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Integrating Social Network Analysis and Topic Modeling in Social Media Research: A Systematic Literature Review of Open-Access Scopus Studies (2016-2026)

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Systematic Review

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Abstract

Background.

Social media research increasingly needs to capture both what people say and how they are connected. Social network analysis (SNA) and topic modeling are the main computational answers, yet how they are combined has not been mapped systematically.

Objective.

To synthesize how SNA and topic modeling are integrated in social media studies published in 2016–2026 and to derive a research agenda.

Methods.

We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guideline. Scopus was searched for open-access, English-language research articles combining network, topic-modeling and social media terms. Of 560 records, 232 were screened and 194 included. Studies were coded for platform, domain, topic model, network type, integration pattern and validation by rule-based extraction from titles, abstracts and keywords, audited on 29 articles.

Results.

Output rose from one article in 2016 to 36 in 2025. X (formerly Twitter) supplied 52% of the data; health (34%) and politics (25%) dominated. LDA (latent Dirichlet allocation) appeared in 32% of articles, BERTopic in 9% and STM (structural topic model) in 6%; half named no algorithm in the abstract. Actor networks (59%) outnumbered semantic (27%) and hybrid (11%) networks. Parallel use of the two methods prevailed (71%); joint models were 9% and topic-built networks 5%. Evaluation was rarely visible in abstracts (2%).

Conclusions.

Integration is widespread but shallow. We propose a four-route taxonomy (parallel, network→topic, topic→network, joint model), a five-stage research model and an eight-point agenda centred on joint and temporal models, validation standards, under-studied platforms and regions, and transparent reporting.

1. Introduction

Social media platforms generate two kinds of evidence at once: text that expresses opinions, frames and emotions, and relational traces such as retweets, mentions, replies, shared links and co-participation that reveal who speaks to whom. Studies that use only one of these layers risk a partial picture. Text analysis

alone cannot show which voices are amplified or which communities form, and network analysis alone cannot show what those communities are talking about. Extracting knowledge from such data is a core task of knowledge and information systems.

Two computational traditions have matured to handle these layers. Social network analysis (SNA) represents interaction as a graph and summarises it through centrality, community structure and diffusion paths (Wasserman & Faust, 1994; Newman, 2006; Blondel et al., 2008). Topic modeling infers latent themes from large text collections, from probabilistic models such as latent Dirichlet allocation (LDA; Blei et al., 2003) and the structural topic model (STM; Roberts et al., 2019), through matrix factorization (Lee & Seung, 1999), to embedding-based approaches such as BERTopic (Grootendorst, 2022).

Combining the two is an old idea that has become routine. Bail (2016) showed that language processing and network analysis can be used together to explain how advocacy organizations stimulate conversation on social media. Walter and Ophir (2019) formalized a network of topic-model outputs as an analytic procedure for frame analysis. Early studies in our corpus applied both methods to health discourse on Twitter and tested whether detected user communities align with the topics they discuss (Surian et al., 2016), and to the public communication of science (Büchi, 2017). Since then the pairing has spread across platforms, languages and domains.

This spread has created three problems for readers and for authors. First, "integration" covers very different designs: some studies run a topic model and a network analysis side by side and compare results, some use community structure to condition topic estimation, and some build the network from topics. Second, networks themselves differ: a retweet graph of accounts and a word co-occurrence graph answer different questions, yet both are called "network analysis". Third, topic models are sensitive to preprocessing, the number of topics and the algorithm, so conclusions about network–topic relations inherit whatever validity checks, if any, the topic model received (Maier et al., 2018).

Existing reviews address neighbouring questions. Karami et al. (2020) used text mining, including topic modeling, as a tool to review a decade of Twitter research; Şencan et al. (2021) reviewed topic detection and community detection on social media and concluded that no single model suits every problem; and Warsito et al. (2025) reviewed embedding and topic-modeling techniques for short social media texts. Judging from their abstracts, none codes how network analysis and topic modeling are integrated, with which kinds of network, on which platforms and with what validation. This article therefore reviews open-access research articles indexed in Scopus between 2016 and 2026 that combine SNA, topic modeling and social media data. It follows the PRISMA 2020 reporting guideline (Page et al., 2021) and the general procedures for systematic reviews set out by Kitchenham and Charters (2007).

We address five research questions.

- **RQ1.** What are the publication trends, platforms, application domains, geographies and venues of studies that combine SNA and topic modeling on social media data?
- **RQ2.** Which topic-modeling approaches and which types of network are used?

- **RQ3.** How are SNA and topic modeling integrated?
- **RQ4.** How are topic models and network results evaluated and validated?
- **RQ5.** What gaps remain, and what should future research prioritize?

The article makes three contributions: (i) an evidence base of 194 coded studies, shared as supplementary material; (ii) a taxonomy of three integration routes with their prevalence over time; and (iii) a research agenda grounded in the observed gaps.

2. Conceptual background

2.1 Networks built from social media

We distinguish two families of network. **Actor networks** connect accounts through observable interaction: retweets, mentions, replies, follower ties, forwarded messages or shared links. They support questions about influence, brokerage, community structure, coordination and diffusion. **Semantic networks** connect words, hashtags, entities or topics through co-occurrence or similarity. They support questions about discourse structure, framing and thematic association. A third, hybrid category links both, for example by connecting users to the topics in which they participate in a multilayer graph. This distinction matters because the two families rest on different data-generating processes and call for different validity arguments.

2.2 Topic-modeling families

Topic-modeling approaches used with social media text fall into four groups.

Family	Examples	Key property for network studies
Probabilistic generative	LDA, correlated and dynamic topic models, STM	Document-topic and topic-word distributions; STM adds metadata covariates such as account type or time
Matrix factorization	NMF and orthogonal variants	Deterministic, often more stable on short text; no explicit generative assumptions
Embedding-based	BERTopic, Top2Vec	Clusters sentence embeddings; better suited to short, noisy posts; sensitive to embedding and clustering choices
LLM-assisted	Prompt-based topic generation	Interpretable labels; reproducibility and cost concerns

Short texts such as tweets are a recurring difficulty for the probabilistic family, which motivated both aggregation strategies (for example pooling a user's posts) and embedding-based alternatives. Choices about the number of topics, preprocessing and seeds can change the topics substantively, so applied work is expected to report how these choices were made and checked (Maier et al., 2018).

2.3 Routes to integration

Conceptually, there are three ways for the two methods to meet:

1. **Topic→network.** Topic-model output defines nodes, edges or node attributes: networks of topics that co-occur, user–topic bipartite or multilayer graphs, or similarity networks between documents or places built from topic distributions.

2. **Network→topic.** Network structure conditions the analysis of content: topics are estimated or compared per detected community, per user cluster or per structural position, or network proximity informs the text representation.

3. **Joint or integrated models.** A single method or framework estimates network and topic structure together, or one algorithm is specifically designed to use both.

A fourth, weaker pattern is **parallel use**, in which the methods run side by side and the results are compared or juxtaposed without one feeding the other. We use this four-way scheme as the coding frame in Section 3.

3. Methodology

3.1 Protocol and reporting

The review follows the PRISMA 2020 statement (Page et al., 2021) and the general staging of systematic reviews described by Kitchenham and Charters (2007): planning, searching, selection, extraction, synthesis and reporting. The protocol was not preregistered.

3.2 Information source and search strategy

Scopus was the only database, chosen because the target outlets are Scopus-indexed and because its open-access filter allows reproducible full-text access. The search combined three concept blocks with AND within title, abstract and keywords: (1) network-analytic terms (for example social network analysis, network centrality, community detection, semantic network, retweet or mention network, co-occurrence network, hashtag network); (2) topic-modeling terms (topic model*, latent Dirichlet allocation, LDA, BERTopic, structural topic model, non-negative matrix factorization, NMF, biterm, dynamic topic model, author-topic); and (3) social media terms (social media, Twitter, Facebook, Reddit, YouTube, Weibo, TikTok, Telegram, online social network*). Limits were publication years 2016–2026, document type article, language English and open access. The full strings are given in Appendix A. The search was run in October 2026.

3.3 Eligibility criteria

Criterion	Include	Exclude
Publication	Peer-reviewed research article, English, open access, 2016–2026	Reviews, conference papers, book chapters, editorials
Data	Content or interaction data from social media or online community platforms	News articles, websites, surveys or documents without social media data
Network analysis	Actor or semantic networks analysed (centrality, communities, structure, similarity)	No network analysis (E1); bibliometric networks of literature (E4)
Topic modeling	A topic-modeling or topic-detection method applied to text	No topic modeling (E2), including NMF used only for sentiment or graph clustering
Design	Empirical study or method paper with an empirical test	Reviews or conceptual papers (E5)

Exclusion codes: E1 no network analysis; E2 no topic modeling; E3 not social media data; E4 bibliometric networks of literature; E5 review or non-empirical.

3.4 Study selection

Scopus returned 560 records. Filtering to articles left 355, to English 335 and to open access 232. No duplicates were found (one database; DOI, EID and title checks). All 232 records were screened on title, abstract and author keywords against the criteria above, with a binary include/exclude decision and no "maybe" category. Screening decisions were proposed by one AI-assisted reviewer (Claude, Anthropic) and were not independently double-screened, so no agreement statistic such as Cohen's kappa (Cohen, 1960) is reported; this is acknowledged as a limitation (Section 7). Where the abstract did not describe a method but the author keywords did, the record was included and flagged for full-text confirmation (R095, R113, R181 in the supplementary file).

3.5 Data extraction and coding

Each included study was coded on the variables below.

Variable	Categories
Platform	X/Twitter, Reddit, YouTube, Weibo, Facebook, Telegram, Instagram, TikTok, Xiaohongshu, other forums and communities (multi-label)
Domain	Health; politics and public discourse; crisis, misinformation and hate; business and consumer; environment, climate and energy; media, science communication and education; culture and games; technology and AI; methodological or general
Topic model	LDA, STM, BERTopic, NMF, dynamic, CTM, HDP, Top2Vec, LLM-assisted, or unspecified (multi-label)
Network type	Actor network, semantic or co-occurrence network, hybrid, other (hyperlink or recommendation), unspecified
Integration pattern	Parallel; network→topic; topic→network; joint model or framework
Study type	Computational case study; mixed (computational plus qualitative or survey); method or tool development
Temporal analysis	Yes or no
Validation mentioned in abstract	Coherence or perplexity; stability, cross-validation or sensitivity; manual or expert validation; network or cluster metrics; none
Country	Country of the first author's affiliation, and all affiliation countries

3.6 Coding procedure and verification

Because full texts for all 194 studies were not retrieved, coding was done by rule-based extraction from titles, abstracts and author and index keywords (regular-expression dictionaries per category). The coded list was then reviewed manually, and 25 network-type codes and 34 domain codes were corrected. To estimate accuracy we drew a sample of 29 articles stratified by integration pattern, re-read each abstract and audited four coded fields (platform, topic model, network type, integration pattern; 116 decisions). Open full-text sources were then consulted for three articles: Yuan et al. (2020) was read in full, while Li et al. (2026) and Xu et al. (2022) were checked only through the open-access text excerpts that could be retrieved. Outcomes are reported in Section 4.6. The coding dictionaries and the audit were prepared with the assistance of Claude (Anthropic). All counts in Section 4 are therefore abstract-level estimates and should be read with that limitation.

3.7 Synthesis

We report counts and percentages, a cross-tabulation of topic model by network type, and comparisons across three periods (2016–2020, 2021–2023, 2024–2026). Because studies are heterogeneous in design and outcome, no meta-analysis and no formal risk-of-bias scoring were performed. The integration taxonomy was derived deductively from Section 2.3 and refined through the coding.

4. Results

4.1 Study selection

Of 560 records identified in Scopus, 232 open-access English-language articles reached screening. Title and abstract screening excluded 38 and retained 194 for coding (Table 1; Fig. 1).

Table 1
PRISMA 2020 flow of records.

Stage	Records	Removed	Reason
Identified in Scopus, 2016–2026	560		
After limiting to articles	355	205	Other document types
After limiting to English	335	20	Other languages
After limiting to open access	232	103	Not open access
Duplicates		0	None found
Screened (title, abstract, keywords)	232	38	E1 no network analysis 12; E2 no topic modeling 6; E3 not social media data 8; E4 bibliometric networks 7; E5 review or non-empirical 5
Included	**194**		

4.2 Overview of the evidence base (RQ1)

Publication trend. The literature is young and accelerating. Only three included articles appeared in 2016–2017, 27 in 2016–2020 once 2018–2020 are added, and output reached 36 in 2025. The 2026 count of 47 covers a partial year (Table 2). The three periods used for comparison contain 27 (2016–2020), 60 (2021–2023) and 107 (2024–2026) articles.

Table 2
Included articles per year.

Year	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026*
Articles	1	2	4	9	11	20	20	20	24	36	47

*Partial year.

Platforms. X (formerly Twitter) was the data source in 101 articles (52.1%), but its share fell from about two thirds in 2016–2020 (18 of 27) and 2021–2023 (41 of 60) to 39% in 2024–2026 (42 of 107). Other platforms entered later: Reddit appears from 2022 (17 articles, 11 of them in 2024–2026), YouTube is concentrated in 2024–2026 (13 of 16), Weibo likewise (14 of 19), Instagram appears only from 2024 (7),

and Telegram from 2022 (8). TikTok appears in a single article (Guan, 2026). Platform labels are multi-label, so percentages do not sum to 100 (Table 3).

Table 3
Platforms (multi-label, abstract-level).

Platform	Articles	Share
X/Twitter	101	52.1%
Weibo	19	9.8%
Reddit	17	8.8%
YouTube	16	8.2%
Facebook	12	6.2%
Telegram	8	4.1%
Instagram	7	3.6%
Xiaohongshu/REDnote	5	2.6%
TikTok	1	0.5%
Other forums and communities	29	14.9%
Not identifiable from abstract	19	9.8%

Domains. Health and public health led with 65 articles (33.5%), followed by politics and public discourse (48; 24.7%), business and consumer research (15; 7.7%), environment, climate and energy (14; 7.2%), methodological or general work (14; 7.2%), media, science communication and education (12; 6.2%), crisis, misinformation and hate (10; 5.2%), culture and games (8; 4.1%) and technology and AI (8; 4.1%). Examples include vaccine and COVID-19 discourse (Surian et al., 2016; Kumar et al., 2022), digital diplomacy and elections (Park et al., 2019; Heiberger et al., 2022), disaster communication (Momin et al., 2024) and climate discourse (Treen et al., 2022; Dubey et al., 2024).

Geography and venues. First authors were affiliated with 40 countries. The United States (42; 21.6%) and China (37; 19.1%) together account for 41% of articles, followed by the United Kingdom and Germany (11 each), South Korea (9), and Spain, Hong Kong and Italy (7 each). Authors based in Asia led 72 articles (37.1%). A total of 58 articles (29.9%) involved affiliations in more than one country. The most frequent venues were the *Journal of Medical Internet Research* (10), *Social Network Analysis and Mining* (7), *IEEE Access* (6), the *International Journal of Environmental Research and Public Health* (5) and *Social Media and Society* (5), which shows that the topic spans health informatics, computer science and communication research. Median citation count was 6; the most cited were Surian et al. (2016; 153 citations) and Ibrahim and Wang (2019; 127).

4.3 Topic-modeling approaches and network types (RQ2)

Topic models. LDA was named in 63 articles (32.5%), and its use grew in absolute terms (11, 17 and 35 articles across the three periods) while its relative share stayed between 28% and 41%. Newer approaches arrived from 2022: BERTopic (17 articles, 16 of them in 2024–2026; for example Xu et al., 2022; Alieva et al., 2024; Fan et al., 2024; Unlu et al., 2025) and STM (11 articles from 2022; for example Heiberger et al., 2022; Hohner et al., 2022; Zehring & Domahidi, 2023). NMF (4 articles; for example Kirn & Hinders, 2022), dynamic topic models (4; for example Yang et al., 2021; Moral, 2023; Tabassum et al., 2023) and LLM-assisted topic generation (4; for example Feng et al., 2026; Xu et al., 2026) remain marginal. One study compared LDA, NMF, BERTopic and Top2Vec on the same tweets and found NMF outperformed LDA (Ramamoorthy et al., 2024). Half of the articles (97; 50.0%) named no algorithm in the abstract, a share that fell only from 56% (2016–2020) to 46% (2024–2026) (Table 4).

Table 4
Topic-modeling approaches by period (multi-label, abstract-level).

Approach	2016–2020 (n = 27)	2021–2023 (n = 60)	2024–2026 (n = 107)	Total (n = 194)
LDA	11	17	35	63 (32.5%)
BERTopic	0	1	16	17 (8.8%)
STM	0	5	6	11 (5.7%)
NMF	0	1	3	4 (2.1%)
Dynamic topic model				4 (2.1%)
LLM-assisted				4 (2.1%)
CTM, HDP or Top2Vec				3 (1.5%)
Algorithm not named in abstract	15	33	49	97 (50.0%)

Networks. Actor networks were analysed in 114 articles (58.8%), semantic or co-occurrence networks in 53 (27.3%), hybrid designs in 22 (11.3%), and other or unspecified networks in 5 (2.6%). Actor-network studies used retweet, mention, reply and forwarding graphs, centrality and influencer measures, community detection with Louvain, Leiden or Infomap, bot and coordination detection, and exponential random graph models (for example Surian et al., 2016; Lu et al., 2024; Kulichkina et al., 2026; Zhao et al., 2026). Semantic-network studies built word, hashtag or entity co-occurrence graphs (for example Wang et al., 2023; Choi et al., 2021). The semantic share was 26%, 22% and 31% across the three periods, and the hybrid share was 15%, 8% and 12%. The mix of topic model and network type is uneven (Table 5): STM was paired with actor networks in 9 of 11 articles, whereas articles that named no algorithm accounted for 16 of 22 hybrid designs, which is consistent with network-based topic detection that does not use a standard topic-model label.

Table 5
Topic model by network type (articles; multi-label, abstract-level).

Topic model	Actor	Semantic	Hybrid	Unspecified or other
LDA	37	20	5	1
STM	9	2	0	0
BERTopic	10	4	1	2
NMF	3	0	1	0
Dynamic	4	0	0	0
Algorithm not named	54	25	16	2

Study type. Computational case studies made up 71.1% of articles (138), mixed designs that add qualitative analysis or surveys 18.6% (36), and method or tool development 10.3% (20). Method development fell from 30% of articles in 2016–2020 to 6% in 2024–2026, while mixed designs rose from 15% to 23%.

4.4 Integration patterns (RQ3)

Parallel use was the norm (137 articles; 70.6%), followed by network→topic designs (30; 15.5%), joint models or frameworks (18; 9.3%) and topic→network designs (9; 4.6%). Parallel use increased from 52% of articles in 2016–2020 to 79% in 2024–2026, whereas network→topic designs fell from 26% to 9% (Table 6).

Table 6
Integration patterns by period (heuristic coding).

Pattern	2016–2020	2021–2023	2024–2026	Total	Examples
Parallel or complementary	14	38	85	137 (70.6%)	Choi et al. (2021): semantic network, topic model and sentiment on fashion-week tweets; Vijaykumar et al. (2021): LDA plus longitudinal SNA of probiotics chatter; Zhao et al. (2026): bot SNA plus LDA
Network→topic	7	13	10	30 (15.5%)	Surian et al. (2016): alignment of Louvain and Infomap communities with LDA topics; Huang (2019): community structure and focal topics on Weibo; Xu et al. (2022): user clusters then BERTopic; Unlu et al. (2025): BERTopic topics per retweet and mention community; Yang et al. (2021): community interaction and topic evolution; He et al. (2017): retweet communities as prior for topic learning
Topic→network	1	2	6	9 (4.6%)	Yuan et al. (2020): LDA per census tract then topic-similarity network; Logan et al. (2023): LDA topics induce a user–topic multilayer network; Orhan et al. (2023): multiplex hashtag networks; Ophir et al. (2026) and Lyu et al. (2026): analysis of topic-model networks; Heiberger et al. (2022): networks of topic overlap from STM; Feng et al. (2026): topic co-occurrence network with centrality
Joint model or framework	5	7	6	18 (9.3%)	Carrera & Jung (2018): SentiFlow, Louvain communities with LDA and a hidden Markov model; Mu et al. (2022): ClusTop, word networks and community detection to find topics; Singh & Singh (2021): keyword co-occurrence graph with label propagation; Liu et al. (2019): geographic topic model for semantic community detection; Apostol et al. (2024): content-based community detection with topic modeling; Gorshkov et al. (2025): BERTopic features with friendship-graph aggregation; Ng et al. (2026): social-proximity signals to train embeddings used in topic modeling; Graells-Garrido et al. (2025): a toolkit combining both

Two observations follow. First, the field has shifted from methodological invention toward routine mixed-method use: joint models were 19% of articles in 2016–2020 but 6% in 2024–2026. Second, topic→network designs, though rare, are increasing (1, 2 and 6 articles), driven by analysis-of-topic-model-network procedures and by LLM- and embedding-based topics that are then related through co-occurrence

graphs. Because the pattern codes rely on abstract text, shifts of a few articles should be read as indicative only.

4.5 Validation and evaluation (RQ4)

At abstract level, evaluation was rarely visible. Coherence or perplexity was mentioned in 4 articles (2.1%), stability, cross-validation or sensitivity checks in 4 (2.1%), manual or expert validation in 3 (1.5%), and modularity or cluster-quality metrics in 3 (1.5%); 182 abstracts (93.8%) mentioned none. Abstracts are a poor place to look for diagnostics, so these figures are lower bounds. The full texts we could check show much richer reporting. Yuan et al. (2020) tuned the number of topics and vocabulary truncation, reported that optimizing perplexity or coherence did not yield more interpretable models, and therefore used interpretability and manual inspection; they chose community-detection parameters by modularity while limiting one-node communities, and tested the geographic coherence of communities with Moran's I. Li et al. (2026) selected the number of topics by five-fold cross-validation on perplexity and related topics to user centrality in a topic-network coupling analysis.

Several studies address validity directly. Surian et al. (2016) introduced a statistical measure of alignment between communities and topics. Barnett et al. (2023) compared topic modeling, community detection and cluster analysis of semantic networks on health tweets and found that the semantic-network and clustering approaches separated subjects more clearly, whereas topic-model subjects overlapped. Ramamoorthy et al. (2024) compared four topic models before selecting one. Buehling (2024) showed that message deletion on Telegram degrades both network analyses and content analyses such as topic modeling, which is a reminder that data completeness affects the two methods jointly.

In the abstracts and in the three full texts we examined, we did not find a systematic test of whether the combined conclusion is robust to the number of topics, the algorithm, or the community-detection resolution. Whether this holds across all 194 studies needs checking in the full texts.

4.6 Verification of the coding

The 29-article audit covered 116 coded decisions. Eight (6.9%) required correction: four network-type codes (Liu et al., 2019; Singh & Singh, 2021; Mu et al., 2022; Wang, 2026) and four integration-pattern codes (the first three plus Cano-Marin et al., 2023). Platform and topic-model codes needed no correction at abstract level. Five of 29 articles (17.2%) had at least one correction. All errors arose in studies that propose network-based topic detection or build networks from topic output, the cases in which abstract wording is most ambiguous. A rule for network-based topic detection was then applied to the full list and moved two further articles from parallel to joint design (Senekal, 2023; Wang et al., 2023); comparison studies such as Barnett et al. (2023) were left unchanged.

The full-text checks refined rather than overturned the codes. Yuan et al. (2020) used LDA, which their abstract did not name, so the abstract-level share of articles with an unnamed algorithm (50.0%) overstates how often the algorithm is genuinely unreported. Xu et al. (2022) confirmed the network→topic design: users were clustered through a text network of profile descriptions, and BERTopic was run within clusters. Li et al. (2026) confirmed LDA with actor-network measures. A fourth article (Lyu et al., 2026)

could not be located in the session and remains abstract-level. Full-text verification and dual coding of all 194 studies is a natural next step.

5. Discussion

5.1 Principal findings

The evidence base shows a field that has grown quickly and diversified in platforms and tools, but whose integration of network and text analysis is mostly shallow. Seven in ten studies ran SNA and topic modeling side by side. Fewer than one in ten proposed a joint model or framework, and fewer than one in twenty used topics to build the network. Platform concentration on X is easing: its share fell from about two thirds to 39% as Reddit, YouTube, Weibo, Instagram and Telegram entered from 2019 onward. Topic-model practice is moving from LDA alone to a mix that includes STM and BERTopic, yet half of the abstracts name no algorithm, and the visible reporting of topic-model evaluation is thin.

5.2 A taxonomy of integration

The coded evidence supports the four-way scheme proposed in Section 2.3. Each route answers a different question and carries a different validity burden (Table 7).

Table 7
Integration routes, the questions they answer and their main validity risks.

Route	Question answered	Typical design	Main validity risk
Parallel	What is said, and who or what is connected?	Separate topic model and network, results juxtaposed	Conclusions about the link between the two are asserted rather than tested
Network→topic	Do communities or positions differ in what they discuss?	Topics per community, user cluster or position	Topic estimates depend on community detection choices and on community size
Topic→network	How do themes relate to each other or to actors?	Topic co-occurrence, user–topic or document-similarity graphs	Edges inherit topic-model instability; threshold and sparsification choices
Joint model or framework	Can structure and content be estimated together?	New algorithm, pipeline or toolkit	Generalisation beyond the demonstration dataset

The distinction between actor and semantic networks cuts across these routes. A parallel design that pairs a retweet graph with LDA tests very different claims from one that pairs a word co-occurrence graph with LDA, yet both are described as "integrating SNA and topic modeling". Authors should state which network family they use and which route they follow.

5.3 Reading the shifts over time

Two shifts stand out. The rising share of parallel designs (52% to 79%) and the falling share of method-development papers (30% to 6%) are consistent with diffusion of accessible tooling: packaged implementations of LDA, STM, BERTopic and network software make the combination easy to run, and applied authors in health, communication and policy adopt it as a standard pipeline. The growth of mixed designs that add qualitative analysis (15% to 23%) points the same way, since topic and network outputs are being used as inputs to interpretation rather than as ends in themselves. The small but rising number of topic→network designs suggests that embedding-based and LLM-assisted topics, whose outputs are easy to relate through co-occurrence, may be opening a route that the earlier probabilistic models did not make convenient. These interpretations rest on counts of a few articles per cell and on heuristic coding, and should be tested on full texts.

5.4 Why integration stays shallow

Three explanations are plausible. First, deeper integration demands extra validity work: a topic→network design must show that the network is stable to the number of topics and to similarity thresholds, and a network→topic design must show that topic differences between communities are not artefacts of community size or detection resolution. Few abstracts signal this work. Second, the two bodies of expertise sit in different communities, so applied studies borrow each method as a black box. Third, journals in health and communication reward substantive findings over methodological contributions, which may explain why method papers are now a small share.

5.5 Implications for practice

For researchers, we recommend that studies (i) name the network family and the integration route, (ii) report the topic algorithm, the choice of K or its equivalent, and a stability or coherence check, (iii) align the unit of analysis across methods (post, user, community), and (iv) state the platform data limitations that affect both methods, such as message deletion or API restrictions (Buehling, 2024). For reviewers and editors, these four items form a short checklist for submissions that claim to combine the methods.

The findings complement the reviews cited in Section 1. Where Şencan et al. (2021) conclude that no single model fits every detection problem, our coding suggests that the integration route and its validation, and not the algorithm alone, deserve explicit choice. For knowledge and information systems research, this implies that pipelines for knowledge discovery from social media should expose the integration route and its validation as design choices, and should treat joint models of structure and text as an open design space.

6. Research agenda (RQ5)

The gaps below follow from the counts in Section 4. Each row pairs the evidence with a concrete direction (Table 8).

Table 8
Research agenda derived from the evidence.

Priority	Evidence from this review	Suggested research
1. Joint models of structure and text	Joint models were 9.3% of articles and fell from 19% to 6% across periods	Adapt models that estimate network and topic structure together to social media interaction data. One stochastic topic block model for networks with textual edges was screened out of this review only because it was tested on email and co-authorship data
2. Validity of the combined conclusion	Evaluation visible in few abstracts (2% coherence or perplexity); no systematic robustness test of the network–topic link found in the abstracts and three full texts checked	Report sensitivity of findings to K, algorithm, seed, similarity threshold and community-detection resolution; adopt permutation or alignment tests as in Surian et al. (2016); add human validation of topics
3. Temporal integration	Temporal analysis in 32.5% of articles; dynamic topic models in 4	Coupled models of evolving communities and evolving topics, for example linking dynamic topics with temporal networks as in Yang et al. (2021) and Tabassum et al. (2023)
4. Embedding- and LLM-based topics with networks	BERTopic was paired with semantic networks in only 4 of 17 articles; LLM-assisted topics in 4 articles	Test the stability and reproducibility of embedding and LLM topics when used to build or condition networks (Feng et al., 2026; Xu et al., 2026)
5. Under-studied platforms and modalities	TikTok in 1 article, Instagram in 7, Telegram in 8; text only	Cross-platform designs as in Deng and Yang (2021), extension to Telegram and short-video platforms (Zehring & Domahidi, 2023), and multimodal inputs
6. Geography and language	41% of first authors in two countries; none of the 12 most frequent first-author countries is in Africa or Latin America; 20 non-English records removed by our language limit	Studies in low-resource languages and in underrepresented regions; multilingual topic and network pipelines
7. From description to explanation	Most studies are computational case studies (71.1%)	Link network–topic patterns to theory (homophily, echo chambers, agenda setting) with designs that allow stronger inference
8. Reporting and reproducibility	Half of abstracts name no topic algorithm; data deletion and access limits bias both methods (Buehling, 2024)	A shared reporting checklist (Section 5.5), open code and data where platform terms allow, as in Yuan et al. (2020)

Taken together, the agenda argues for moving from "using both methods" to "testing the relation between them": stating the integration route, validating the combined inference, and building joint models that treat text and structure as one system.

6.1 A recommended research model

Figure 2 turns the agenda into a five-stage model for future studies: data, representation, integration, validation and inference, with a reporting checklist that cuts across all stages. The model is a proposal derived from the gaps found in this review. It has not yet been tested empirically.

The five stages work as follows.

1. **Data.** Broaden beyond X (52% of studies) to platforms that are rare in the corpus (Telegram, Instagram, TikTok), to cross-platform designs, and to multilingual and multimodal inputs. Document data gaps such as message deletion and API limits that bias both methods (Buehling, 2024).

2. **Represent.** Build two named layers: a network layer (actor, semantic or hybrid) and a topic layer (algorithm, K and seed stated). Half of the abstracts in the corpus name no algorithm.

3. **Integrate.** Choose the route deliberately (Table 9). Parallel use is acceptable for purely descriptive questions, but questions about links between communities and themes call for network→topic, topic→network or joint designs.

4. **Validate.** Test the combined claim, not only each method: sensitivity to K, algorithm and seed; community resolution and edge thresholds; an alignment or permutation test of the topic–community link (as in Surian et al., 2016); and human validation of topics.

5. **Infer.** Move from description to explanation by using temporal designs and linking patterns to theory such as homophily, echo chambers and agenda setting.

Table 9
Decision rule linking the research question to the integration route and minimum validation.

If the question is...	Route	Minimum validation
Which themes and which accounts dominate?	Parallel	Report algorithm, K and a sensitivity check
Do groups differ in what they discuss?	Network→topic	Resolution sensitivity; control for community size; alignment test
How do themes relate to each other or to actors?	Topic→network	Topic stability under resampling; threshold sensitivity; human check of labels
Do structure and text jointly explain an outcome such as diffusion or polarization?	Joint model	Out-of-sample test; ablation against single-layer models

The model suggests three propositions for future work:

• **P1.** For a non-trivial share of published studies, conclusions about topic–community links change when K or community-detection resolution varies. A robustness re-analysis of open datasets would test this.

• **P2.** Joint models outperform parallel designs on predicting diffusion or engagement outcomes, when compared by ablation.

• **P3.** Embedding- and LLM-based topics yield less stable network edges under resampling than probabilistic topics, so topic→network designs need stability reporting.

7. Limitations

1. **Source and access.** Only Scopus was searched, and only open-access articles were kept; 103 of 335 English-language articles were removed by the open-access filter. Open-access availability differs by field and publisher, so health informatics and mega-journals may be over-represented. Conference papers, a major outlet in computer science, were excluded together with other non-article types (205 records).

2. **Language.** Only English-language articles were included, which affects the geographic conclusions in Section 4.2.

3. **Search terms.** Matching was on title, abstract and keywords. Ambiguous abbreviations such as LDA, and studies that describe themselves with other terms (for example "keyword network" or "tweet clustering" without "network analysis"), may have been missed. One phrase in the first run contained a leading space (Appendix A); future work should re-run the search with the corrected string and confirm the counts.

4. **Screening.** Screening was done by one AI-assisted reviewer without a second independent reviewer, and no agreement statistic has yet been computed. Boundary decisions (survey-based text, news corpora, non-social networks such as funding or road networks) could reasonably differ.

5. **Coding.** Codes were derived from titles, abstracts and keywords with rule-based extraction. A 29-article audit found 6.9% of audited decisions needing correction, and open full-text sources were checked for only three articles (one read in full). Abstracts under-report algorithms and validation, so shares for these variables are lower bounds. Integration-pattern codes are heuristic and most uncertain for studies that propose network-based topic detection.

6. **Appraisal and bias.** No formal quality appraisal was performed, publication bias was not assessed, and 2026 is a partial year, so the apparent acceleration partly reflects indexing and the year not being complete.

7. **Geography.** Country is the first author's affiliation and not the origin of the data.

8. Conclusion

This review mapped 194 open-access research articles that combine social network analysis and topic modeling on social media data between 2016 and 2026. The combination is now routine: output grew from one article in 2016 to 36 in 2025, X remains the main data source but its share is falling, and BERTopic and STM are joining LDA. Integration, however, is mostly parallel (71%), joint models are rare (9%) and falling in share, and topic-model evaluation is rarely visible. The taxonomy of four integration

routes, the distinction between actor and semantic networks, and the eight-point agenda in Table 8 give authors a common vocabulary and a set of priorities. The main next step for this review is full-text verification and dual coding of all 194 studies, which would convert the abstract-level estimates reported here into confirmed findings.

Declarations

Data availability. The screening sheet (232 records) and the extraction and mapping workbook (194 studies) are provided as Supplementary Information (S1 and S2) with this article. The rule-based coding procedure is described in Section 3.6.

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Author contributions. Dwi Jaya Saputra is the sole author and was responsible for conceptualization, methodology, investigation, data curation, formal analysis, visualization, and writing (original draft, review and editing).

Ethics approval, consent to participate and consent for publication. Not applicable. The review used published articles only and involved no human participants.

Use of AI tools. Claude (Anthropic) was used to propose title-and-abstract screening decisions, to run rule-based coding of the included studies, to draft the manuscript and to format tables and figures; its use is described in Sections 3.4 and 3.6. The author is responsible for the content of the manuscript. No AI tool is listed as an author.

Author Contribution

Dwi Jaya Saputra is the sole author and was responsible for conceptualization, methodology, investigation, data curation, formal analysis, visualization, and writing (original draft, review and editing).

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Figures

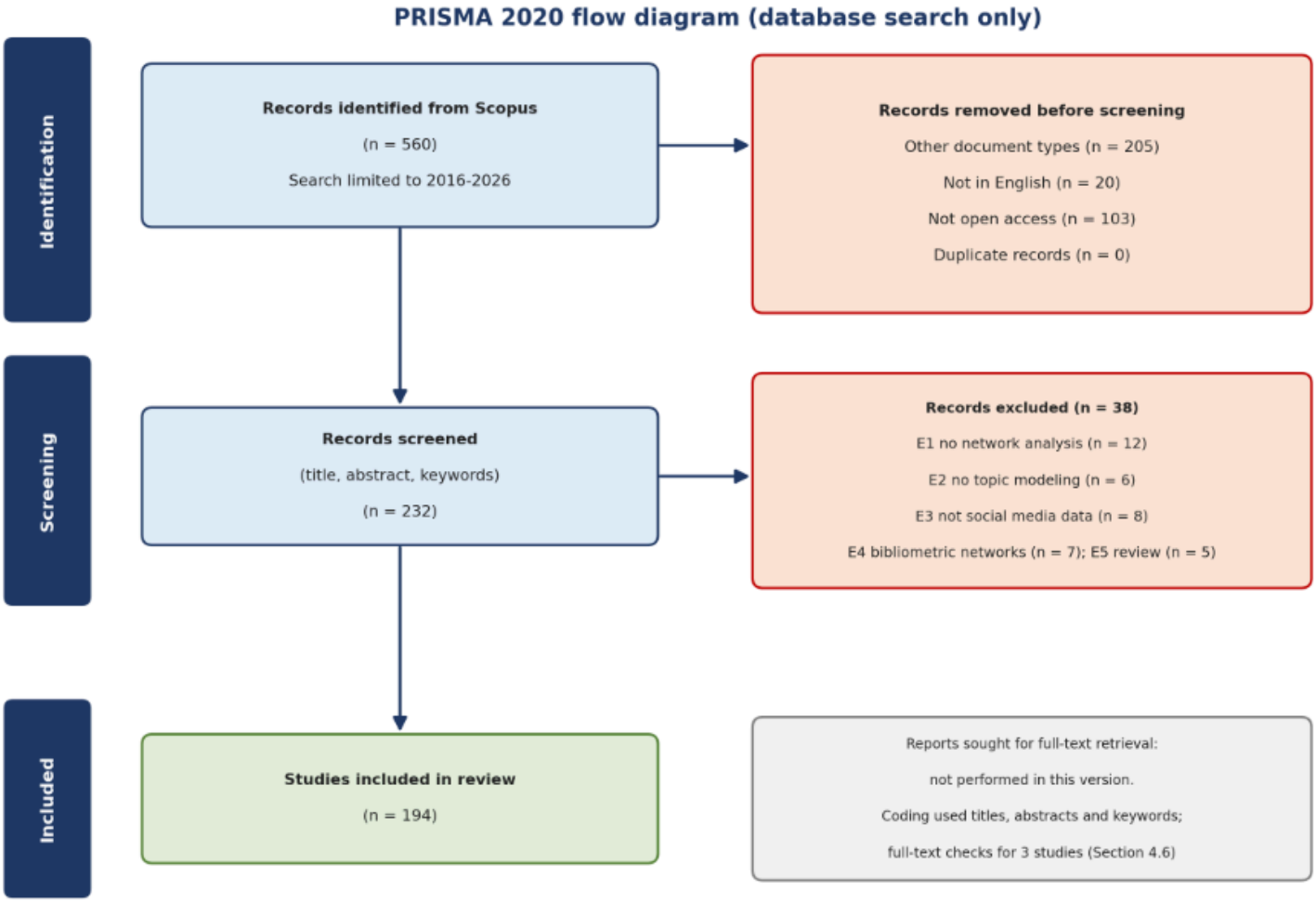


Figure 1

PRISMA 2020 flow diagram for the database search (Scopus).

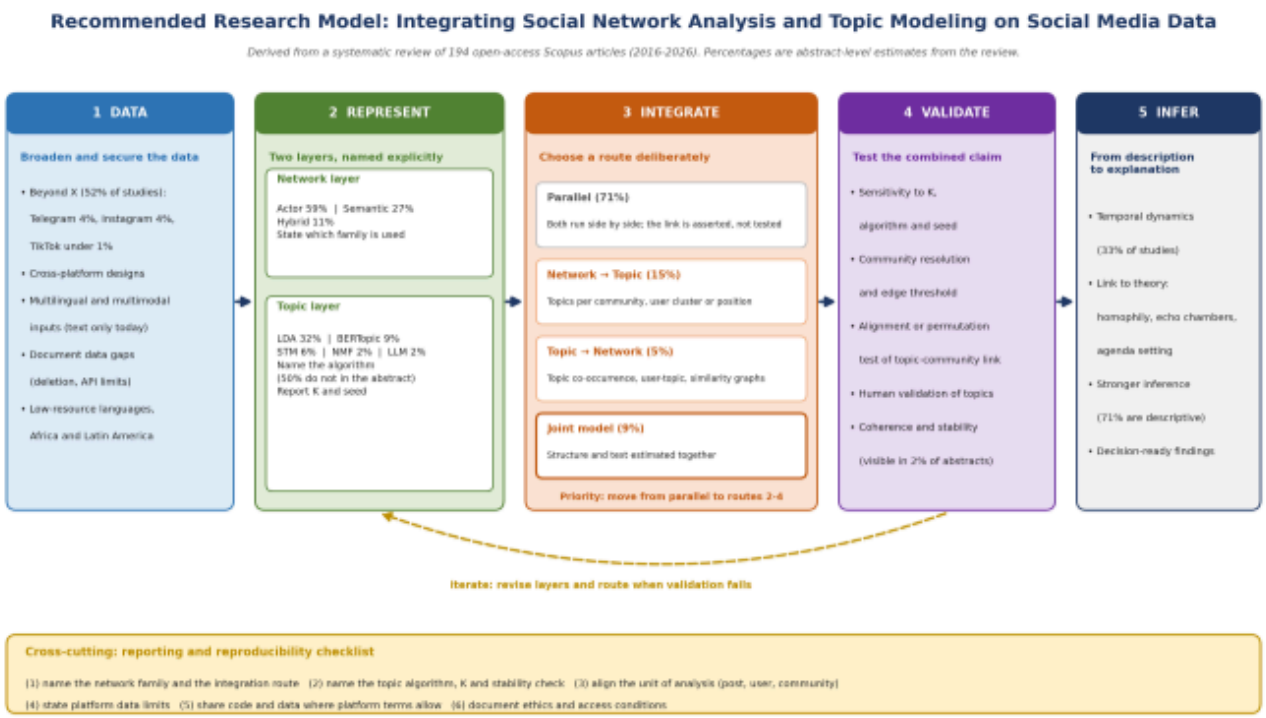


Figure 2

Recommended research model derived from the systematic review (194 studies, 2016–2026). Percentages are abstract-level estimates from Section 4.

Supplementary Files

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- AppendixA.docx