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SURVEY

Echo Chambers in Online Social Networks: A Systematic Literature Review

AMIN MAHMOUDI[1], **DARIUSZ JEMIELNIAK**[1,2], **AND LEON CIECHANOWSKI**[1,3]
[1]Management in Networked and Digital Societies (MINDS) Department, Kozminski University, 59 Jagiellonska Street, 03-301 Warsaw, Poland
[2]Berkman-Klein Center for Internet and Society, Harvard University, Cambridge, MA 02138, USA
[3]MIT Center for Collective Intelligence, Massachusetts Institute of Technology, Cambridge, MA 02139, USA

Corresponding author: Amin Mahmoudi (amahmoudi@kozminski.edu.pl)

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ABSTRACT Echo chambers, a recent phenomenon in the realm of social networks, have garnered significant attention from researchers due to their profound implications. Their role in propagating information, reinforcing beliefs and opinions, and potentially fostering inequality within networks and societies underscores the critical need for comprehensive understanding. Despite the lack of a clear definition, existing research has primarily concentrated on five aspects of echo chambers: their attributes, underlying mechanisms, modeling, detection, and mitigation strategies. The main objectives of this systematic review are to identify terminology, examine the effects of echo chambers, analyze approaches to echo chamber mechanisms, assess modeling and detection techniques, and evaluate metrics used to specify echo chambers in online social networks. By doing so, this article aims to illuminate the strengths and weaknesses of current approaches. To conduct this study, a systematic review was conducted of studies published from 2013 to October 2022, peer-reviewed in five prestigious publishers, including ACM Digital Library, IEEE Xplore, Science Direct, Springer, and Nature. The methodology of this systematic review was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement. Ultimately, 28 studies were selected for the final review. The findings of this study highlight several main limitations. Firstly, there is a lack of an accurate definition for echo chambers. Secondly, there is a lack of a solid approach to address the components of echo chambers. Thirdly, there is a controversial issue regarding the effect of echo chambers. Lastly, the measures used mostly did not adequately specify echo chambers.

INDEX TERMS Echo chambers, online social network, systematic literature review, social media.

I. INTRODUCTION

A. RATIONAL

Today, online social networks (OSNs) are essential for understanding fields as different as politics [1], economy [2], sports [3] and society in general [4]. According to [5] Social media, having reached their maturity stage, boasts approximately 4.5 billion users as of the close of 2022. Given this vast user base, it is unsurprising that these platforms have become arenas for the clash of diverse beliefs and thoughts. This has given rise to a phenomenon known as echo chambers, where similar views reverberate within specific user groups. Echo chambers, as per the group polarization theory, typically form in OSNs, when like-minded users predominantly interact amongst themselves, rather than engaging with a broader user base [6].

Echo chambers are not confined to any specific topic; they span a wide array of subjects, from abortion, gender and climate change to vaccines, to name just a few topics of current heated topics [7], [8], [9], [10]. The influence of these echo chambers is far-reaching, with the potential to alter national policies and even impact the global population [11], [12], [13]. Therefore, a detailed understanding of them is crucial. However, their characteristics remain inadequately addressed, and even the term itself lacks a clear explanation [14].

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Recent literature has begun to explore the influence of echo chambers on decision-making, and the society as a whole [15], [16], [17]. Although it seems that very few have actually attempted a full review of Echo Chambers. Also, these studies have limitations that we will mention in the next section. Therefore, in this study, we tried to have a more comprehensive view of this issue with a systematic review and present a greater view to the readers by synthesizing existing studies and methods. This work underscores the importance of understanding echo chambers in the context of broader societal and political trends.

B. OBJECTIVES

In the realm of echo chambers, four primary areas of concern have been identified: mechanism, modeling, detection, and mitigation [18]. The systematic literature review (SLR) conducted in this study specifically targeted research addressing the first three aspects. We consciously chose to exclude the issue of mitigation, as our primary objective is to explore studies centered on the creation and modeling of echo chambers. Moreover, our research findings suggest that, from certain perspectives, echo chambers may not pose a threat and thus may not necessitate mitigation. We have opted for a neutral stance on the phenomenon, prioritizing its identification and analysis over policy-oriented interventions.

Another challenge lies in the fact that the full effects of echo chambers are not yet fully understood. There is a lack of consensus on whether their net effect is detrimental and significant, or not harmful at all [19].

Echo Chambers, as a broad concept, encompasses many topics and is influenced by various scientific fields. However, this phenomenon and its dimensions are not well understood, and there is no consensus regarding its definition and effects. Different opinions exist about the causes of its occurrence, but these opinions are not well organized. Additionally, the modeling and identification of echo chambers involve a wide range of methods, which require a more organized classification. Therefore, the objectives of this study are as follows:

- Present existing definitions and synthesize them to achieve a comprehensive definition.
- Provide new insights into the effects of echo chambers, which have previously been limited to destructive effects only.
- Present the existing mechanisms that contribute to the creation of echo chambers and highlight their limitations.
- Present the methods that attempt to model and discover this phenomenon and highlight their limitations.
- Provide new directions for future research.

C. STRUCTURE OF THE PAPER

The remainder of this paper is structured as follows: Section II presents an overview of surveys conducted on echo chambers. This is followed by Section III, which provides a detailed description of the research methodology. Section IV presents the results of the search process, introduces the classification framework, and comparison metrics. Subsequently, in Section V, we present and discuss the results of the Systematic Literature Review (SLR). Section VI provides a critical review in accordance with the research questions. Finally, Section VII draws conclusions from the study.

II. OVERVIEW OF SURVEYS ON ECHO CHAMBERS

In recent years, a proliferation of research has emerged, focusing on the phenomenon of echo chambers [18], [20], [21], [22]. This study aims to delve into the modeling, detection, and mechanisms of echo chambers. A comparison between our study and existing studies in this domain highlights the novelty of this study. Table 1 presents criteria by which our study demonstrates its novelty and discrimination from existing surveys on echo chambers.

Alatawi et al. in [18] proposed an array of methods for echo chamber modeling, despite these techniques not being originally conceived for this specific purpose. They embarked on a classification of the challenges and issues surrounding echo chambers, resulting in a four-pronged categorization: attributes, mechanisms, detection-modeling, and prevention-mitigation. In a separate study, Terren and Borge [22] conducted a systematic literature review of 55 studies, scrutinizing the existence of echo chambers on social media. Their research bifurcated into two distinct areas: studies examining communication and interaction in social media as they relate to echo chambers, and studies focusing more on content exposure on social media, a concept closely tied to the filter bubble phenomenon.

Arguedas et al. in [20] undertook a comprehensive review of echo chambers, filter bubbles, and polarization within online social networks. Their analysis of existing literature led to three key conclusions: firstly, echo chambers are far less prevalent than commonly believed; secondly, there is no substantial evidence supporting the existence of filter bubbles; and thirdly, the role of news media in polarization presents a complex and mixed picture. Moreover, they observed a lack of scientific consensus on the definitions of these terms, noting their frequent misuse in political and public discourse. Their methodology was primarily descriptive, focusing on recent studies within the social sciences. However, they refrained from discussing existing models of echo chambers, stating that their objective was not to "outline normative positions on these but to summarize the relevant evidence" [20, p. 7]. Interian et al. in [21] offered an annotated review of measures and reduction methods concerning network polarization, echo chambers, and filter bubbles. Their analysis revealed that the volume of research on echo chambers surpasses that on filter bubbles. However, their primary focus was on the topic of polarization, with only 6.6% of the 78 papers reviewed addressing echo chambers. They scrutinized papers that delved into the mathematical or computational modeling of network polarization.

TABLE 1. Comparison between this study and other existing surveys.

Criteria	This study	[18]	[22]	[20]	[21]
Is an SLR study provided?	Yes	No	Yes	No	No
Does it exclusively cover the study of echo chambers?	Yes	Yes	No	No	No
Do they criticize existing studies in this field regarding the possibility of positive effects of echo chambers?	Yes	No	No	No	No
Are all components in the definition of this phenomenon fully investigated?	Yes	No	No	No	No
Have the three main computation methods, such as recommender systems, information propagation, and opinion dynamics, been mentioned in the mechanisms that form this phenomenon?	Yes	Partially	No	No	No
Have structural approaches been mentioned in the mechanisms that form this phenomenon?	Yes	No	No	No	No
Apart from homophily, do other methods in social science theories, such as social influence and social contagion, consider mechanisms that create echo chambers?	Yes	No	No	No	No
Regarding cognitive system approaches in creating echo chambers, are selective exposure, motivated reasoning, backfire effect, and biased assimilation considered?	Yes	No	No	No	No
Has a critical study been provided?	Yes	No	No	No	No
Do existing surveys include measurement criteria for the echo chamber, such as the Calinski-Harabasz index, ARI and Euclidean distance, Purity, Echo chamber size, Gap coefficient and normalized expected degree, Information transmission between groups and inside groups, Segregation index, closed triads, Bimodality index and balance distribution, Spatial groups with close distance, purity and conductance, Polarized groups based on activity and sentiment, M_Value, and edge homogeneity?	Yes	No	No	No	No

III. METHODS

Methodology plays a crucial role in conducting a systematic literature review (SLR) in a systematic manner. Various methods have been developed for this purpose, such as the PRISMA Statement [23], [24] and three-phase methodology employed by [25]. For this study, we have chosen to follow the approach outlined in the PRISMA Statement, which is a widely accepted checklist used by researchers worldwide to guide and inform the development of SLRs.

A. ELIGIBILITY CRITERIA

Prior to addressing eligibility criteria, it is imperative to define the research scope. To accomplish this, we employ the CIMO (Context-Intervention-Mechanisms-Outcomes) framework, also proposed by Booth et al. [24]. The research scope of this study is centered on the following research questions:

RQ1: How do existing studies define echo chambers within online social networks?

RQ2: What impacts do echo chambers have within online social networks?

RQ 3: What mechanisms do existing studies propose for the formation of echo chambers within online social networks?

RQ 4: How do existing studies model and detect echo chambers within online social networks?

RQ 5: What criteria and metrics do existing studies use to specify echo chambers?

To systematically categorize the selected papers for review, we have organized these five questions into a hierarchical classification framework, as illustrated in Figure 1.

In light of these research questions, the components of the CIMO framework are as follows:

Context: Echo Chambers within online social networks

Intervention: The study and analysis of echo chambers

Mechanisms: The formation, modeling, and detection of echo chambers within online social networks

Outcomes: The elucidation of the characteristics of echo chambers

Consequently, the scope of this study encompasses all research that addresses the modeling, detection, and mechanisms of echo chambers within online social networks.

We established four criteria for inclusion: the article must (1) be published in a peer-reviewed academic research journal or conference proceedings, (2) be written in English, (3) be published between 2013 and October 2022, and (4) have its full text available.

B. INFORMATION SOURCES

Regarding the field of this research and best practices in the field, five databases were selected for this research including ScienceDirect, ACM digital library, IEEE Xplore, Nature and Springer.

C. SEARCH STRATEGY

The issue of echo chambers can be explored across various platforms, including print media, broadcast news, and online social networks. However, this study selectively focuses on research that addresses the problem of echo chambers within online social networks. In alignment with the scope of this research, we employed the keyword "echo chamber?". The question mark (?) is interpreted as a wildcard, substituting for any single character. This is due to the occasional use of the singular form "echo chamber" in some studies. Given the myriad combinations of terms relevant to the scope of this

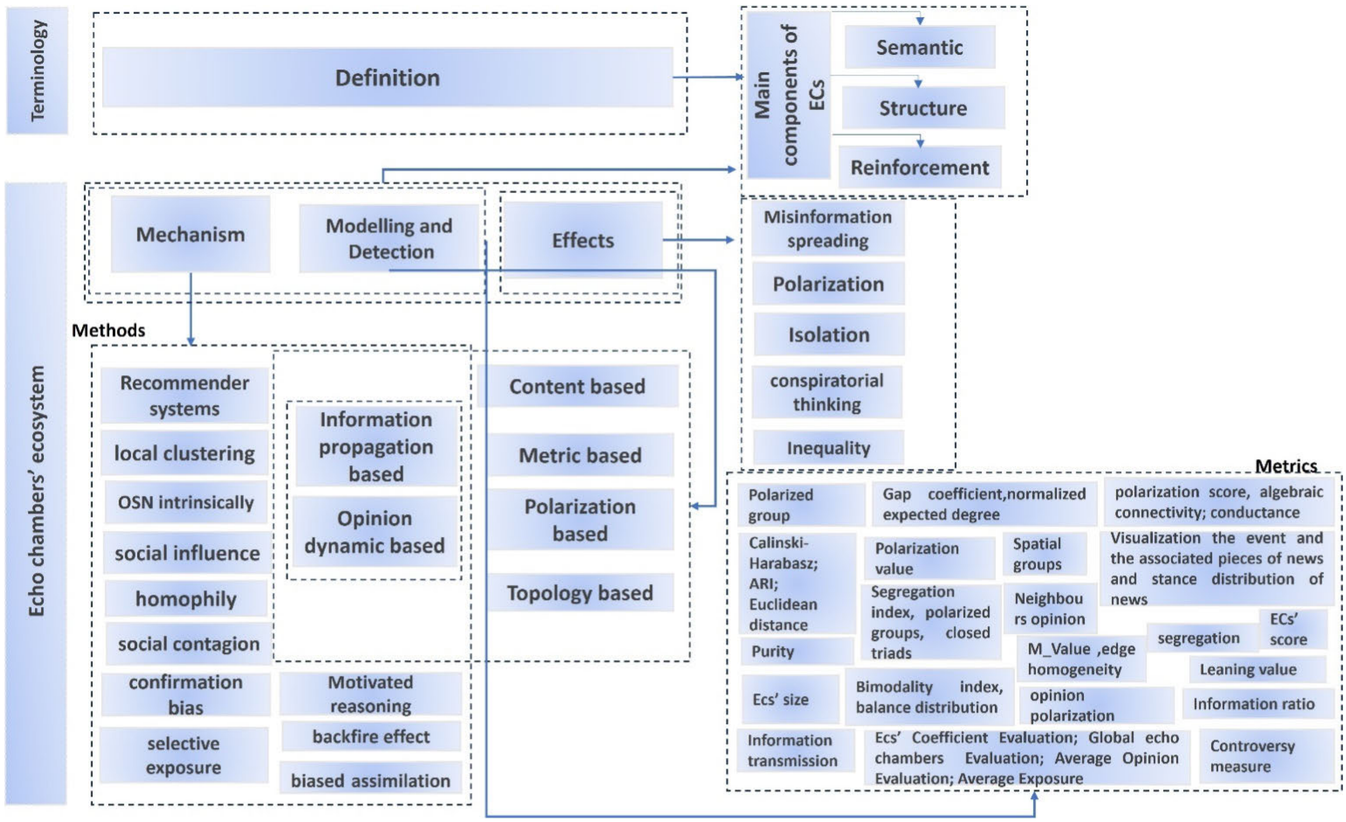

FIGURE 1. Framework for the literature analysis and classification of echo chambers.

study, we opted to use the single term "echo chambers" to ensure an efficient and comprehensive search.

The publication statistics for each database are presented in Table 2.

Figure 2 illustrates the number of publications per year, revealing a surge in publications over the most recent three years (2020 to 2022).

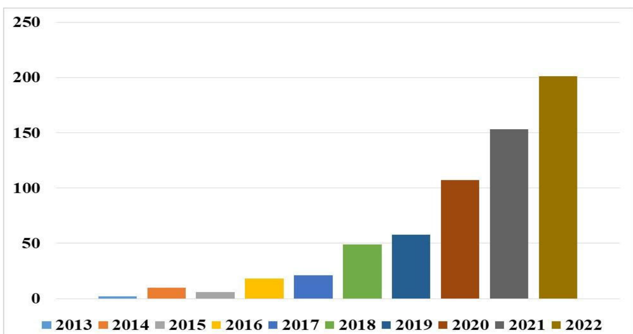

FIGURE 2. Publication statistics about echo chambers between 2013 and 2022.

D. SELECTION PROCESS

The search process was refined by reading the abstract and skimming the content, as a result we selected 57 studies. After the second round of pruning (in-depth screening process-reading full text) 28 papers remained for the final analysis. The PRISMA flow chart diagram shown in Fig 3 represents the process of inclusion/exclusion visually for the reader.

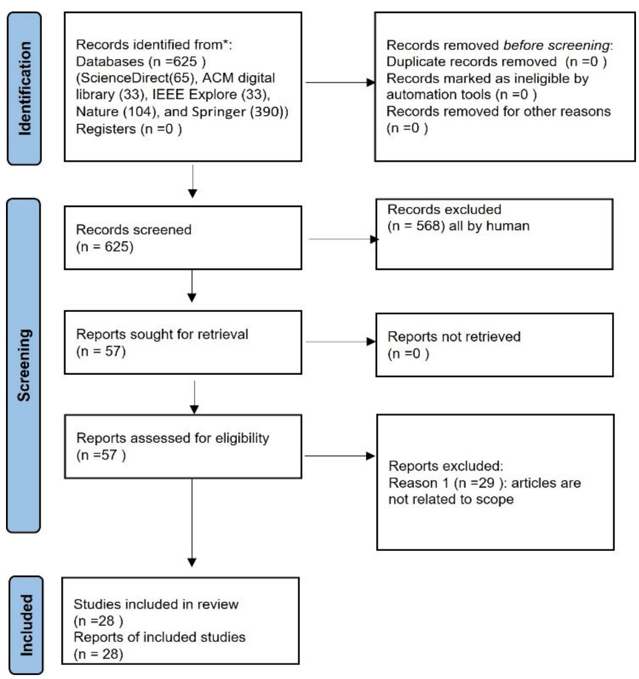

FIGURE 3. PRISMA flow diagram.

TABLE 2. Publication statistics.

Database	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Total
ScienceDirect	1	0	3	3	2	7	10	9	16	14	65
ACM digital library	1	1	0	2	1	5	4	9	8	2	33
IEEE Xplore	0	0	0	0	3	10	5	8	3	4	33
Nature	0	0	2	3	6	8	14	15	31	25	104
Springer	0	9	1	10	9	19	25	66	95	156	390
Sum	2	10	6	18	21	49	58	107	153	201	**625**

E. STUDY RISK OF BIAS ASSESMENT

To achieve the ambitious objectives of this research, stringent project organization and an efficient management strategy will be essential. The core of this research will follow a two-cycle process, involving selection studies and synthesis. Risk assessment will control the output, including the selection of journals and synthesis, and ensure a continuous monitoring process. Table 3 presents the anticipated risks of bias, along with their effects, probabilities, and mitigation methods. The risk analysis will be regularly updated as part of the selection phase and synthesis. There are three main biases to consider: bias in selection studies, bias in selection results, and bias in synthesis. The first bias refers to any potential bias that may occur during the selection of studies. The second bias pertains to any bias that may arise during the selection of results from each study. The final bias is associated with synthesis, which holds significant importance as it can determine the overall quality of this article. This bias refers to instances where the researcher may exhibit bias in adapting each study to the synthesis and interpreting it based on their own perspective.

F. CRITERIA FOR QUALITY ASSESMENT

To assess the quality of the papers, we established a set of criteria outlined in Table 4 and applied them to all the papers selected for inclusion in our review. Each study was evaluated on a three-point scale: "yes," "partly," and "no," with corresponding numerical values assigned to quantify them as 1 for "yes," 0.5 for "partly," and 0 for "no." Additionally, each criterion was assigned a weight coefficient as shown in Table 4, indicating its relative importance. The final quality score represents the overall assessment of the study's quality. The computation of the final quality score is based on equations (1) and (2).

$$QA_{p1} = \sum\nolimits_{i=1}^{4} Q_i W_i \tag{1}$$

$$QA_{overall} = \frac{\sum_{i=1}^{n} QA_{pi}}{n} \in [0, 6] \tag{2}$$

Here, 'n' is the number of papers, QA_{pi} represents the quality value of the i^{th} paper, W_i denotes the weight of each criterion, and, Q_i as the value of the i^{th} criterion is considered for each paper, with assigned values of 1, 0.5, or 0.

The overall score is 4.30, and Appendix III displays the value of each paper concerning the criteria defined in Table 4.

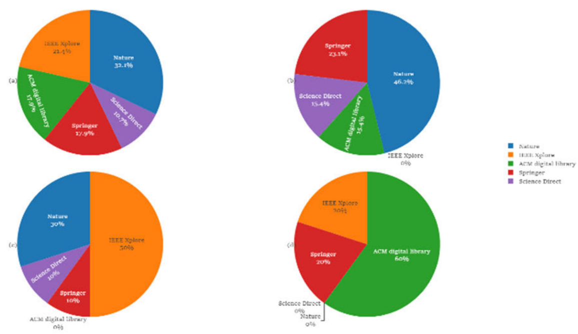

FIGURE 4. (a) distribution of papers in the five mentioned databases, (b) database distribution focusing on addressing echo chambers' mechanisms, (c) database distribution focused on addressing echo chambers' modeling, and (d) database distribution pertaining to addressing echo chambers' detection.

IV. RESULTS

In this section, we aim to organize and cluster the papers that we have selected for final review. This classification will assist the reader in understanding the applicable field of each paper within echo chambers studies. Based on the five research questions proposed in section III, we have outlined the five corresponding classifications below.

A. DATABASE CLUSTERING

A preliminary classification is based on the databases we used to address the three main parts of this systematic review: mechanism, modeling, and detection. We have provided a pie chart in Figure 4(a) to display the statistical distribution of papers across the five aforementioned databases. Additionally, Figure 4(b) illustrates the database distribution regarding the addressing of echo chambers mechanisms, while Figure 4(c) depicts the database distribution in relation to echo chambers modeling. Furthermore, Figure 4(d) presents the database distribution concerning echo chambers detection.

TABLE 3. Risk assessment.

Risk No	Risks	Impact	Probability	Mitigation method
R1	Bias in selection studies	High	low	1) Following a robust methodology such as PRISMA. 2) All authors reviewed the selected studies multiple times. 3) Reviewing the selected studies within a research circle of the faculty.
R2	Bias in selection results	High	Medium	Ensure that the results are consistent with the research questions, which were taken into consideration for the report.
R3	Bias in synthesis	High	High	1) The matching process was conducted several times. 2) Conducted a cross-review among the authors to avoid cognitive errors.

TABLE 4. Quality assessment criteria.

ID	Quality Criteria	Yes (1)	Partly (0.5)	NO (0)	Weight
Q.1	Does the study properly address the characteristics of echo chambers with respect to semantic, structure and reinforcement?				1
Q.2	Does the study address any effect of echo chambers?				1
Q.3	Does the paper present any methods in the context of echo chambers' mechanism, modeling, or detection?				2
Q.4	Does the paper provide any metrics to specify echo chambers?				2

B. CLASSIFICATION BASED ON ECHO CHAMBERS CHARACTERSTICS

A classification can be based on studies that aim to propose a definition addressing the three main components of echo chambers: 1) the formation of a group by like-minded individuals, 2) the prevalence of interactions within the group compared to interactions with users outside the group, and 3) the reinforcement of beliefs within the group. An echo chamber can be defined as a group possessing these three characteristics, which pertain to semantic, structure, and reinforcement in echo chambers, respectively. The distribution of studies related to this particular classification is presented in Table 5. To enhance readability, Figure 5 provides a bar chart that elaborates on the information contained in Table 5, which is likely to be more visually appealing for the reader.

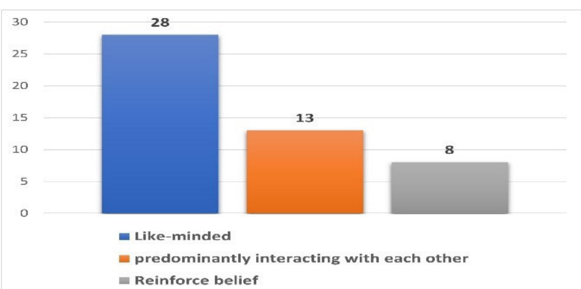

FIGURE 5. The distribution of papers by definition, based on the three main components of echo chambers that are used to define them, along with their corresponding frequencies.

C. ECHO CHAMBERS EFFECT

Echo chambers have diverse effects on networks, ranging from the spread of misinformation such as fake news and rumors to contributing to economic inequality. Figure 6 highlights the well-known and highly cited effects identified by each study.

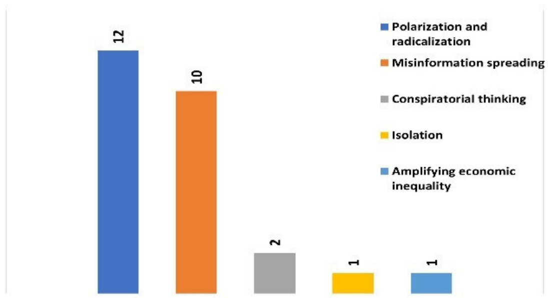

FIGURE 6. Papers distribution by effect.

D. MECHANISM

Several mechanisms that contribute to the formation of echo chambers have been introduced, and these approaches are classified into four main categories, as outlined in Table 6. These mechanisms include computational-based approaches, structural-based approaches, approaches based on social science theories, and approaches based on cognitive science.

It is important to note that when we classify a mechanism, such as a social science-based approach, it indicates that these features are extensively utilized to construct a model that gives rise to echo chambers. In other words, computational

TABLE 5. Each study and components of echo chambers.

ID	Studies	Components of Echo chambers*			Effect	Database	Issues
		1	2	3			
1	[26]	✓	✓	✓	N/A	ACM	Detection
2	[27]	✓	-	-	Misinformation	ACM	Detection
3	[28]	✓	✓	✓	Polarization	ACM	Detection
4	[29]	✓	✓	✓	Misinformation	IEEE	Detection
5	[30]	✓	✓	-	Polarization	Springer	Detection
6	[31]	✓	-	-	Misinformation, Polarization	ACM	Mechanism
7	[32]	✓	✓	✓	Isolating users	ACM	Mechanism
8	[33]	✓	✓	-	N/A	Nature	Mechanism
9	[34]	✓	✓	✓	Polarization and radicalization	Nature	Mechanism
10	[35]	✓	-	-	Misinformation, information transmission biases	Nature	Mechanism
11	[36]	✓	✓	✓	Conspiratorial thinking	Nature	Mechanism
12	[37]	✓	✓	✓	N/A	Nature	Mechanism
13	[38]	✓	-	-	Misinformation	Nature	Mechanism
14	[39]	✓	-	-	Polarization	SD	Mechanism
15	[40]	✓	-	-	Polarization	SD	Mechanism
16	[41]	✓	✓	✓	Misinformation	Springer	Mechanism
17	[42]	✓	✓	✓	Polarization	Springer	Mechanism
18	[43]	✓	-	-	Polarization, cyber-balkanization	Springer	Mechanism
19	[44]	✓	-	-	Polarization	IEEE	Modeling
20	[45]	✓	-	-	Misinformation	IEEE	Modeling
21	[46]	✓	-	-	Spread of fake news (misinformation)	IEEE	Modeling
22	[47]	✓	-	-	Polarization, fake news (misinformation)	IEEE	Modeling
23	[48]	✓	✓	-	Amplifying economic inequality	IEEE	Modeling
24	[49]	✓	-	-	Polarization	Nature	Modeling
25	[50]	✓	-	-	Fake news (misinformation) and conspiracy theories	Nature	Modeling
26	[51]	✓	-	-	Polarization	Nature	Modeling
27	[52]	✓	✓	-	Polarization and radicalization	SD	Modelling
28	[53]	✓	✓	-	Misinformation	Springer	Modelling

*Main components of echo chambers are: 1) semantic, 2) structure, and 3)reinforcement

approaches employ these features to form echo chambers in OSNs, and these approaches play a dominant role.

E. MODELING AND DETECTION

Table 7 highlights the approaches for modeling and detecting echo chambers. In section V, we delve into a detailed discussion of these approaches.

Additionally, given the powerful role of machine learning, especially deep learning techniques, in certain downstream tasks within echo chamber studies, we have highlighted the techniques used by existing studies for specific purposes, as shown in Table 8. Detailed discussions will be provided in Section V.

TABLE 6. Mechanisms classification.

Abstract level	Mechanisms	Studies
Computational	Recommender systems	[31], [32]
	Information propagation model	[35], [41]
	Opinion dynamics model	[33], [39]–[41]
Structural	Local clustering	[40], [42]
	OSN intrinsically	[36]
Social science theories	Social influence	[35], [37], [38], [43],
	Homophily	[31], [32], [37], [38]
	Social contagion	[35]
Cognitive system	Confirmation bias	[34], [38], [42], [54]
	Selective exposure	[33], [41], [43]
	Motivated reasoning	[42]
	Backfire effect	[42]
	Biased assimilation	[42]

TABLE 7. Modeling and detection classification.

Approaches	studies
Content based	[26]–[28], [30], [45], [46], [54]
Information propagation based	[28], [29], [53]
Metric based	[47], [51], [52], [55]
Opinion dynamic based	[44], [45]
Polarization based	[47], [49]–[51], [54]
Topology based	[28]–[30], [48], [52], [53]

TABLE 8. Machine learning and deep learning techniques which used in echo chambers.

Techniques	studies
Attention based mechanism	[26]
BERT	[27]
GCN	[28]
SVM	[49]

F. METRICS AND CRETERIA TO SPECIFY THE ECHO CHAMBERS

During this study, we realized that one of the important limitations of existing studies is the lack of a solid metric to specify echo chambers. This means that existing studies mostly do not provide a metric to measure echo chambers. In this part, we provide a list of studies that measure echo chambers effectively with a solid metric. However, in the next section, we discuss this issue in detail. Table 9 showcases each study and its metric for addressing echo chambers, focusing on the three main components of each echo chamber. The last column, labeled "Diverse leaning values," indicates whether the relevant study considers diverse leaning values. If the study only addresses a bipolar leaning value (e.g., -1 and 1), it is denoted by a × symbol.

TABLE 9. Metrics of measurement echo chambers.

ID	Studies	Metric	Semantic	Structure	reinforcement	Diverse leaning values
1	[42]	Polarized group	✓	×	×	✓
2	[32]	Calinski-Harabasz index, ARI and Euclidean distance	✓	✓	✓	×
3	[36]	Purity	✓	×	✓	×
4	[40]	Echo chamber size	✓	✓	✓	×
5	[31]	Gap coefficient and normalized expected degree	✓	×	✓	×
6	[34]	Polarization value	✓	×	✓	×
7	[35]	Information transmission between groups and inside groups	✓	×	×	×
8	[43]	Segregation index, polarized groups, closed triads	✓	✓	✓	✓
9	[39]	Bimodality index and the balance distribution	✓	✓	×	✓
10	[38]	Spatial groups with close distance	✓	✓	×	✓
11	[33]	Neighbors opinion at two time stamp	✓	×	✓	×
12	[41]	M_Value and edge homogeneity	✓	×	×	✓
13	[52]	**N/A**	×	×	×	×
14	[37]	**N/A**	×	×	×	×
15	[45]	Echo chambers Coefficient Evaluation; Global echo chambers Evaluation; Average Opinion Evaluation; Average Exposure	✓	✓	✓	✓
16	[46]	Opinion polarization	✓	×	×	✓
17	[47]	Polarization score, algebraic connectivity and conductance	✓	✓	×	×
18	[48]	Segregation	✓	×	✓	×
19	[44]	**N/A**	×	×	×	×
20	[53]	Leaning value	✓	×	×	✓
21	[51]	**N/A**	×	×	×	×
22	[50]	Information ratio	✓	×	×	✓
23	[49]	Polarized groups based on activity and sentiment	✓	✓	×	×
24	[29]	N/A	×	×	×	×
25	[26]	Echo chamber score	✓	×	×	✓
26	[28]	Purity and conductance	✓	✓	×	✓
27	[27]	1) visualizing the event and the associated pieces of news; and 2) visualizing the stance distribution of news from news sources of different political ideology	✓	×	×	✓
28	[30]	Controversy measure	✓	✓	×	✓

V. DISCUSSION

In this section, we delve into the results obtained from the previous section, highlighting their significance in relation to the scope of this study and the research questions posed.

It is important to note that the categorization of mechanisms differs from that of modeling and detection. Before delving into the existing approaches, it is crucial to emphasize the distinction between mechanisms and modeling, as the concept of detection is relatively straightforward. According to the definition provided by Boyraz et al. in [56], a mechanism refers to a process, technique, or system that facilitates a specific outcome—in this case, the formation of echo chambers. On the other hand, a model pertains to the internal dynamics that illustrate how various components interact within a system. To visualize the echo chambers ecosystem, Figure 7 has been included.

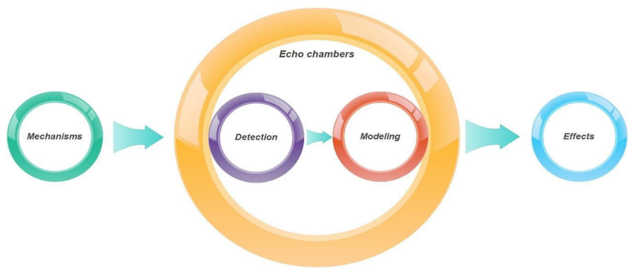

FIGURE 7. Echo chambers' ecosystem.

With this distinction in mind, we have classified the methods that contribute to the formation of echo chambers as mechanisms. Conversely, methods that elucidate the relationships between variables within echo chambers are categorized under modeling and detection.

A. RQ1: HOW DO EXISTING STUDIES DEFINE ECHO CHAMBERS WITHIN ONLINE SOCIAL NETWORKS?

In our introductory section, we highlighted the inadequacy of the existing definitions of "echo chambers". Precise terminology in scientific studies is vital to prevent misunderstandings and misconceptions about a subject [57]. Without a comprehensive explanation of this term, a full understanding of all its facets remains elusive. We collected the definition of each study about echo chambers as shown in Table 10. To assess the effectiveness of existing definitions, it is necessary to establish a pivot definition. Therefore, based on the results of the existing definitions, the interpretation of previous studies, and an analysis of the function of echo chambers, we have arrived at a reference definition:

Definition 1 (echo chamber): **An echo chamber is a phenomenon prevalent in online social networks, characterized by like-minded users predominantly interacting with each other. Within these echo chambers, users express and reinforce their beliefs on specific issues, thereby amplifying their shared viewpoints.**

Our definition encompasses three fundamental aspects of echo chambers:

1. They are formed by **like-minded users who share similar beliefs and perspectives.**
2. **These users tend to interact more frequently with each other** compared to interactions with users outside of the echo chamber.

TABLE 10. ECHO chambers definition by studies.

ID	reference	definitions
1	[26]	A situation where beliefs are amplified within a closed network, and social media platforms provide an ideal environment for this phenomenon.
2	[27]	Phenomena wherein online users exhibit selective exposure and ideological segregation on political issues.
3	[28]	Groups of users exposed only to like-minded individuals tend to reinforce pre-existing opinions, a phenomenon scrutinized as a possible cause of increased polarization.
4	[29]	The amplification of opinions through communication and repetition within a relatively closed social system.
5	[30]	Distinct groups of individuals with highly polarized ideas on certain topics, known as echo chambers, where people only 'hear their own voice,' and divergent visions are no longer taken into account
6	[31]	N/A
7	[32]	The reinforcement of user interests through repeated exposure to similar content.
8	[33]	N/A
9	[34]	Users reinforce their preexisting beliefs by leveraging the activity of like-minded neighbors, and this trend grows with user engagement.
10	[35]	Situations where information transmission within the same opinion group is dominant, while transmission among individuals with different opinions is hindered.
11	[36]	Enclosed epistemic circles where like-minded people communicate and reinforce pre-existing beliefs.
12	[37]	Information becomes an 'echo' when it repeats pre-existing beliefs. A 'chamber' is the smallest network structure that facilitates the transmission of the same information from one source to one recipient through different paths.
13	[38]	N/A
14	[39]	Groups of connected people with similar opinions.
15	[40]	Situations where individuals are exposed to the same content or are surrounded by others with the same opinion.
16	[41]	Like-minded people interact with limited exposure to different viewpoints.
17	[42]	An amplification process in which individuals increase their confidence in a view by sorting themselves in a way that leads to an echo effect in a chamber of discussion.
18	[43]	Segregated and polarized clusters.
19	[44]	An individual is said to be in an echo chamber if they have no access to information that contradicts their own views.
20	[45]	People are only surrounded by people of similar opinions.
21	[46]	People are only surrounded by similar opinions.
22	[47]	N/A
23	[48]	Situations where one is exposed only to agreeing opinions.
24	[49]	Groups of like-minded people polarizing their opinions.
25	[50]	N/A
26	[51]	The same opinions keep being bounced around.
27	[52]	A situations or environments where only value-congruent ideas, information, or opinions are shared and alternative perspectives are not considered.
28	[53]	Users prefer to interact only with ideologically-aligned peers, are believed to facilitate misinformation spreading and contribute to radicalize political discourse.

3. Within these chambers, beliefs are reinforced through the echo chamber dynamics, leading to a **reinforcement of existing viewpoints**.

When conducting a study on echo chambers, it is important to address these key elements. The mentioned characteristics relate to the semantic (shared beliefs), structure (interaction patterns), and reinforcement (strengthening of beliefs) within echo chambers, respectively.

As described in Table 10, various researchers have presented different perspectives on the term "echo chamber." These definitions are crucial as they reveal the researchers' viewpoints on this phenomenon. A comparison between Table 10 and Table 5 demonstrates that studies presenting definitions that consider semantic incorporate terms such as 'ideological segregation,' 'like-minded individuals,' 'opinion in a closed social system,' 'group of highly polarized ideas,' 'similar content,' 'like-minded neighbors,' 'same opinion group,' 'similar opinion,' 'value-congruent ideas,' and 'ideologically-aligned peers.' These definitions explicitly address the semantic aspect of echo chambers, as shown in Table 5.

On the other hand, studies employing terms that convey the meaning of interaction within groups (echo chambers), such as 'closed network,' 'closed system,' 'distinct groups,' 'repeated exposure to similar contents,' 'activity of their neighbors,' 'transmission of information among groups,' 'communicate,' 'smallest network structure,' 'interact with little exposure to different viewpoints,' and 'interact only with ideologically aligned,' predominantly address the structural component in their approach. Furthermore, studies utilizing terms that convey the meaning of reinforcement, such as 'amplified beliefs,' 'reinforce each other's pre-existing opinions,' 'amplify opinion,' and 'amplification process,' mainly address the aspect of reinforcement within echo chambers. However, there are studies that do not explicitly provide a definition but address the components of echo chambers within their context, and vice versa.

B. RQ2: WHAT IMPACTS DO ECHO CHAMBERS HAVE WITHIN ONLINE SOCIAL NETWORKS?

The literature presents two interpretations of the echo chamber effect. The first interpretation considers echo chambers as a phenomenon that arises within online social networks. The second interpretation encompasses the consequences of echo chambers, such as polarization, the spread of fake news, rumors, and other related issues. In this review, we adopt the latter perspective

Through our analysis, we found that the majority of existing studies in this review explicitly or implicitly view echo chambers as harmful, while the remaining studies do not provide a clear stance on the matter. The studies we reviewed highlighted that the primary effect and implication of echo chambers in online social networks is polarization and radicalization [28], [30], [31], [34], [39], [40], [42], [43], [44], [47], [49], [51], [52].

The prevailing viewpoint in these studies is that echo chambers are characterized by polarized groups. In fact, most existing studies define echo chambers in terms of two groups, such as red and blue, conservative and democrats, or majority and minority. Thus, it becomes apparent that based on this assumption, the effect of echo chambers is polarization. However, in the real world, there is an infinite number of echo chambers, as there exist infinite real numbers between -1 and 1. Polarization can be considered as a type of echo chamber (bipolar and unipolar), but it can also be seen as segregation within diverse groups.

Some studies [34], [41], [43] observed polarization in their research through experiments, while [47] observed polarization as an effect of echo chambers through an experiment conducted on Twitter data related to the 2020 US election. However, it should be noted that this conclusion is two-fold, meaning that they consider this segregation as an echo chamber. This issue poses a challenge in echo chamber studies, particularly in those studies that equate polarization with echo chambers. In reality, it should be recognized that in this scenario, polarization is not an effect of echo chambers, but rather polarization itself leads to the formation of echo chambers.

The second effect of echo chambers, as indicated by existing studies, is the spreading of misinformation, including fake news and rumors [27], [29], [31], [35], [38], [41], [45], [46], [47], [50], [53]. However, most of these studies do not provide experimental results on real data to demonstrate this effect, even theoretically, such as [31], [38], [41], [46], and [47]. For instance, [31], [38], [41], [46], [47] merely mention that polarization and the spread of fake news can be side effects of echo chambers.

Diaz-Diaz et al. in [35] report two side effects of echo chambers, namely misinformation and information transmission bias. For the former, they refer to another work, while for the latter, they observe this effect through experimental results on real data. Al Atiqi et al. in [45] attempt to explore the relationship between misinformation spreading and echo chambers through an experiment conducted on a random network. Asatani et al. in [50] examine misinformation in the form of fake news and attempt to understand information spreading by analyzing Japanese tweet texts. Using quantitative analysis and statistics, they examine the behavior of each echo chamber in terms of retweets and replies, ultimately highlighting the role of influencers in each community for information dissemination. Cota et al. in [53] employ information propagation models to examine how information spreads within an echo chamber. They utilize a SIS model and tweet data related to the impeachment process of the former Brazilian President in 2016. Their experimental results demonstrate the relationship between political position and spreading capacity.

In addition to polarization and misinformation, some other effects have been reported. Madsen et al. in [36] suggest that echo chambers lead to conspiratorial thinking, although they do not provide specific characteristics for this effect. In contrast, Asatani et al. in [50] observed this behavior in their study and report that "co-reply/retweet core users radically use offensive words and claim conspiracy theories." Ge et al. in [32] addressed another effect of echo chambers, which is isolation. They observed this effect through experiments conducted on real-world data, where users, guided by a recommender system, fall into echo chambers and find themselves in isolated groups of items. Another important effect is inequality, which is mentioned by [48], although there is no specific observation provided through experimentation.

It is worth noting that while these effects are discussed in the literature, some of them lack concrete experimental observations to support their claims.

C. RQ3: WHAT MECHANISMS DO EXISTING STUDIES PROPOSE FOR THE FORMATION OF ECHO CHAMBERS WITHIN ONLINE SOCIAL NETWORKS?

As discussed in section IV, there are four main categories of mechanisms that contribute to the formation of echo chambers: computational (algorithmic), cognitive systems, structural, and social science theories. In this section, we will delve into the significance and limitations of existing studies, while also addressing any limitations that may be present.

It is important to note that studies often incorporate a combination of approaches, although the role of one approach may be more prominent than others. For example, a study might consider the concepts of confirmation bias, structural factors, selective exposure, and homophily. However, in some cases, the role of selective exposure might be stronger compared to the other three approaches.

By analyzing the significance and limitations of existing studies, we can gain a comprehensive understanding of the mechanisms behind echo chambers and their impact on social dynamics.

1) COMPUTATIONAL APPROACHES

This approach comprises three elements:

- Recommender algorithms play a crucial role in consolidating similar beliefs or interests around specific items, products, or topics. These algorithms contribute to the formation of echo chambers by suggesting content that aligns with users' existing preferences and reinforcing their beliefs.
- Information propagation modeling plays a significant role in situating network users within echo chambers. By studying how information spreads within a network, researchers can understand the mechanisms that lead to the formation and maintenance of echo chambers.
- Opinion dynamic models guide the evolution of beliefs within a network. These models take into account factors such as homophily and selective exposure, which result in like-minded individuals being grouped together. By studying opinion dynamics, researchers can gain insights into the mechanisms that contribute to the formation of echo chambers.

By considering these three elements, researchers can gain a deeper understanding of how recommender algorithms, information propagation, and opinion dynamics interact to shape the formation and dynamics of echo chambers within a network.

As mentioned, one mechanism that leads to the formation of echo chambers is the use of recommender systems, which are artificial methods based on algorithms. The question arises of how these recommendations influence user preferences and behaviors, ultimately resulting in the formation of echo chambers. There are two main approaches to demonstrate the effect of recommender systems on the creation of echo chambers:

1. Experimental Results on Real Data: Researchers can conduct experiments using real-world data to study the impact of recommender systems on the formation of echo chambers. They can analyze user behaviors and preferences in the presence of personalized recommendations and measure the presence of echo chambers using relevant metrics. By observing how recommendations influence user interactions and the resulting formation of echo chambers, researchers can gain insights into the mechanisms at play.
2. Theoretical Modeling and Synthetic Datasets: Another approach involves conducting theoretical studies using synthetic datasets. Researchers can design models that simulate the behavior of users and tune relevant parameters to observe the emergence of echo chambers in the data. While this approach may not directly utilize real-world data, it allows researchers to understand the fundamental mechanisms and dynamics that contribute to the formation of echo chambers under controlled conditions.

By employing these approaches, researchers can explore and evaluate the influence of recommender systems on the creation of echo chambers, both through empirical analysis of real data and through theoretical modeling and simulations.

The study conducted by Ge et al. in [32] provides empirical evidence of the effect of recommender systems on the presence of echo chambers. In their research, they conducted an experiment on Alibaba & Taobao, which are popular e-commerce platforms. By analyzing user interactions and behaviors within these platforms, Ge et al. in [32] aimed to detect the presence of echo chambers. They likely investigated how recommender systems influenced users' preferences, choices, and interactions, which ultimately contributed to the formation of echo chambers.

They implemented clustering on user embeddings and measured the change in user interests (referred to as the echo chamber effect) using cluster validity indexes (in this case, the Calinski-Harabasz index) and the Adjusted Rand Index (ARI). Stoica and Chaintreau in [31] used the second approach, they implicitly analyze the dominance of a group under certain parameters such as homophily and item acceptance. They created a network model on social media in which items are content, tweets, and so on. The network is created based on Minority-majority partition, item creation, reposting parameter and homophily parameter. They also created a recommendation model, which is an extended version of the network model with added recommendation parameters. To show the effect of recommendation they computed the expected degree of one side under recommendation parameter and without it. They observed recommendations exacerbate the gap between these two subgroups.

Information propagation models form another category within the computational approach to understanding echo chambers. In this type of mechanism, the focus is on examining how information spreads over a network and how it contributes to the formation of echo chambers. Researchers define various parameters and simulate the propagation process to observe the dynamics of information dissemination. However, it is important to note that the explicit conclusion regarding the presence of echo chambers may not always be the primary objective of these information propagation models. Instead, the primary focus may be on studying the mechanisms of information diffusion and the factors that influence its spread within a network. The presence of echo chambers may be implicit within these models, as they aim to understand the patterns and dynamics of information flow rather than explicitly identifying and characterizing echo chambers.

Diaz-Diaz et al. in [35] analyzed information transition bias and focused on differences in the transmission induced by intrinsic properties of the node that emits and/or receives the information in the network. They showed that hybrid contagion leads to three information transmission biases: emissivity bias, receptivity bias, and echo chamber bias. They defined two groups as the majority and minority. The combination of Simple and Complex Contagion (Hybrid Contagion) leads not only to strong emissivity biases for a wide range of homophily but also to the emergence of echo chambers in the homophilic regime. They experimented with their model on a real-world network (a network of scientific citations) and found an echo chamber effect on information transition (echo chamber bias). Their model shows that algorithms can form echo chambers in the network, where hybrid contagion models for information propagation create echo chambers. In essence, they demonstrated that as homophily parameters increase, echo chambers emerge, and information cannot be transmitted between groups.

The third subcategory of methods within the computational approach is opinion dynamic-based models. They typically consist of two main components: activation mechanisms and sorting algorithms.

- Activation mechanisms in opinion dynamic-based models encompass two processes:
- Broadcast: This process involves individuals expressing their opinions or sharing information with others in the network.
- Update Opinion: This process involves individuals updating their opinions based on the information they receive from others.
- Sorting algorithms play a crucial role in these models as they determine the selection of opinions on a timeline.

Botte et al. in [40] analyzed the role of local clustering, community structure, and filtering algorithms (for updating opinion) on echo chambers and tested their models on different random networks with varying community structures and numbers of clusters. Their experimental results show that the model with higher clustering results in significantly larger echo chambers compared to models with lower clustering. Therefore, they concluded that local clustering plays a crucial role in the formation of echo chambers, while the community structure alone is relatively less important. They also discovered that increasing the stubbornness level decreases the size of echo chambers with the PR algorithm (where opinions are ordered based on the current opinion of individual i). Conversely, using REC (where the S most recent posts in the hidden timeline Li(t) are utilized) increases the sizes of echo chambers. Furthermore, when they conducted experiments on empirical datasets, the results indicated that in the absence of stubbornness, the number of echo chambers is significantly lower in empirical structures. A noteworthy finding was that, without stubbornness, echo chambers are mostly not formed. However, there seems to be a contradiction between the experimental results obtained from empirical data and random networks.

Similar to previous study Perra and Rocha's aim to provide a model that demonstrates the impact of social interactions and algorithmic exposure on user and group opinion dynamics [33]. Their model consists of three main components: 1) the social network structure, 2) an activation mechanism 3) an algorithmic filtering mechanism. The authors found that individuals adopt opinions based on the viewpoints they are exposed to, and algorithmic filtering can influence the sharing and distribution of opinions. Their experimental results reveal that in networks with high clustering, strong polarization emerges when considering different filtering algorithms. In general, their study demonstrates varying levels of polarization and the presence of echo chambers depending on the network model and filtering algorithm employed. For example, echo chambers appear in the LA network (regular lattice) which exhibits no clustering but has strong spatial correlations. The emergence of echo chambers is observed with different distributions in networks such as Watts-Strogatz and LA.

Some researchers have addressed the formation of echo chambers by considering the source of information. One of the primary sources of information is news, which has the power to influence and change opinions. Prasetya and Murata in [41] proposed a model in which opinion dynamics are influenced by news propagation, specifically focusing on selective exposure and the presence of partisan news items. The underlying concept of their model is the propagation of news in online social networks (OSNs), leading to changes in users' opinions. They formulated the probability of successful propagation based on connection strength and a function that represents the influence of opinion similarity growth. Their model considers several factors such as nodes' opinions, connection strength, news items' opinion scores, sets of initial spreader nodes for each news item, and update rates for opinions and connection strength. The behavior of their formula can be summarized as follows: the probability that a neighbor v of user u will accept a piece of news i with a certain opinion is a combination of the strength of their connection and the similarity between their opinions. Although opinion dynamic is the basis of their model, they highlight the role of network structure as well. Their experimental results on Twitter data demonstrate that the combination of a high clustering coefficient and a low average shortest path length leads to increased susceptibility to polarization. They concluded that opinion polarization occurs simultaneously with the segregation of the news propagation structure, which is reflected by strong edges in the network. This segregation ultimately leads to the formation of echo chambers.

Ferraz de Arruda et al. in [39] presented an opinion dynamic model for social networks, where users generate posts that are selectively received by their neighbors based on social network algorithms. The model considers two scenarios: neighbors either update their opinions in response to the post (attraction) or strongly disagree and rewire their friendship (repulsion). By running their model, the authors observed the emergence of echo chambers. They found that high polarization in opinions is a fundamental factor in the formation of echo chambers. The authors also emphasized the role of a rewiring strategy in shaping echo chambers. While their model mainly focuses on bipolar echo chambers, it should be noted that in some cases, echo chambers can exist with numerous groups exhibiting different polarity values. Overall, the model proposed by [39] is intriguing, but it primarily addresses echo chambers characterized by two polarized groups. It is important to recognize that echo chambers can manifest with varying degrees of polarity and encompass multiple distinct groups.

2) COGNITIVE SYSTEM

In this section, we will review studies that focus on the human cognitive system. Formulating psychology theories in computer science applications is of great importance. One such theory in psychology is confirmation bias, which some researchers have attempted to utilize in addressing the issue of echo chambers. Brugnoli et al. in [34] serves as an example where confirmation bias was employed. They used this term and conducted experiments using real data to explore its effects. They explored confirmation bias through two bases: challenge avoidance and reinforcement seeking. They conducted their research using two categories of news, namely conspiracy news and science news, on Facebook pages. Their study found that users tend to consume content that aligns closely with their beliefs. Most users exhibit high polarization, and "polarized users not only tend to surround themselves with friends who share similar belief systems, but they also actively engage within the same community pages" [34]. The authors also demonstrated the effect of the reinforcement seeking mechanism, which limits the influence of neighbors and drives content diffusion within like-minded groups.

Baumgaertner and Justwan in [42] examined the influence of biased assimilation and motivated reasoning in the formation of echo chambers. In their model, an agent updates its beliefs based on the beliefs of its friends. When presented with a belief, agents with empty beliefs may adopt it if it aligns with their ideology. If the belief is incongruent with their ideology, they adopt it with a probability of 1 minus the motivated bias. The authors simulated different levels of motivated bias, including 0, 0.25, 0.5, and 0.75, with each parameter setting being simulated 200 times. In their model, motivated bias serves as a mechanism of exclusion, which contributes to the formation of echo chambers. Motivated reasoning occurs when individuals actively seek reasons to support their existing beliefs and reject facts that do not align with their beliefs. The study concluded that social media platforms can facilitate and exacerbate polarization. The authors also highlighted the presence of epistemic communities, where individuals tend to connect with like-minded people who share a similar mindset. Furthermore, Jasny et al. in [37] emphasized the role of two components, namely the homogeneity of information (the ''echo'') and multi-path information transmission (the ''chamber''), in the formation of echo chambers among US climate policy makers.

3) STRUCTURAL

During our review of existing studies, we made a significant observation regarding the role of network structure in the mechanisms of echo chambers. It became evident that the network structure itself acts as a mechanism for the creation of echo chambers. This finding holds immense importance because it suggests that, regardless of other approaches employed, the inherent structure of the network tends to facilitate the formation of echo chambers within it. In this regardMadsen et al. in [36] argue that social networks alone are causally sufficient to promote the formation of echo chambers. They attempt to address the question of whether echo chambers can emerge even in idealized conditions where equal, rational, and honest Bayesian agents are present. The authors demonstrate that in large social networks, agents tend to develop high levels of confidence in their own views and disregard interactions with agents who hold differing opinions. This behavior ultimately leads to the emergence of echo chambers. The experimental results indicate that, after several iterations, agents converge towards the objective truth, resulting in maximum belief purity. However, it should be noted that the results are valid for a synthetic random network.

4) SOCIAL SCIENCE THEORIES

The role of the social science category, particularly the concept of homophily, is highly significant in understanding echo chambers. As discussed in section IV, echo chambers can be seen as a manifestation of homophily, where like-minded individuals tend to form groups and reinforce their existing beliefs. In this regard Starnini et al. in [38] conducted an analysis on the emergence of meta-populations and echo chambers using a mobile agent model. They defined three parameters: homophily, social influence, and confirmation bias. Confirmation bias was operationalized through a parameter of bounded confidence, which assumed that individuals would not interact with others whose opinions were dissimilar to their own. The individuals interacted with each other in a square box, representing a 2D space, with randomly assigned opinion values. The study concluded that different values of the parameters resulted in different group structures. For instance, when the confirmation bias was at its maximum value (equal to 1), a stable group with an echo chamber emerged, where individuals ignored each other within the same spatial group. The authors investigated the behavior of the groups and the movement of their members by varying the aforementioned parameters.

Sasahara et al. in [43] conducted a study that employed a combination of approaches to analyze the formation of echo chambers. Their model showcased how confirmation bias, social influence, and selective exposure contribute to the creation of these chambers. They incorporated a bounded confidence distance, which represents the difference between an individual's opinion and the opinion of messages received from friends. The authors developed a model that considers opinion dynamics and the rewiring of social ties. However, there are two key components in their approach. Firstly, their opinion model assigns continuous values, and unfriending is based on the concept of bounded confidence. Secondly, when rewiring links, they do not necessarily select nodes with concordant opinions. However, it is evident that when their model incorporates bounded confidence to determine concordant opinions, users with similar opinions form connections while unfriending dissimilar friends. This process ultimately leads to the formation of echo chambers. The authors demonstrated that with a bounded confidence value of 0.4, irrespective of rewiring and social influence, like-minded users cluster together. They stated that ''The joint effect of social influence and rewiring accelerates the joint emergence of both polarization and segregation'' [43]. The study emphasized the significance of **selective exposure** and unfollowing in the formation of echo chambers, rather than the specific mechanism by which individuals select new friends to follow. The rewiring strategy also influences the development of closed social triads, which serve as the smallest unit of an echo chamber. Agents adjust their opinions based on their connected users (**social influence**) and rewire their ties based on shared opinions (social selection). Disagreement-driven unfollowing is identified as a sufficient rewiring condition for the emergence of echo chambers. Additionally, the study revealed an interesting result **that triadic closure** connects individuals to friends of their friends, reinforcing beliefs and behaviors.

Table 11 briefly presents the characteristics of studies that address the mechanism of echo chambers.

D. RQ4: HOW DO EXISTING STUDIES MODEL AND DETECT ECHO CHAMBERS WITHIN ONLINE SOCIAL NETWORKS?

As presented in section IV, there are several main approaches for modeling and detecting echo chambers. These approaches include: Content based, Information propagation based, Metric based, Opinion dynamic based, Polarization based and Topology based.

TABLE 11. Modeling and detection studies.

Reference	Focus of study	Highlight of approach	Challenges	basis of approach	measuring	datasets
[42]	Motivated reasoning and biased assimilation were analyzed as mechanisms of exclusion, which serve as the origin of echo chamber formation	When considering epistemic communities, it is observed that an increase in motivated reasoning contributes to polarization.	There is a lack of solid criteria for effectively demonstrating polarization.	Biased assimilation and motivated reasoning	Polarization in the network	• stochastic algorithm to generate a small-world networks random graph
[40]	Local social clustering plays a pivotal role in the formation of echo chambers, and when combined with community structure, it can further amplify polarization, especially in the presence of filtering algorithms.	• Factors: local clustering + PR algorithm+ no stubbornness. • Their approach incorporates three different opinion dynamic models, which form the fundamental part of their methodology	• The study solely focuses on the size of echo chambers. • It considers the formation of a bipolar echo chamber, represented by groups A and B. • The study highlights the strong correlation between echo chamber formation and filtering algorithms. • The experimental results contradict findings from empirical and random network data.	• Local clustering, community structure Filtering algorithm (PR)	define echo chamber size $\Omega = \left(\frac{N_A^t}{N_A^0}\right) + \left(\frac{N_B^t}{N_B^0}\right)$	• Random network: Watts–Strogatz model , Erdős–Rényi model (ER) and stochastic block model (SBM) • real networks: on-line friendship network (Last.fm) on-line social network of users of the Pretty-Good-Privacy (PGP)
[34]	They defined user polarization by examining the number of likes on conspiracy and science pages. The study focused on analyzing the causal effect of neighbors on user behavior, revealing that users tend to exhibit similar behavior to that of their neighbors.	A notable strength of their study is the emphasis they place on reinforcement.	Do all conspiracy and science pages exhibit a similar degree of polarization?	Confirmation bias	The polarization value is defined based on the number of likes on pages	Facebook dataset
[35]	The study aims to demonstrate the effect of echo chambers by developing an algorithmic approach based on an information propagation model.	The study proposes a hybrid containment approach and investigates information transmission bias in the presence of echo chambers.	• The proposed model is specifically designed for two groups. It is evident that increasing the h value leads to the formation of echo chambers.	• Homophily Social contagion	The quantification of echo chamber bias is based on the measurement of information transmission between groups and within each group. A higher value indicates the presence of echo chambers, where information predominantly propagates within each group	• Barabasi–Albert-homophily model network of scientific citations between papers published in the journals of the American Physical Society
[39]	The study presents an opinion dynamic model that incorporates a rewiring strategy to observe the formation of echo chambers based on polarization and rewiring behavior.	• Introducing the balance measure for polarization. Using rewiring strategy	It addressed bipolar echo chamberThe study specifically addresses the formation of bipolar echo chambers.s.	algorithmic	Bimodality index and the distribution balance	• Twitter dataset Random network
[32]	The study considers the role of recommender systems in demonstrating the effect of echo chambers.	They employ clustering techniques on user embeddings and quantify the change in user interests, which the authors refer to as the echo chamber effect.	The conclusion that the recommender system functions correctly cannot be drawn solely from a decrease in the CH value. There is no guarantee that changes in the final user interaction block clustering are more relevant to users' interests compared to the first interaction block	Homophily	• Cluster validity indexes(Calinski-Harabasz) • ARI Euclidean distance	Alibaba Taobao — one of the largest e-commerce platforms
[36]	They presented this question, whether echo chambers can emerge under idealized conditions where agents are equal, rational, and honest Bayesian agents.	Social networks inherently produce echo chambers	How is the result of their method in real world data?	Social network structure	Purity in beliefs	Random and scale free network
[43]	The study aims to illustrate how echo chambers and segregation occur in online social networks (OSNs) through the examination of factors such as social influence, selective exposure,	The study highlights the role of the rewiring strategy and unfriending in the formation of echo chambers		• Social influence • Selective exposure	• Segregation index Polarization	• Twitter A synthetic dataset

TABLE 11. ***(Continued.)*** **Modeling and detection studies.**

	confirmation bias, and rewiring strategies.			Confirmation bias		
[38]	The study analyzes the influence of social influence, homophily, and confirmation bias on group formation and agent mobility by employing an opinion dynamic model in a 2D space..	• There is a direct relationship between physical distance and opinion distance. Echo chambers emerge based on spatial distance	Implement 2D space on real world data	• Social influence • Homophily Confirmation bias	In spatial groups with close distances, heterogeneous agents coexist.	A synthetic agent network
[31]	The study examines the impact of recommendation systems on polarization and hegemonic dynamics.	The study demonstrates that item recommendations consistently accelerate and exacerbate the misrepresentation of minority viewpoints.		Homophily	The study calculates the expected degree, both with and without the recommendation parameter, to determine the Gap coefficient and the normalized expected degree of one side in a network.	Instagram
[41]	• The study introduced an opinion dynamic model based on an information propagation model. The polarization of opinions occurs simultaneously with the segregation of the news propagation structure, as evidenced by strong edges in the network, leading to the formation of echo chambers.	News polarization leads to echo chambers	• The method for assigning opinion scores and connection strengths to Twitter data is not clearly explained. The functionality of the M_Value is not functioning properly	Selective exposure	• M_Value Edge homogeneity	Synthetic and Twitter dataset
[33]	The study investigates the impact of various network topologies and filtering algorithms on opinion change, polarization, and the formation of echo chambers.	High clustering and spatial correlation, such as nodes in a regular lattice, result in the formation of strong echo chambers.	• The study considers a bipartisan network. • Experiments are conducted on synthetic networks. However, the study does not address reinforcement.	Algorithmic	Neighbors opinion	CM, LA, WS network mode

1) TOPOLOGY BASED (STRUCTURAL)

The structural-based approach refers to a situation where the network's structure itself reveals the presence of echo chambers. Some studies aim to establish a connection between the study of echo chambers and community detection. These studies view the concepts of echo chambers and communities as synonymous or closely related. For example, Tsai et al. in [52] introduced the concepts of "echoers" and "bridgers" as two social mediators to analyze information flow within and between communities. They constructed three networks based on retweets, mentions, and replies to examine communication patterns. The retweet and mention networks exhibited a highly modular structure, characterized by the presence of several large clusters with a high degree of political homophily. These networks suggested the potential formation of echo chambers, primarily consisting of ideologically similar users. Del Vicario et al. in [49] investigated the structural evolution of interest-based communities on Facebook by examining users' emotions and engagement. They focused on two groups, namely conspiracy and science communities, and defined echo chambers as polarized groups of users. Their analysis explored sentiment analysis and activity within these echo chambers. The findings revealed that users' emotions were influenced by their engagement within the echo chambers, with more active users displaying a higher tendency to express negative emotions in their comments. Their work's success relies significantly on sentiment analysis and the identification of polarized groups based on user comments' sentiment, making sentiment classification a pivotal part of their approach. They employed two linear-kernel Support Vector Machines (SVMs) specifically trained to differentiate extreme classes (negative and positive) and combined neutral classes (neutral plus positive and neutral plus negative). During prediction, agreement between both classifiers yields the common class; otherwise, in case of disagreement, the assigned class is neutral. Deploying SVM, a state-of-the-art supervised learning algorithm, involves a four-step process: manual sentiment annotation of a text sample, training and fine-tuning the classifier using the labeled set, evaluation on an independent test set or through cross-validation, and application to the entire set of texts.

Indeed, segregation is closely related to the structure of a network and plays a significant role in the formation of echo chambers. If we can quantify the level of segregation within a network, it becomes possible to model and analyze the formation of echo chambers. Chkhartishvili and Kozitsin in [55] proposed a binary separation index (BSI) to quantify the level of separation or echo chamber formation in a network. The BSI is based on the number of users and the number of information sources. The authors defined two sets of information, I_1 and I_2, and two sets of users, U_1 and U_2, where each set is exclusively connected to one information source. They introduced coefficients, $\alpha = \frac{|U_1|}{U}$, $\beta = \frac{|U_2|}{U}$ and defined the BSI as $BSI = 4 * \alpha * \beta$. The BSI provides a measure of separation in the network, with a higher value indicating a stronger echo chamber effect.

Luo et al. in [48] aimed to propose a model for controlling segregation and echo chambers by promoting inter-community interactions. They devised a game setting where users were provided with external incentives to establish connections with members of other communities. The study defined two groups, namely the red and blue groups, and introduced a segregation measure based on the ratio of edges between the two communities (R and B) to the number of nodes in each community. This measure resembled the boundary connectivity measure. The authors presented the Algorithmic Recommendation Mechanism (ARM) as their model, drawing inspiration from the weak ties theory. ARM featured a utility function, and the objective was to maximize this utility by encouraging interactions between nodes belonging to different groups. They demonstrated that their model effectively mitigated segregation, as indicated by the segregation measures. The study's opinion dynamics model was based on the work of [58], which focused on learning from social feedback. In this model, users considered alternative views based on the social feedback expressed within their group. Opinion dynamics operated through acceptance probabilities. The results of the study illustrated that the ARM method effectively controlled segregation.

2) POLARIZATION BASED

A majority of studies related to echo chambers consider two polarized groups as echo chambers. We discussed in detail this assumption is not true. Asatani et al. in [50] examined the role of core nodes and influencers in information spreading and the formation of echo chambers using a dataset of 42 million Japanese Twitter users. They employed the Leiden clustering algorithm to identify highly **polarized clusters,** which they referred to as echo chambers. Their measure for the presence of echo chambers was based on polarization. The study observed that a majority of tweets, replies, and retweets were confined within the same echo chambers. The authors suggested that densely connected and highly influential core nodes exist within echo chambers, and they found that bias reinforcement in the social network can be explained by repeated cascades of information. The results also highlighted the significant role of core nodes in information spreading within echo chambers. Additionally, the study identified a strong connection between top influencers and the spread of information by core users, leading to the formation of homogeneous opinion regimes. Furthermore, the findings indicated that influencers within each echo chamber contributed to creating a negative atmosphere within the community, while core users tended to engage early in information cascades.

Sikder et al. in [51] approached the problem by formulating it as a graph of agents seeking ground truth on a binary statement while receiving signals from various sources. The authors considered two types of agents: biased and unbiased. Biased agents had a confirmation bias parameter that allowed them to distort information, while unbiased agents received information from their neighbors without distortion. Experimental results demonstrated that biased agents were responsible for polarizing unbiased agents. The authors defined echo chambers as groups of unbiased agents surrounded by biased agents, where the unbiased agents held information sets that were unrepresentative of the broader network's information. They further showed that the fraction of agents within the echo chamber increased with higher confirmation bias and decreased with increased social connectivity.

Luo et al. in [47] conducted a study that incorporated both the composition of like-minded user groups and the structure of these groups, with a focus on utilizing the concept of Markovian processes. By employing the Hidden Markov Bridge (HMB), their experimental results demonstrated its superior performance compared to the Hidden Markov Model (HMM) in predicting segregation within social networks. The study applied this approach in the context of social media marketing scenarios, where the relationship between companies and customers was modeled as a Markov Bridge (MB). The authors implemented an HMB filter to estimate inter-community distance based on observed edge weights, sampled observations, and additive Gaussian noise. The HMB filter outperformed the hidden Markov chain filter in terms of mean-squared error. Additionally, the authors utilized MB to predict the level of echo chambers in a Twitter dataset that contained tweets related to the 2020 U.S. presidential election. They employed the HMB filter to estimate the polarization score based on observed interactions between users. The observations were based on the ratio of the number of interactions within each group to the total interactions. Boundary connection measures were used to capture the interaction patterns between the two major political parties, Republicans and Democrats, over a 28-day period, with 30 days of data used for training purposes.

3) OPINION DYNAMIC BASED

One of the common methods in modeling and mechanism is the methods based on opinion dynamics. Kozitsin and Chkhartishvili in [44] developed an agent-based model to address echo chamber problems, emphasizing the role of polarization systems within social networks. They employed the DeGrootian opinion dynamic [59] in their study to update agent opinions. After a number of iterations, the system exhibited two states: consensus, where the difference between the highest and lowest opinions was less than 0.05, and fragmentation. The authors conducted experiments on two synthetic networks, where each agent's initial opinion was randomly assigned from a uniform distribution between 0 and 1. They found that more active users had a greater tendency to enter echo chambers. Their hypothesis suggested that highly active users provide personalized systems with more information about their preferences, leading to an increased likelihood of entering echo chambers. They highlighted the importance of accessing cross-ideological content to model echo chambers, suggesting that detecting a group of agents lacking access to such content could be indicative of the presence of echo chambers.

4) CONTENT BASED

Content in OSNs can be used as a rich source to identify semantic, which is one of the three main components of echo chambers. Therefore it is possible to detect echo chambers and model it based on content. One of the methods to identify content is the user's stance. Küçük and Fazli in [60] defined stance detection as a classification problem where the goal is to determine the stance of the author towards a specific target, using a category label from the set {Favor, Against, Neither}. There are two subclasses of stance detection: multi-target stance detection, which deals with situations involving multiple targets and aims to detect the author's stance towards each target, and cross-target stance detection, which involves having stance annotations for different targets. Stance detection plays a crucial role in various areas such as rumor detection, fake news detection, and any study that aims to understand users' positions on specific issues. In the context of echo chambers, stance detection can be employed to compute users' leaning or polarity regarding a targeted topic. Overall, stance detection offers valuable insights into understanding users' opinions and can be a useful tool in studying echo chambers.

Calderón et al. in [26] employed two content-based features for the detection of echo chambers: stance detection and the intensity of emotion elicited by a subject. They considered the degree of comments toward a post as an indicator of an echo chamber. To quantify echoing behavior through post-comment pairing, they utilized a graph-based approach for extracting stance and emotion intensity features. The ECHO model, introduced by the authors, includes three neural network classifiers and one attention neural network. It processes input features extracted from both posts and comments, generating two features for each—target stance and emotion intensity. Pairing these features results in Target Stance Feature Pairs and Emotion Intensity Feature Pairs. The model considers these pairs as inputs and employs an attention mechanism to evaluate their impact on decision-making. Three types of input are examined: Target Stance Feature Pair, Emotion Intensity Feature Pair, and the combination of both Feature Pairs. Each undergoes classification using individual neural networks optimized with Adam. The output from the dense layers before the softmax is fed into an attention neural network. The goal is to learn a mapping from the given sequence to a sequence of importance weights, with the tanh activation function used in the final stage. As a result, each post-comment pair is labeled as either echoing or not echoing. Experimental results demonstrated that their model outperformed other approaches in terms of the echoing value (based on annotations), indicating its effectiveness in indexing echo chambers. In a similar vein, Lo et al. [27] presented two methods for examining the effects of echo chambers: visualizing events and their associated news pieces, and visualizing the stance distribution of news from sources with diverse political ideologies. The foundation of echo chamber studies lies in stance detection, which reveals the positions of users or news based on a leaning value. In their methodology, the headline of the top-ranked news retrieved by the search engine is designated as the claim of the event. A stance classification model is then employed to determine the stance of selected news articles related to this claim. They utilized BERT (Bidirectional Encoder Representations from Transformers) to encode the representations of the claim and the news perspective. These representations were created based on the claim and the news content, respectively. The authors employed cosine similarity to measure the consistency between the claim and perspective representations. These representations were then processed in the subsequent dense layer, combined with the perspective representation, to categorize the news stance into four categories: "Agree", "Disagree", "Discuss" and "Unrelated".

Al Atiqi et al. in [45] presented a model involving two players: users within a network and external news sources. Drawing on the Ising and Deffuant models, they assigned opinions to each user and sentiments to news articles on a chosen topic within the range of $[-1, 1]$. The authors defined four indicators for echo chambers: 1) Individual Echo Chambers Coefficient, which evaluates the level of similarity among neighboring agents' opinions; 2) Global Echo Chamber, which measures the clustering of opinions in the network based on the Hamilton function in the Ising model; 3) Average Opinion, obtained by calculating the average opinion of all users; and 4) Average Exposure, which quantifies the diversity of sentiment in the information. They further categorized news into five groups based on sentiment values: random news, positive extreme news, negative extreme news, two-sided extreme news, and moderate news. The authors computed each echo chamber indicator for different news groups and observed the distribution of opinions in the network based on the news source. They found that extreme news articles resulted in the lowest presence of echo chambers, while one-sided extreme news articles were more likely to foster echo chamber dynamics. Their study emphasizes the significance of the news sources to which users are exposed in the context of echo chambers. In a related study, Al Atiqi et al. in [46] investigated the role of media in societal polarization and confirmed the findings of [61]. They computed the average opinion based on agents' political awareness and conducted experiments on random networks, finding that echo chambers are more prevalent in highly polarized media when society itself is polarized. However, they did not provide specific criteria for detecting echo chambers; rather, they inferred the presence of echo chambers based on average opinion values.

Another study that incorporated both content and structure in echo chamber detection is [30]. However community (structure) is very important in their approach; the role of semantic (content) is stronger, where they assign the weight of edges based on sentiment and topic similarity. They examined the structure and semantic of echo chambers, starting with an exploration of the key personality traits exhibited by users within these chambers. These traits included a tendency to interact with close friends (low extraversion), emotional stability (high emotional stability), suspicion and antagonism towards others (low agreeableness), engagement in antisocial behavior (low conscientiousness), and unconventional interests (high openness). The authors discussed two crucial elements contributing to the emergence of echo chambers within a network: controversy among group members and homogeneity within the group. To detect echo chambers, Villa et al. proposed a three-phase approach: (1) modeling the conversation graph, (2) partitioning the graph into two groups, and (3) quantifying polarization by assessing controversy and homogeneity, homogeneity was assessed through sentiment and topic similarity. They constructed an ego network based on user mentions in a Twitter dataset. In addition to the network structure, they considered sentiment and topic similarity as semantic properties of echo chambers. The authors employed the METIS algorithm for community detection purposes, which resulted in partitions characterized by (i) a high level of controversy and (ii) a high level of homogeneity among members.

Choi et al. in [54] conducted an analysis on rumor echo chambers, which they defined as groups of users involved in propagating at least two common rumors. Their assumption was that users who spread similar rumors share like-mindedness. They identified a key characteristic of rumor echo chamber members: their active participation in rumor propagation during the early stages. The study categorized users' political polarity based on two factors: 1) the politicians they followed, and 2) the polarity scores of URLs shared in their tweets. This categorization placed users into left-wing or right-wing groups. The results of the study indicated that echo chamber members tended to share similar political views. The study also introduced the concept of political homophily, which quantified the similarity of user polarities. Furthermore, the study analyzed the cascades within rumor echo chambers and found that these chambers tended to have larger, deeper, and wider propagation compared to those outside of echo chambers. They observed that rumors originating from echo chamber members primarily spread among other echo chamber members, but also extended to non-echo chamber members. Notably, the study revealed that rumors propagated quickly within these echo chambers. In terms of network structure, the study discovered that echo chambers exhibited a high degree of connections with other users.

5) INFORMATION PROPAGATION BASED

A good example for this approach is [29]. They aimed to examine the role of group influence in opinion dynamics and information propagation, with a specific focus on the impact of echo chambers. They explored influence maximization by incorporating the concept of group influence, which they equated to the effect of echo chambers. The authors formulated an influence maximization (IM) problem, where a set of users are responsible for propagating information, with the objective of maximizing the number of influenced users. In their model, Zhu et al. considered that each activated node is influenced not only by its neighbors but also by the group it belongs to. They utilized the Ising model to illustrate the effect of echo chambers. By computing the group influence, they investigated two scenarios for information propagation: one with echo chamber effect and one without. The experimental results, obtained from analyzing Weibo, YouTube, and TheMarker datasets, indicated that the number of activated users was higher when the echo chamber effect was present.

Minici et al. in [28] employed a hybrid approach to detect echo chambers by investigating the propagation of polarized information in a social network, drawing inspiration from community detection studies. They distinguished between two types of communities: echo chambers and social communities. Their proposed algorithm for echo chamber detection involved randomly assigning values for community polarization, social engagement, and polarization parameters, which were subsequently measured to identify echo chambers. The algorithm considered item propagation and link formation dynamics. The authors posited that highly polarized communities correspond to echo chambers, and polarized cascades are only likely to occur within such echo chambers. Additionally, a user's likelihood of participating in a cascade depended on their level of engagement within the associated community. Each community was assigned a polarity value within the range of $[-1, 1]$. For an item to propagate, the sign of the user's engagement had to match the sign of the community. The experimental results demonstrated that communities with a high polarity value were successfully identified using the proposed echo chamber detection algorithm. The algorithm introduced by the authors presents an innovative approach rooted in deep learning techniques, specifically tailored for a graph structure. The implementation adopts the Graph Convolutional Network (GCN) architecture. Initially, a vector of polarization values undergoes a hyperbolic tangent (tanh) transformation to constrain its values within the range of $[-1, 1]$. Polarized engagement and social engagement are modeled through a two-layer GCN with 1024 hidden units. The model incorporates the social graph, one-hot encoding attributes, and an output layer with the number of community components. The resulting outputs are fed into a softmax and a sigmoid function for polarized users' engagement and social engagement users, respectively. Training encompasses the entire architecture using the stochastic algorithm mentioned earlier, employing the Adam optimizer with default settings and one epoch. To address class imbalance between links and propagations, the minority class is randomly oversampled, ensuring a balanced distribution.

Cota et al. aimed to demonstrate and model the homogeneity within echo chambers in a political communication (PC) network on Twitter, focusing on the impeachment process of the former Brazilian President [53]. They assigned a leaning value to each tweet (−1, 0, 1) and calculated the user leaning based on the average leaning of their tweets. The study revealed that more active users tended to be more radical in their political views. The PC network exhibited two large communities, each consisting of approximately 10^4 users, with opposing leanings but similar absolute values (P+ ≈ 0.82 and P– ≈ – 0.70). The authors provided topological evidence of echo chambers by quantifying echo chambers based on a user's political position, considering the leaning of the tweets they received and the leaning of their neighbors. They found that users expressing both pro- and anti-impeachment leanings were more likely to interact with users who shared their political opinions. To examine the impact of echo chambers on information diffusion, Cota et al. employed susceptible-infected-susceptible (SIS) and susceptible-infected-recovered (SIR) models. They quantified the spreading capacity ($\boldsymbol{S_i}$) of each user, representing the relative size of their influence, i.e., the individuals reached by messages sent by that user. However, the study did not find a strong direct relationship between a user's political position and their spreading capacity.

Table 12 briefly presents the characteristics of studies that address the modeling and detection of echo chambers

E. RQ5: WHAT ARE THE CRITERIA AND METRICS OF EXISTING STUDIES TO SPECIFY ECHO CHAMBERS?

One of the main objectives of this study is to find that which criteria and metrics existing studies are considered to specify echo chambers in the network. There is a main question, when we can say echo chambers formed, according to semantic, structure and reinforcement what is the metric for measuring semantic, how specify like-minded which metric is used and what threshold is considered for this term. like minded can be vary in a range between −1 and 1. Botte et al. in [40] addressed the semantic (like-minded) in a synthetic manner by considering number of users who have same opinion, where they just consider two types of opinion such as A and B. Stoica and Chaintreau in [31] also used this method to show like-minded people by considering two types of opinion as minority and majority on the synthetic network. Perra and Rocha in [33] addressed this component by considering the number of a user's neighbors with the same opinion at time $t = 0$, they also considered two types of opinion such as A and B in advance. Madsen, to demonstrate the emergence of echo chambers is the purity of beliefs. Purity is another metric that can be employed. It measures the ratio of users with the same ideological alignment, often calculated based on the average polarity of the tweets they reshare (e.g., on Twitter). Minici et al. in [28] also used purity measures to address like-minded users. One of the significant approaches for addressing semantic is the work of [30] and can be used as a reference for future works in the domain of echo chambers. Villa et al. in [30] tried to assign a weight to edges of the network and then detect a group of users based on these weights. The weight is computed based on sentiment and topic similarity.

Another component of echo chambers is structure. Structure refers to the number of interaction between members of echo chamber that should be higher than interaction with others echo chambers in the network. This term (structure) can be addressed by communities. Meaning that, members in echo chambers similar to community should have higher interaction inside the echo chambers rather than the rest of the network. To address structure, existing studies follow different approaches. Ge et al. in [32] used ARI which is a well-known community detection metric. Tsai et al. in [52] categorized users as ''echoers'' and ''bridgers.'' Their analysis revealed that bridgers had higher in-degree and out-degree centrality, indicating that they received more attention from other users in terms of retweets, mentions, and replies.

A metric that is very valuable to address the structure is the Controversy metric. A well-defined echo chamber is characterized by a sense of hegemony among its members and a state of controversy with users outside the chamber. Therefore, one possible approach to identify echo chambers is through the detection of controversy, which is often based on community detection methods. One metric that can be used to measure polarization and controversy is the Random Walk Controversy (RWC) proposed by [62]. This metric involves two partitions, X and Y, where X ∪ Y = V, X ∩ Y = ∅, and two random walks—one ending in partition X and the other ending in partition Y. The RWC measure is computed based on the probability of changing the partition for each of the random walks using the formula $RWC = P_{xx}P_{yy} - P_{xy}P_{yx}$, where P_{xy} represents the probability of starting in partition x and ending in partition y. In this regard, to quantify controversy, Villa et al. in [30] introduced four measures: RWC, Authoritative Random Walk Controversy (ARWC), Displacement Random Walk Controversy (DRWC), and Boundary Connectivity (BC). In addition Vila used the Boundary Connectivity measure to show the structure. This measure focuses on the boundary nodes that connect nodes in one partition to nodes in another partition. The presence of strong connections between boundary users and internal users indicates the existence of an echo chamber. Ideally, the desired state is achieved when the number of boundary nodes is zero, indicating complete isolation of the two partitions.

Another measure that is used in echo chambers studies and primarily in community detection studies to show how a community is well-designed is conductance. Conductance in graph theory is a measure that shows how a graph is partitioned [63]. Luo et al. in [48] utilized graph conductance and algebraic connectivity (the second smallest eigenvalue of the relevant Laplacian matrix) as measures of segregation.

The third component of echo chambers is reinforcement, which we observed from Table 5. Rarely have studies addressed this important feature in echo chambers. This attribute refers to the fact that, from the timestamp t, the subsequent opinion values within echo chamber i should not decrease. According to the definition of echo chambers,

TABLE 12. Modeling and detection studies.

Reference	Focus of study	Highlight of approach	Challenges	basis of approach	measuring	datasets
[46]	The study focuses on modeling the effects of news media on polarization and the formation of echo chambers	The study confirm Zallar's findings regarding the relationship between political awareness and opinion consistency	The study lacks an examination of important characteristics of echo chambers, such as reinforcement dynamics and network structure.	• Agent based model implicitly Selective exposure	opinion polarization	Watts- Strogatz network (random network)
[45]	The study focuses on analyzing the impact of different news types on the overall opinion formation of social networking site (SNS) users. It involves modeling echo chambers based on specific indicators and differentiating between various news categories	• The study investigates how different kinds of news contribute to the formation of echo chambers. It introduces four indicators to measure and identify echo chambers.	• The classification of news types is based on sentiment values towards the topic. • The initial value of the opinion is not clearly defined.	Opinion dynamics	• echo chambers Coefficient Evaluation • Global echo chambers Evaluation • Average Opinion Evaluation Average Exposure	Barabasi albert graph
[50]	The study presented a quantitative analysis of Japanese tweet text to examine the characteristics of echo chambers. It specifically analyzed the role of core nodes (influencers) in disseminating information within each echo chamber	The study revealed the crucial role of core nodes in spreading information within echo chambers. It identified two polarized communities in which the majority of users primarily interact within their respective communities.	The study's definition of echo chambers is not precise, and it fails to address the issue of reinforcement within echo chambers	Polarized community	The primary measure used to determine communities is the average degree of users in terms of retweets and replies.	Japanese Tweet data
[53]	The study models echo chambers by considering network topology and the leaning values of individuals and their neighbors, aiming to demonstrate information propagation within the context of echo chambers.	• The study introduces the concept of spreading capacity, which represents the average number of influenced users by like-minded individuals (those with similar leaning values). It defines a bidirectional leaning value based on the leaning of incoming tweets and the average position of nearest neighbors.	It doesn't address reinforcement	Leaning value of users and its neighbors (content and structure based)	The study defines a continuous political leaning measure by categorizing the hashtags used in tweets as either expressing a leaning in favor or against the impeachment, which is independent of the network's reconstruction.	Tweet data about impeachment process of the former Brazilian President during 2016
[49]	The study examined the structural evolution of communities of interests on Facebook by analyzing users' emotions and engagement within two communities, namely conspiracy and science.	The study demonstrates that communities exhibit strong similarities, and the behavior of users within each community is notably similar.	The study solely focuses on the analysis of bipolar echo chambers.	Polarization	Activity and sentiment in each echo chamber (community)	Italian Facebook data
[44]	The study proposed an agent-based model that incorporates the DeGroot model for opinion updating. It was found that the number of activities such as publishing posts and liking influenced users' tendency to enter echo chambers. However, the study also emphasized the significance of accessing cross-ideological content to counteract the effects of echo chambers	The results indicate that network topology does not have a significant impact on the type of final opinion distribution.	The study suggests that the number of activities plays a more significant role than network structure in influencing outcomes	Opinion dynamic	Reaching consensus or fragmentation.	• Barabasi-Albert network Watts–Strogatz graph
[47]	A Hidden Markov Bridge model to estimate segregation in social networks based on polarity observation. Computing polarization as a fraction of the number of interactions in each group (democrat and republican before 2020 election.) in 30 days.	-Using Markovian process idea for echo chambers problem -show segregation by conductance and algebraic connectivity measures	-Consider bipolar networks -it doesn't address reinforcement	Markov Random Process by considering two groups and content (mix approach)	observation is based on boundary connectivity measure	Twitter dataset And a sample company-customer social network
[48]	Try to control echo chamber effect and segregation in networks based on developing a game to maximize the utility function, if users interact with different communities. then the utility function increases.	Present segregation measure and a dynamic model based on acceptance probability.	it define for bipolar echo chambers	-Mix approach Network structure (when it consider number of connection between two groups) and content (when	segregation	directed stochastic block model

TABLE 12. *(Continued.)* **Modeling and detection studies.**

				they define two groups of users)		
[51]	Provide a model based on biased agents and unbiased agents, they model the impact of biased agents on unbiased agents.	Increasing social connectivity, bypassing biased agents and fragment in echo chamber, while confirmation bias increases fraction of agents in echo chamber	biased agent behavior	confirmation bias and social connectivity		k-regular, Erdős-Rényi Barabasi-Albert and Small-world networks.
[55]	The study defined two sets of information sources and collected a balanced dataset of users with known political preferences within the specified ideological space. They attempted to measure the degree of separation based on cross-ideological interactions.	The study introduces a binary separation index, which is calculated based on the fraction of users connected with the same group members (information sources).	It doesn't address reinforcement	Structure based	BSI measure	Russian online social network Vkontakte
[52]	The study presents quantitative research on the role of echoers and bridgers within social networks, conducting experiments on a Twitter dataset. The objective is to examine the interaction patterns between dissimilar groups of users. The study reports that, for example, 99.5% of the retweet interaction pairs and 82.37% of the mentioned pairs shared the same political view, indicating a high level of homogeneity within these communication networks.	The study introduces two new mediators in social networks, namely echoers and bridgers.	The study found that bridgers tend to have higher in and out degree centrality compared to echoers, leading to stronger community formation among bridgers. This finding suggests that the echo chambers they considered do not align with the traditional definition of echo chambers, where members of an echo chamber typically exhibit higher interaction among themselves compared to the rest of the network.	Network structure	Manually determine user political stance (i.e., unclear, pro-, or anti-Trump)	Twitter dataset
[54]	They present a model for an echo chamber network that consists of a set of echo chambers and a set of users who participate in multiple echo chambers, particularly sharing common rumors.	Identify the characteristics of the rumor echo chamber effect, including factors such as speed, size, depth, and width.	• The study does not address the issue of reinforcement within echo chambers. The definition of an echo chamber is solely based on the propagation of common rumors.	content and structure (mix)	An echo chamber is formed when there is a significant number of users who share two or more common rumors.	Twitter dataset
[26]	The study proposed an ECHO model, which incorporates three neural network classifiers and one attention neural network. The model takes as input features extracted from posts and comments, including stance and the intensity of emotions elicited by a subject.	Echo chamber index based on comments label (annotation based)	The study solely focuses on the echoing property of comments and attempts to classify them.	Stance and emotion intensity	Annotators assign a value in the range of [-1, 1] to a post on a page to indicate whether it echoes or not. The average value represents the echo chamber index.	Facebook pages.
[27]	• Their approach relies on visualizations that are based on stance detection of news articles, using the headline as an event. This allows them to define the left and right wings of belief orientation in these articles. However, they do not provide specific characteristics or factors for echo chambers. In their perspective, an echo chamber is simply a biased opinion towards a particular topic.	They implement a news platform with the claim that users can break free from echo chambers. The platform considers various news sources categorized into five media bias categories.		Stance detection	They ladled political orientation manually	NELA-GT-2019 dataset, which collected up to 260 news sources with 1.12 million news articles
[28]	The study proposed an algorithm for detecting echo chambers, based on two key factors: item propagation (e.g., tweets) and link generation.	The study considers both semantic factors, such as polarity value, and network structure for the detection of echo chambers.		The relationship between purity and conductance shows the echo chamber.	A supervised learning computes the polarity of tweets based on labeled data.	• Brexit discourse • Referendum VaxNoVax
[30]	The study adopts a structure and semantic-based approach by constructing ego networks based on user mentions within a Twitter dataset.	The study enriches the topological representation of the network by incorporating a set of semantic features, including topic similarity and sentiment similarity	Their approach utilizes a metric-based method for echo chamber detection; however, it does not effectively address the issue of reinforcement within echo	Content based	Controversy measure show the echo chambers	10 million tweets

TABLE 12. *(Continued.)* **Modeling and detection studies.**

			chambers			
[29]	The study considers group influence in opinion dynamics and information propagation, using the Ising model. Each node is not only influenced by its neighbors but also by the group environment, referred to as the echo chamber effect.	The study presents a formula for computing the probability in the Ising model.	• One limitation is that they assume the existence of the echo chamber effect and base their detection on this assumption. Another drawback is that they did not incorporate semantic properties into their model.	Ising model (opinion dynamics)	-Maximum activated nodes	Weibo, YouTube, and TheMarker

the belief strength within echo chambers, represented by the average leaning value, should always remain constant or increase. However, existing studies do not formally address reinforcement, although some attempt to demonstrate it in their models. Ge et al. [32], show that the recommender system narrows down the scope of items presented to users. They used the Content Diversity measure to analyze whether the recommender system affected the strengthening of user interests by narrowing. down the scope of items exposed to users (here, Euclidean distance is computed between two item embeddings). Stoica and Chaintreau in [31] have shown the reinforcement by using the effect of recommendation on expected degree of one group under recommendation parameter and without it, recommendations exacerbate the gap between these two subgroups. Their results reveal that item recommendations always accelerate the hegemonic dynamics, exacerbating the misrepresentation of a minority viewpoint. To demonstrate reinforcement, some research utilized the concept of comparing opinions between two different timestamps [40].

Some studies addressed like-minded as two polarized groups, Brugnoli et al. in [34] defined the polarization ρ(u) of a user u as the ratio of likes that u performed on conspiracy posts, assuming that u performed x likes on conspiracy posts and y likes on science posts. Thus, $\rho(u) = (x - y) / (x + y)$. Ferraz de Arruda et al. in [39] quantify the level of polarization in opinions, the authors employed the bimodality coefficient introduced by [64]. They also introduced a measure called balance, which is calculated by dividing the minimum number of nodes from two sets of opinions by the maximum number of nodes from those sets. Tsai. To assess the existence of echo chambers used the measure of the number of pairs in each network that communicated with each other. For instance, they reported that 99.5% of retweet interaction pairs and 82.37% of mention pairs shared the same political view. Sikdar et al. in [51] introduced a polarization measure as:

$$x_i(t) = \frac{N_i^+(t)}{N_i^+(t) + N_i^-(t)}[51]$$

where $N_i^+(t)$ is the number of positive signals at time t. They denoted the fraction of positively oriented agents in a group of nodes C as $y_c(t)$, and polarization $Z_c(t)$ as $(y_c(t), 1 - y_c(t))$. Polarization is zero when all agents are either positively or negatively oriented, and it is maximized when the group is evenly split between the two orientations. As discussed earlier, Chkhartishvili and Kozitsin in [55] introduced BSI to measure segregation.

Prasetya and Murata in [41] In an attempt to demonstrate polarization, they utilized the m-value measure (introduced by [65]). Another measure they defined is homogeneity, represented by the formula:

$$hom_w = \frac{\sum_{e(u,v)} C_{uv} q_u q_v}{\sum_{e(u,v)} C_{uv}}[41]$$

Here, C_{uv} represents the connection strength between nodes u and v, and q_u represents the opinion of node u.

VI. CRITICAL REVIEW

A. ANALYSIS OF RQ1: HOW DO EXISTING STUDIES DEFINE ECHO CHAMBERS WITHIN ONLINE SOCIAL NETWORKS?

As shown in Table 5 and Table 10, fewer than 30% of the existing studies in this systematic review address the reinforcement of echo chambers, and less than 50% address the structure in their definition. On the other hand, all of them consider semantic in their definition, regardless of whether they present a metric to measure it or not. Addressing semantic without metrics reveals an important fact: when mass communication occurs in the network, an echo chamber seems to emerge. However, specifying the number of communications among like-minded users is necessary. As previously mentioned, the opinion values can be real numbers in the range of -1 to 1, but existing studies do not address this fact either in the definition or in their approach.

Another issue with the existing definition is the equating of polarization in the network with echo chambers, and subsequently, many of these studies attempt to propose an approach to address polarization. This assumption seems to stem from one of the earlier studies in this field, where [49], an important reference, defined echo chambers as ‘groups of like-minded people where they polarize their opinion’.

B. ANALYSIS OF RQ2: WHAT IMPACTS DO ECHO CHAMBERS HAVE WITHIN ONLINE SOCIAL NETWORKS?

As discussed in RQ1 of Section V, all studies have addressed echo chambers as a harmful phenomenon in online social networks, attributing them to the spread of misinformation, radicalization, social isolation, and societal inequality.

However, due to the significance of this issue to the authors, an investigation was conducted to determine whether the effects of echo chambers are solely negative. Surprisingly, our investigation reveals that some researchers question the assumption that echo chambers only have detrimental effects, as highlighted by [19] and [66].

Jann and Schottmüller in [19] pose the question, "Why are echo chambers useful?" They argue that segregation into small, homogeneous groups can maximize communication efficiency, leading to a Pareto-efficient allocation of resources. Their perspective, rooted in economics, suggests that echo chambers—or segregated groups—provide useful, comprehensive information, eliminating the need for individuals to expend additional energy seeking desirable information within larger groups. Their analysis posits that segregation into small, homogeneous groups can be a rational choice, maximizing the amount of information available to each individual. Levy and Razin in [66] examine voter behavior, questioning whether polarization—a form of echo chamber—is necessarily harmful. They suggest that cognitive bias can have positive impacts on aggregate welfare. They argue, "Even if each behavioral voter does not vote optimally from her own point of view (compared to a rational voter), the whole electorate may reach better, more informed, outcomes (compared to a rational electorate)." In essence, the authors equate polarization with crowdsourcing, where consensus within a group on a particular issue can lead to more informed outcomes. Wang et al. in [67] explore the role of echo chambers in rumor rebuttal during the COVID-19 pandemic, analyzing a mention and retweet network from the Weibo dataset in China. Their results indicate that echo chambers can positively influence rumor rebuttal, with a significant echo chamber effect observed when users retweeted or commented on true rumor rebuttals.

The aforementioned case studies suggest that the perceived benefits or detriments of echo chambers depend on the perspective from which this phenomenon is viewed and the domain in which it is considered. From an economic viewpoint, echo chambers can be Pareto-efficient. They can be beneficial for a campaign attempting to rebut rumors or for an election campaign seeking to amplify its voice. However, a key characteristic of echo chambers is their resistance to opposing opinions.

Regardless of whether echo chambers are deemed good or bad, it is crucial to understand and predict user behavior within different contexts. For instance, Bara et al. [68] attempt to predict voter behavior by considering echo chambers. They introduce a metric called the influence gap (IG), which measures the homogeneity of a group and represents the relative advantage of one party over its rival. They use this metric to develop a model for predicting voter behavior, demonstrating that a network rife with echo chambers emerges when the homophily parameter h exceeds 0.5. Their definition of echo chambers is based on the number of like-minded friends within a party.

C. ANALYSIS OF RQ 3: WHAT MECHANISMS DO EXISTING STUDIES PROPOSE FOR THE FORMATION OF ECHO CHAMBERS WITHIN ONLINE SOCIAL NETWORKS?

As discussed, there are four main approaches to address the mechanism of echo chambers. However, the main problem lies in the lack of clarity in formulating some of these approaches, such as the backfire effect or biased assimilation. Additionally, another issue arises when some studies only consider a single approach to address echo chamber formation, despite echo chambers being an interdisciplinary field influenced by diverse and potentially contradictory parameters. For instance, social influence is an important feature that can contribute to the formation of echo chambers, while confirmation bias also plays a significant role. However, these two factors may have contradictory functions

The major drawback of the existing mechanisms is their limited attention to addressing and measuring the structure. The structure plays a crucial role in the study of echo chambers. To illustrate its importance, let's consider two groups: the first group consists of a large number of like-minded users with high interaction among themselves as well as with users outside the group (with equal intensity). In contrast, the second group is smaller but has high internal interaction and no connection with users outside the group. It is evident that the second group exhibits characteristics of echo chambers, while the first group does not. Unfortunately, existing studies tend to overlook this component.

Another limitation observed in this systematic review is the lack of experimentation with real-world data. As we discussed, adjusting parameters like homophily and demonstrating echo chamber formation becomes trivial. The real challenge lies in showcasing echo chambers using actual data from the real world.

Furthermore, a common issue in existing studies is the preconceived consideration of two main groups, often labeled as bipolar networks (e.g., red and blue, majority and minority, or opinion A and B), followed by attempts to demonstrate how echo chambers form.

D. ANALYSIS Of RQ 4: HOW DO EXISTING STUDIES MODEL AND DETECT ECHO CHAMBERS WITHIN ONLINE SOCIAL NETWORKS?

In addition to the limitations discussed earlier that are common to mechanism-based approaches, a community-based approach poses a challenge in studying echo chambers. Some studies consider communities as echo chambers and attempt to identify them using community detection algorithms, without taking into account semantic and reinforcement. However, interpreting the findings of [52] presents a challenge. It was observed that bridgers had higher in-degree and out-degree centrality compared to echoers. This suggests that the bridger community is stronger and more interconnected than the echoers. Consequently, the notion of echo chambers presented in this study does not align with the typical definition, as members of an echo chamber would be expected to have higher interaction with each other compared to the rest of the network.

Another drawback is that some studies attempt to utilize the echo chamber effect to illustrate a different problem. For instance, Zhu et al. in [29] explored the influence maximization problem by associating groups with echo chambers and demonstrating that the presence of the echo chamber effect leads to higher influence maximization compared to its absence. However, their detection of the echo chamber effect is based on their assumption rather than a formal definition. Another challenge arises from certain limitations observed in study results. For example, while the role of network structure in the mechanism is highlighted by [36], Kozitsin and Chkhartishvili in [44] argued that the number of activities holds greater importance than network structure in their modeling. They report that network topology has no significant impact on the type of the final opinion distribution.

When employing an opinion dynamic approach in some models, an important question arises regarding how users become aware of other users' opinions, which is a crucial aspect of echo chamber formation. Modeling the formation of echo chambers after users become aware of each other's opinions presents an additional challenge. Therefore, if a propagation model can capture the process of opinion awareness, it becomes a valuable approach for studying echo chamber formation.

E. ANALYSIS OF RQ 5: WHAT CRITERIA AND METRICS DO EXISTING STUDIES USE TO SPECIFY ECHO CHAMBERS?

The main drawback of existing studies lies in the research question itself. Although each study attempts to introduce or utilize a metric for its model, there is a strong need for a coherent metric that encompasses the components of an echo chamber. However, some studies have successfully employed robust metrics to measure the structure, such as controversy metric, conductance, algebraic connectivity, boundary connectivity, modularity, and ARI. On the other hand, there is a lack of diverse metrics addressing semantic exceptions for purity.

Another drawback we observed during this study is the improper use of certain metrics. For instance, in the study by Prasetya and Murata [41], the M_value measure was utilized to demonstrate polarization. However, it appears that this measure does not function correctly. For example, if we have four histograms with a distribution of (2, 3, 5, 3), the M_value is calculated as 1, whereas their model considers it as a unimodal (one peak) distribution when the M_value is 2. Similarly, in the study by [32], the CH metric is used to show the difference in user interests and is interpreted as the recommender system's (RS) influence on user preferences. However, decreasing the CH value does not necessarily indicate that the RS is functioning properly. There is no guarantee that the changes in clusters within the final user interaction block are more relevant to users' interests compared to the first interaction block. Another limitation arises in measuring reinforcement when, for example, a study attempts to compare the opinions of a group at different time stamps. The problem lies in the fact that beliefs within an echo chamber should strengthen over time. However, it is possible that at certain points between the two considered time points, the amount of opinion decreases and then increases again, leading to potential misunderstandings.

TABLE 13. List of symbols and descriptions.

Symbols	Descriptions
Ω	echo chamber size
N_A^t	having all their social contacts (i.e. neighbors, nn) with the same opinion A at time t
N_A^0	the initial random distribution of opinion A across the population
I	information
U	user
P_{XY}	represents the probability of starting in partition x and ending in partition y
$\rho(u)$	polarization of a user u
$N_i^+(t)$	the number of positive signals at time *t*
$y_c(t)$	the fraction of positively oriented agents in a group of nodes c
C_{uv}	represents the connection strength between nodes *u* and *v*
q_u	represents the opinion of node u

F. RESEARCH DIRECTIONS

According to this comprehensive study of echo chambers, the following research directions are highlighted:

- Echo chambers represent a new and emerging phenomenon observed in online social networks. Despite gaining attention from researchers, the components and characteristics of echo chambers have not been thoroughly addressed. An important avenue for research is determining when echo chambers stabilize and reach an equilibrium of interactions among members, considering that they form over time and may dissipate later.
- While the dominant effect of echo chambers is often negative, this study explores scenarios where echo chambers can be viewed positively. Consequently, another research avenue involves investigating the potential advantages of echo chambers.
- The role of the cognitive system is not well-addressed in existing studies, with only a few considering cognitive factors such as selective exposure, motivated reasoning, backfire effect, and biased assimilation. Given the influence of the human cognitive system in joining echo chambers and shaping this phenomenon, conducting empirical studies in this domain can provide valuable insights.
- An intriguing and valuable approach to echo chamber detection involves the use of deep learning techniques, particularly due to the graph structure of social networks. Graph Neural Networks (GNNs) prove highly beneficial in this context. However, according to this study, only a few studies have explored GNN techniques. Therefore, another research avenue involves deploying GNN techniques in echo chamber detection.

TABLE 14. List of abbreviations.

Term	abbreviation
Online Social Network	OSN
Systematic Literature Review	SLR
Context-Intervention-Mechanisms-Outcomes	CIMO
Preferred Reporting Items for Systematic Reviews and Meta-Analyses	PRISMA
Calinski-Harabasz index	CH index
Adjusted Rand Index	ARI
Watts–Strogatz model	WS
Erdős–Rényi model	ER
Stochastic Block Model	SBM
Preference algorithm	PR
Recent algorithm	REC
Reference algorithm	REF
Lattice	LA
Binary Separation Index	BSI
Support Vector Machine	SVM
Algorithmic Recommendation Mechanism	ARM
Hidden Markov Bridge	HMB
Hidden Markov Model	HMM
Markov Bridge	MB
influence maximization	IM
Graph Convolutional Network	GCN
political communication	PC
Susceptible-Infected-Susceptible	SIS
Susceptible-Infected-Recovered	SIR
Random Walk Controversy	RWC
Authoritative Random Walk Controversy	ARWC
Displacement Random Walk Controversy	DRWC
Boundary Connectivity	BC
Homogeneity	HOM
Influence Gap	IG
Recommender System	RS

TABLE 15. Quality assessment of each work.

ID	study	q1	q2	q3	q4	wq1	wq2	wq3	wq4	sum
1	[26]	1	0	1	0.5	1	0	2	1	4
2	[27]	0.5	1	1	0.5	0.5	1	2	1	4.5
3	[28]	1	1	1	1	1	1	2	2	6
4	[29]	0.5	1	0.5	0	0.5	1	1	0	2.5
5	[30]	1	1	1	1	1	1	2	2	6
6	[31]	0	1	0.5	1	0	1	1	2	4
7	[32]	0.5	1	1	1	0.5	1	2	2	5.5
8	[33]	0	0	1	0.5	0	0	2	1	3
9	[34]	1	1	1	0.5	1	1	2	1	5
10	[35]	1	1	1	0.5	1	1	2	1	5
11	[36]	1	1	1	0.5	1	1	2	1	5
12	[37]	1	0	0.5	0	1	0	1	0	2
13	[38]	0	1	1	0.5	0	1	2	1	4
14	[39]	0.5	1	1	0.5	0.5	1	2	1	4.5
15	[40]	0.5	1	1	0.5	0.5	1	2	1	4.5
16	[41]	0.5	1	1	0.5	0.5	1	2	1	4.5
17	[42]	1	1	1	0.5	1	1	2	1	5
18	[43]	0.5	1	1	1	0.5	1	2	2	5.5
19	[44]	0.5	1	1	0	0.5	1	2	0	3.5
20	[45]	0.5	1	1	1	0.5	1	2	2	5.5
21	[46]	0.5	1	0.5	0.5	0.5	1	1	1	3.5
22	[47]	0.5	1	1	0.5	0.5	1	2	1	4.5
23	[48]	1	1	0.5	0.5	1	1	1	1	4
24	[49]	0.5	1	1	0.5	0.5	1	2	1	4.5
25	[50]	0	1	1	0.5	0	1	2	1	4
26	[51]	0.5	1	0.5	0	0.5	1	1	0	2.5
27	[52]	1	1	0.5	0	1	1	1	0	3
28	[53]	1	1	1	0.5	1	1	2	1	5

VII. CONCLUSION

This study aimed to address a novel and complex issue that has recently emerged in online social networks. Our research revealed the extensive scope of the echo chamber phenomenon, encompassing various scientific disciplines such as mathematics, social sciences, information sciences, statistics, cognitive science, and computer science. The interdisciplinary nature of echo chambers makes it challenging to categorize existing studies, as they employ diverse approaches to tackle this phenomenon.

Our findings emphasized the significant influence of cognitive and social factors in the formation of echo chambers. Even when algorithms are employed to artificially create echo chambers, they rely on these underlying factors. We also highlighted studies indicating that social networks themselves inherently contribute to the emergence of echo chambers.

In the modeling and detection of echo chambers, many existing models have focused on polarization without a precise understanding of this concept. Additionally, a common approach has been to consider the number of interactions as an indicator of the presence of echo chambers. Notably, studies that measured the degree of leaning or opinion were prominent, as it is crucial to quantify echo chambers without a measure of opinion. Furthermore, stance detection methods have shown promise in this field.

However, a significant limitation of existing research is the lack of attention given to the reinforcement of beliefs within echo chambers, with only a few studies addressing this issue. In this study, we shed light on the concept of the usefulness of echo chambers, challenging the prevailing notion that they are solely detrimental. Moreover, we aimed to provide a comprehensive definition of the concept through a consensus among existing definitions.

Echo chambers, as a concept, encompass a wide range of associated issues. These include modeling, detection, mechanisms, and attributes, each of which has been the subject of extensive research. However, most studies tend to concentrate on one or two aspects of echo chambers, with comprehensive investigations that consider all facets of echo chambers being relatively scarce. Furthermore, throughout our research, we observed that numerous studies have tackled the topic of echo chambers without adhering to a specific set of criteria.

As a result, we propose that formulating the concept of echo chambers should be a research direction of utmost importance. Additionally, exploring the life cycle of this phenomenon can offer valuable insights into information propagation, opinion dynamics, and inequality within social networks.

APPENDIX A

See Table 13.

APPENDIX B

See Table 14.

APPENDIX C

See Table 15.

DECLARATION OF COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose. They have no conflicts of interest to declare that are relevant to the content of this article.

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AMIN MAHMOUDI received the Ph.D. degree from the National University of Malaysia. He has teaching and research experience in different universities, such as the Czech Academy of Sciences; Lingnan University, Hong Kong; the University of Pardubice, Czech Republic; and the Sentiment Analysis Laboratory, UKM, Malaysia. He is currently a Postdoctoral Researcher with the Management in Networked and Digital Societies (MINDS) Department, Kozminski University, Warsaw, Poland, with a focus on online social network analysis.

DARIUSZ JEMIELNIAK is currently a Full Professor and the Head of the Management in Networked and Digital Societies (MINDS) Department, Kozminski University, and the Faculty Associate with the Berkman-Klein Center for Internet and Society, Harvard University. His current research interests include disinformation and bot detection. He is a member of the Polish Academy of Sciences. He currently serves on the Wikimedia Foundation Board of Trustees. He is the Vice-President of the Polish Academy of Sciences.

LEON CIECHANOWSKI is currently a Cognitive Scientist, a Philosopher, a Culture Science Expert, and an Assistant Professor with the Management in Networked and Digital Societies (MINDS) Department, Kozminski University, and the University of Social Sciences and Humanities SWPS (Psychology Department), Warsaw. He is working in the domain of human–computer interaction, phenomenology, and sense of agency/control. He is involved in the study of chatbots, robots, and wearables in cooperation with MIT. He is also a Consultant for various business sectors (banking, data analytics, and telecommunication).