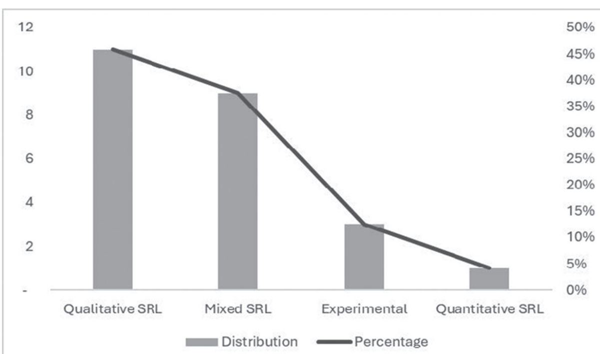

Figure 7. Distribution of methodological approaches

5. DISCUSSION

This section analyses and synthesises the main findings obtained in the research. It begins by presenting a strategic mapping (5.1) that outlines a research framework — the core objective of this paper — which enables to understand the origins, influence, and societal spread of biases, as well as their transmission to intelligent algorithms (5.2). This framework also provides valuable insights into how biases have been studied over time, identifying both saturated research areas and opportunities for future research (5.3).

5.1. STRATEGIC MAPPING WITH 20 CLUSTERS

In this study, we identified and analysed 20 strategic areas or clusters that offer a more complete vision of how cognitive biases can manifest and spread in different contexts, ecosystems, and situations. An ordered visualization of the clusters obtained in the strategic mapping is presented in Figure 8, arranged from smallest to largest in terms of the number of related studies.

Figure 8. Results of the systematic mapping to detect strategic areas

In exploring these areas, we identified four key perspectives of interest for addressing the phenomenon of the influence and propagation of biases: the functioning or the norms of the *context*, the *influence* and the *transmission* to society (with an emphasis on semantics and culture), and the *propagation* into smart algorithms and the digital ecosystem.

5.2. RESEARCH FRAMEWORK: CONTEXT, INFLUENCE, TRANSMISSION, AND PROPAGATION

The research framework developed in this study was used to establish a comprehensive overview of knowledge about cognitive biases and explore the *context*, in terms of the definitions, origins and various classifications of the concept, according to authors such as Kahneman, Slovic, and Tversky (1982). This approach provided a deeper understanding of the impact and *influence* of decision-making biases and allowed us to approach a specific direction, such as social influence, through the transmission of information (Deutsch & Gerard, 1955) in different social contexts involving culture and semantics (Larrick, 2016). This aspect is an important breakthrough in this field, as it explains an important channel of the *transmission* of biases to society and supports an understanding of how biases are transmitted among members of the population and how their transmission can affect different contexts, including their *propagation* to algorithms (Zook, et al., 2017).

The findings from this study have been grouped into two major domains of knowledge, each providing a distinct yet complementary perspective on cognitive biases and their impact. On the one hand, the *theoretical-conceptual domain* focuses on a deeper understanding of the nature of biases, encompassing their classification, their interaction with trust, and their influence on the formation and persistence of beliefs. Additionally, this domain explores the crucial role that narratives play in shaping reality, influencing how individuals interpret and process information. On the other hand, the *behavioral-business domain* addresses the practical implications of biases, highlighting strategies developed to mitigate their influence on decision-making. This domain examines the impact of biases in social and organizational contexts, as well as their propagation through digital ecosystems and algorithms, which is increasingly relevant in today's era of big data and artificial intelligence. While distinct, both domains offer a comprehensive view of cognitive biases and their importance in both theoretical understanding and practical application.

Thus, the four key perspectives — *context, influence, transmission to society, and propagation to algorithms* — are explored from both the theoretical-conceptual and behavioral domains. This dual approach allows for a comprehensive examination of cognitive biases, addressing their foundational understanding as well as their practical implications in both societal and technological scopes.

Among the main findings from the perspective of understanding the general *context* of cognitive biases (theoretical-conceptual domain) is the fact that trust and cognitive/social biases are related in an isomorphic way in that they function as reducers of cognitive effort and facilitators/inhibitors of action (Patent, 2022). When the understanding of cognitive biases is integrated with concepts such as trust, mistrust and dysfunctional trust, the idea that biases affect the perception of trustworthiness, risk and control is highlighted, as is how these biases can influence individual and collective decisions in various contexts (Patent, 2022). These insights into the relationship between trust and cognitive biases (behavioral-business domain) highlight how biases can shape perceptions of trustworthiness and influence decision-making in various contexts. Understanding this dynamic is crucial for developing strategies to mitigate the negative effects of biases (Kremer, 2023). Specifically, design thinking (behavioral-business domain), which is used in creative processes, can be an effective tool to reduce individual cognitive biases and improve innovation results by providing a framework for solving problems more creatively and collaboratively (Liedtka, 2015).

In terms of the *influence* on perception (theoretical-conceptual domain), it was found that people tend to overestimate the control they have over many aspects of their lives. However, this tendency does not extend to the interpersonal sphere, where individuals often lack confidence in their ability to influence others to act according to their desires (Bohns & Flynn, 2013). This finding highlights how cognitive biases affect not only self-perception but also social interactions and perceptions of influence. Furthermore, cognitive biases (theoretical-conceptual domain) play a crucial role in the formation and persistence of beliefs. Research reveals that these biases significantly shape mental processes related to the adoption and maintenance of ideas, as well as the way motivation can reinforce certain beliefs to fulfill individual and social needs (Gagliardi, 2023). This highlights the interconnectedness of cognitive biases with broader psychological and social processes. When considering decision-making (behavioral-business domain), studies indicate that cultural differences can serve as moderators in decision processes. Factors such as leadership styles, communication practices, power distance, and norm perceptions are key influences on both individual and collective decisions. The social context thus becomes pivotal: while it can enhance decision-making by allowing the exchange of diverse knowledge, it can also create shared blind spots that reduce the overall quality of decisions (Larrick, 2016). This dual nature of social influence underlines both the potential benefits and pitfalls of collective decision-making, showcasing how biases manifest not only at the individual level but also within groups.

The *transmission* of biases (theoretical-conceptual domain) is linked to the exchange of information (Deutsch & Gerard, 1955) highlighting that biases are inherently embedded in communication processes and the narratives themselves. This finding underscores the implicit role that everyday interactions and communication play in perpetuating biases within society. Narratives, in this sense, play a pivotal role in how individuals interpret their identity and understand the world around them (Sheldrake, 2016). By shaping specific perspectives, narratives influence not only personal interpretation but also social perceptions, allowing biases to be transmitted and reinforced at a broader level. From this conceptual viewpoint, narratives serve as both vehicles for conveying biases and tools for constructing reality. Linguistic perception (theoretical-conceptual and behavioral-business domains) also plays a significant role in this transmission process. Linguistic perceptions, which encompass how language is interpreted and understood, can shape public attitudes and behaviors, influencing how individuals react to specific topics (Shymko & Babadzhanova, 2020). The social and cultural context in which language is used thus becomes a critical factor in how biases are transmitted and interpreted, affecting both individual and collective behaviours. Moreover, practical studies (behavioural-business domain) suggest that mastery of specific contexts, along with critical thinking and training, can enhance the interpretation and dissemination of information. This improved understanding can lead to more effective communication strategies that mitigate the transmission of biases and foster more objective perceptions of social and cultural phenomena (Legare, Opfer, Busch, & Shtulman, 2018). This highlights the importance of education and awareness in reducing the negative effects of biases and promoting a more informed society.

In the process of information *propagation*, understanding bias and trust plays a particularly significant role in the study of digital ecosystems. From a theoretical-conceptual perspective, biases influence how information is perceived and filtered, shaping trust and decision-making on an individual level. However, when applied to behavioural-business contexts, the systematic processes that filter and select information on these platforms can produce large-scale dysfunctional effects, far beyond interpersonal or small group dynamics (Patent, 2022). This reinforces the need to analyse biases not only in human interactions but also in broader, more complex systems, including digital platforms where organizational and social decisions are increasingly mediated. From the perspective of the propagation of biases into algorithms, there is an increasing demand for intelligent systems in companies due to the vast amounts of data they generate and store. From a theoretical-conceptual standpoint, this raises concerns about how biases become embedded in the data and algorithms through learning techniques and data quality issues. On the behavioural-business side, the need for automated and advanced analysis has led to the rise of big data technologies, which, while powerful, can perpetuate existing biases if not carefully managed (Zook, et al., 2017). The literature review highlights that understanding how biases are embedded and sustained in AI systems requires scrutinizing both the quality of the data and the learning techniques applied. Additionally, attention must be paid to the influence of programming teams and the surrounding external context, as these factors shape the decisions and outcomes generated by AI systems (Mateos & Gómez, 2019).

The main findings are next presented, distinguishing those oriented towards a greater understanding of the *context* of biases; those related to studies on the *influence* of biases, taking into account relevant aspects such as semantics or culture; and those related to explaining the *transmission* of biases in society and their *spread* into intelligent algorithms and the internet media. The information is arranged with attention to the strategic mapping presented in section 3.1 of this document, allowing these findings to be regrouped into two large domains of knowledge: the theoretical-conceptual (Table 3) and the behavioural-business (Table 4) domains.

This domain of knowledge includes findings of the articles belonging to the following clusters: social beliefs and social behaviour; education, critical thinking, and decisions; cognitive and behavioural research; and linguistics and communication.

Table 3. Findings in the theoretical–conceptual domain

Context	Influence	Social transmission	Digital propagation
Demographic diversity in decision-making groups affects the quality and legitimacy of the decisions made.	The social context influences individual decision-making, both enhancing it by allowing the exchange of diverse knowledge and creating shared perspectives and shared blind spots.	Linguistic perceptions can shape public perception on a specific topic and affect people's attitudes and behaviours.	The quality of the data is crucial to understanding how biases spread.
	Understanding a context can influence the perception and interpretation of social and cultural phenomena.	The dissemination of information and knowledge can be made more effective by offering training and fostering critical thinking.	Processes that systematically filter and select information can produce notable dysfunctional effects on a large scale.

Table 4. Findings in the behavioural–business domain.

Context	Influence	Social transmission	Digital propagation
Cognitive biases, such as hindsight and biased confirmation, distort decisions in the business context.	Employees tend to underestimate their influence in the workplace due to cognitive biases.	There are strategies to mitigate the impacts of misinformation.	To understand the propagation of biases in algorithms, it is necessary to consider the influence of programming teams and the external context.
Biases affect the perception of reliability, risk, and control.	The perceptions of reliability, risk and control can influence individual and collective decisions in various contexts.	The underestimation of influence can impact corporate culture.	There are strategies to mitigate biases.

This domain of knowledge includes findings of the articles belonging to the following clusters: financial and business decision-making; decision-making and entrepreneurship; organizational change and decision-making; and social media, AI, technology, and biases.

5.3. SATURATED AREAS AND AREAS OF OPPORTUNITY

The most saturated areas of research regarding the analysis of cognitive biases were identified via keyword analysis through directed graphs, which revealed the most relevant relationships between keywords. For example, areas such as decision-making, business behaviour, financial behaviour, strategic behaviour, and trust (and mistrust) emerge as the main focuses of research, indicating that they have been widely studied by numerous researchers. However, the absence of relevant relationships between other pairs of keywords, such as culture, semantics, influence, transmission, and female entrepreneurship, suggests the existence of the opportunity to undertake new research in these less explored fields.

This finding highlights the need and utility of deepening the understanding of these areas and exploring these perspectives in future research. Such studies could significantly contribute to scientific knowledge, especially in the context of cognitive biases and their influence on various aspects of society and business behaviour, as well as their transmission to society and algorithms.

Table 5. Saturated research areas and areas of opportunity in the study of biases

Saturated research areas	Areas of opportunity
Decision-making	Culture
Business behaviour	Semantics
Financial behaviour	Influence
Strategic behaviour	Transmission
Trust (mistrust)	Female entrepreneurship
	Entrepreneurship role models

6. CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

In this paper, a review of research studies on the existence, influence, and transfer of biases in society is presented as a general framework to understand the functioning of biases in specific contexts and their propagation to algorithms. Below, we highlight our main conclusions (6.1), opportunities for future research directions in female entrepreneurship and foundational principles upon which to build an algorithmic ethics (6.2), and the limitations of this study (6.3).

6.1. CONCLUSIONS: A MOTIVATING HORIZON

The research sheds light on the context of biases and their influence on individual and collective decision-making. It emphasizes the critical role of culture and semantics in shaping perceptions and highlights the importance of understanding how biases are transmitted within society. These biases, whether in analogical or digital contexts, impact social structures and algorithms alike.

From a more operational point of view, research has advanced in the direction of identifying specific guidelines to set the agenda for future research. Thus, it is concluded that, within the analysis of cognitive biases, there are saturated lines of research and niches of opportunity in terms of new paradigms to explore and genuine knowledge to offer to the research community. The strategic classification framework presented in this document can guide future research and may be useful to researchers aiming to explore aspects of the influence and transmission of cognitive biases to society and digital ecosystems. In addition, guidelines are provided for professionals working in fields (un)related to ML techniques and tools, which can help broaden the perspectives of analysis in different fields of application.

Among the main conclusions of this study is the significant role that cognitive biases play in the formation and updating of beliefs (Gagliardi, 2023). This highlights the influence of biases in shaping perceptions of social and political events across cultural and political contexts. Additionally, the findings underscore how the social context can either enhance or limit individual decision-making, pointing to the need for further exploration of how demographic diversity and social norms impact these processes (Larrick, 2016). Furthermore, while cognitive obstacles that hinder understanding have been identified, this study opens the opportunity to explore how critical thinking and effective approaches to training and information dissemination can be integrated into decision-making processes (Legare et al., 2018).

These conclusions emphasize the importance of individual interactions and the transmission of biases in various social settings, providing valuable insights into how biases may influence broader systems, including digital ecosystems.

The following section presents the framework for future research based on these key conclusions, focusing on the exploration of biases in broader social, cultural, and technological contexts.

6.2. FUTURE RESEARCH DIRECTIONS ON BIASES IN FEMALE ENTREPRENEURSHIP

The research carried out in this work enabled us to identify four key perspectives for exploring biases in the context of female entrepreneurship: the functioning or the norms of the context, the influence and transmission of biases to society (with emphasis on semantics and culture), and the propagation in the digital ecosystem.

From the perspective of *context*, factors such as business infrastructure (Bohns & Flynn, 2013), social norms, culture, education, communication and politics can influence the formation and manifestation of cognitive biases (Larrick, 2016). This initial understanding provides us with a solid foundation for future research, specifically focusing on how these contextual factors impact the opinions, decisions, or perceptions of and about female entrepreneurs.

Furthermore, when considering the *influence* of semantics and culture on cognitive biases (Larrick, 2016), we have begun to understand how the perceptions and meanings attributed to certain concepts could affect the decisions of female entrepreneurs. This perspective allows us to anticipate how biases may manifest in diverse cultural and linguistic contexts, which is essential for developing effective strategies to support female entrepreneurship.

Another research opportunity related to the effect of influence and the impact of language and semantics concerns how cognitive biases *influence* the formation of opinions, attitudes and behaviours in society (Shymko & Babadzhanova, 2020). Such research could explore how biases affect the perception of public or political information, the formation of stereotypes, decision-making or the construction of social prejudices. Undoubtedly, an interesting avenue would be the investigation of the elements that influence favourable perceptions of something, which would allow exploration of how specific cognitive biases impact trust (McKnight, Cummings, & Chervany, 1998) and social interactions in organizational relationships. For example, understanding how these biases affect the business decisions of female entrepreneurs can reveal how the social perception of their role in the entrepreneurial ecosystem is influenced by cultural and cognitive factors, which in turn affects their trust and the dynamics of interaction within this area.

On the other hand, and related to the *transmission* of biases, a valuable research opportunity could be to consider how cognitive biases are transmitted and perpetuated in society through social interactions, the media and institutions (Larrick, 2016). Thanks to this work, we have begun to understand how these biases are *transmitted* and amplified through polarized groups and social networks (Gagliardi, 2023). This perspective provides a clearer view of how biases are perpetuated in contemporary society and prepares the way for future research that specifically addresses how these phenomena affect female entrepreneurs in digital environments.

Finally, to move towards a comprehensive ethics for intelligent algorithms, it is essential to consider the implications of the findings regarding biases inherent in these systems. The analysis of the literature highlights the importance of examining the quality of the data, the environment and the learning techniques used, taking into account the influence of programming teams and the external context, to understand how they cause, *propagate* and maintain biases in artificial intelligence systems (Mateos & Gómez, 2019).

To mitigate these biases, it is crucial to intervene in the algorithm design process, promoting human participation in bias correction and fostering the creation of diverse and inclusive teams. Ultimately, algorithmic ethics should prioritize transparency, fairness, and inclusion, aiming to correct biases while enhancing the visibility and equitable representation of women's leadership in business and entrepreneurship. Biased algorithms often reinforce harmful and limiting stereotypes as evidenced by the word search experiment with terms like "CEO" and "CTO".

The information on future lines of research is organized with attention to the strategic mapping presented in section 4.1, such that the different research directions are regrouped under two large domains of knowledge: the theoretical–conceptual domain (Table 6), and the behavioural–business domain (Table 7).

This study provides a solid basis for future research on biases regarding female entrepreneurship, establishing a methodology that starts from a global analysis and then focuses on a more fine-grained approach. Future research will be essential to better understand how cognitive biases affect the business decisions of female entrepreneurs and their perceptions, and how such biases can be mitigated in an ethical and effective way to promote greater gender equity in the business environment.

Table 6. Research directions in the theoretical–conceptual domain

Context	Influence	Social transmission	Digital propagation
Study how contextual factors impact the opinions, decisions, or perceptions of and about female entrepreneurs.	Explore how demographic diversity in decision-making groups affects the quality and legitimacy of decisions made.	Explore how promoting critical thinking and diversity of perspectives in the design process can affect the acceptance and success of innovative decisions.	Consider how social norms and decision-making patterns are transmitted and maintained within social groups, organizations, and communities and how they spread to digital ecosystems.
	Explore how to design processes to promote inclusion and equity in group decision-making.	Consider how resistance can be addressed in different communities and contexts.	

Table 7. Research directions in the behavioural–business domain

Context	Influence	Social transmission	Digital propagation
Explore how to combat misinformation caused by human biases and how it affects female entrepreneurship.	Seek to better understand cognitive bias repair strategies and evaluate the effectiveness of these strategies.	Explore how irrational behaviours can influence public policy and civil conflict.	Explore how cognitive biases are transmitted and perpetuated through social interactions, the media, institutions in society and different media on the internet.
	Study how cognitive biases influence the formation of opinions, attitudes, and behaviours in society.		

6.3. STUDY LIMITATIONS

The present work contributes significantly to the establishment of a comprehensive knowledge framework on cognitive biases, as well as their influence on individual and collective decisions and their propagation in society. Four fundamental aspects are explored in detail: the context, influence, and transmission of these biases, including their definition, origin, types and interaction with culture and semantics, and their propagation to algorithms.

However, it is crucial to recognize the limitations of this research. The exclusive selection of reviewed papers, although initially advantageous for providing a quick overview of the topic, could have restricted the global understanding and mastery of the central topic by excluding individual studies. Furthermore, the limited number of articles reviewed, and the choice of different ranges of publication dates, could have led to the omission of relevant research.

With respect to the unsupervised approach methodology, although the K-means algorithm has been useful for the identification of strategic areas, the application of more refined algorithms, such as DBSCAN, could offer greater precision in the clustering process and even allow hierarchical relationships to be established between the documents analysed. In addition, regarding the NLP used for the vectorization of texts, although the TF-IDF method has been found effective, it would be advisable to explore more advanced alternatives, such as embedded models (for example, word2vec or BERT), which may better capture the semantics and contextual nuances present in the data, providing a richer and more accurate representation of the analysed texts.

In addition, the analysis of keywords through graphs, limited to review-type articles, could have skewed our understanding of areas of opportunity and saturated research areas.

In conclusion, although this study offers valuable insight into biases in the studied context, their influence on decision-making and perceptions, and their transmission to different ecosystems, it is essential to consider these limitations when interpreting the results and propose future studies that address these deficiencies for a more complete and accurate understanding of the phenomenon studied.

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