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REVIEW

Unlocking the Power of Graph Neural Networks—A Systematic Literature Review of Application-Oriented GNN Studies

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ABSTRACT: Graph neural networks (GNNs) have demonstrated promising results in enhancing machine learning and artificial intelligence techniques by addressing graph-related problems, including graph categorization, edge prediction, and node prediction. Despite the rapid growth of the field, a structured synthesis of recent application-oriented GNN research is necessary. This systematic literature review analyzes 363 peer-reviewed, application-oriented GNN studies published from 2019 through February 2026 from four scientific repositories. These studies are organized by GNN model variant, (including single and multimodel approaches), and four classification task categories: graph, link, node, and node and edge combined. In addition, the review assesses the use of learning settings, graph types, loss functions, aggregation mechanisms, embedding-representation models, implementation toolkits, datasets, and within-study base-model comparisons. In the reviewed corpus, the graph convolutional network (GCN) is the most common single-model family, which is most often associated with favorable within-study comparisons. In contrast, the model combining GCN with a graph attention network (GAT) is the most frequent multimodel configuration and is most often associated with favorable within-study comparisons. The reviewed corpus yields three broader insights: 1) multimodel architectures have become increasingly prominent after 2023, 2) heterogeneous graphs and a few broad-spectrum backbone families define a wide range of cross-domain applications, and 3) reporting transparency improves unevenly across implementation-oriented studies. This study aims to answer critical research questions regarding the analysis of dataset evolution, feature trends, and learning strategies in GNNs. The findings suggest that future GNN research should report learning settings, implementation toolkits, auxiliary representation models, and layer usage more systematically and evaluate multimodel proposals against strong, clearly identified single-model baselines. These findings provide valuable insight for researchers and practitioners in the field.

KEYWORDS: Graph neural networks (GNNs); graph theory; systematic literature review; machine learning; artificial intelligence

1 Introduction

Graph theory advances machine learning efficiency by addressing graph generation, link, and node classification [1]. Recent methods have focused on learning graph representations, with graph neural networks (GNNs) emerging as the most advanced method, influencing node classification [2], edge prediction [3], and detecting communities [4]. The GNN significantly contributes to diverse fields and domains, including (e.g., to classify advertiser behavior) [5], finance (e.g., to distinguish phishing and nonphishing nodes) [6], and traffic management (e.g., to predict average outflow trips per station) [7]. The GNN is based on graph convolution or message passing, adapted from convolutional neural networks (CNNs). Each graph node contains a set of attributes known as a feature vector or embedding. The graph convolution estimates the node features in the next layer as a function of the neighboring node features. By stacking GNN layers, a node can incorporate information from nodes further away. For example, after n layers, a node has information about nodes n steps away [8]. GNNs include several implementation components, such as embedding representation, learning method, aggregation, pooling, dropout, loss function, readout, and embedding size. Different GNN variants, including graph convolutional networks (GCNs), graph attention networks (GATs), graph isomorphism networks (GINs), and GraphSAGE, implement these components differently. Therefore, selecting a suitable GNN variant depends on the application domain, dataset properties, graph type, learning strategy, classification task, and implementation constraints [9]. Recent GNN studies have also employed diverse toolkits, datasets, graph types, loss functions, aggregation functions, and layers; however, these elements are often analyzed separately rather than synthesized together in an application-oriented review. This gap motivates the present systematic literature review (SLR).

The GNN has been extensively studied across diverse domains, with multiple survey articles analyzing its architecture, applications, and limitations. However, most surveys have focused on general GNN principles, specific application domains, or theoretical insights, often lacking a comprehensive empirical evaluation across datasets, feature trends, and scalability concerns. In contrast, the current study offers a systematic analysis of GNN advancements from 2019 to 2026, addressing critical gaps identified in prior literature. This work analyzes dataset evolution, feature-engineering trends, implementation-oriented reporting patterns, and benchmarking-related comparison behavior, offering a broader synthesis of recent GNN practices than is available in the existing domain-specific or theory-centric surveys. This review is compared with the most recent high-visibility GNN surveys to clarify overlap and contributions. In this study, "high-visibility" is employed as an operational comparison label rather than as a formal quality ranking. The surveys were selected to provide a recent, representative comparison set across foundational, domain-specific, theoretical, industrial, and dynamic-graph perspectives. In practice, this means prioritizing surveys that are recent, published in widely recognized venues, clearly focused on GNNs or a substantial GNN subarea, and broad enough to serve as meaningful comparisons for this systematic literature review (SLR). The comparison employs a simple operational rubric: "Yes" indicates explicit, substantive treatment with a dedicated discussion or structured synthesis. "Limited" marks an partial, narrow, or nonsystematic treatment, and "No" marks an absence of meaningful discussion on that dimension. These labels are applied for comparative positioning rather than study-quality scores. Table 1 presents the feature-level comparison with recent surveys and positions the present SLR against related high-visibility reviews.

Table 1: Comparison of this systematic literature review with recent high-visibility graph neural network (GNN) surveys and reviews.

Survey	Venue/Year	Primary Focus	Datasets	Feature Trends	Scalability/ Security	Applications	Toolkits/ Frameworks
Corso et al. [10]	Nature Rev. Methods Primers/2024	Foundational GNN primer covering core concepts, operators, training, explainability, and scientific use cases.	No	Limited	No	Yes	No

(Continued)

Table 1 (continued)

Survey	Venue/Year	Primary Focus	Datasets	Feature Trends	Scalability/ Security	Applications	Toolkits/ Frameworks
Sharma et al. [11]	ACM Comput. Surv./2024	Social recommender systems with GNNs, benchmark datasets, and recommendation-oriented taxonomies.	Yes	Limited	No	Yes	No
Li et al. [12]	ACM Comput. Surv./2025	Graph neural networks for tabular-data learning, graph construction strategies, and research directions.	Yes	Limited	Limited	Limited	No
Zhang et al. [13]	IEEE TKDE/2025	Expressive power of GNNs, architectural mechanisms, and theoretical enhancement strategies.	No	Yes	Limited	No	No
Lu et al. [14]	Neurocompu-ting/2025	Broad review of GNN methods with emphasis on industrial application scenarios.	Limited	Limited	No	Yes	No
Feng et al. [15]	IEEE TKDE/2026	Dynamic GNN models, frameworks, benchmarks, experiments, and challenges.	Yes	Yes	Limited	Yes	Limited
Our SLR	**2019–2026**	**Repository-based systematic synthesis across 363 selected studies covering variants, task granularity, datasets and availability, toolkits, graph types, learning settings, losses, representations, aggregation, layers, and base-model comparisons.**	**Yes**	**Yes**	**Limited**	**Yes**	**Yes**

Note: Yes = explicit and substantive treatment with dedicated discussion or structured synthesis; Limited = partial, domain-restricted, or non-systematic treatment; No = absent or only incidental mention.

Recent high-visibility surveys have examined GNNs from complementary perspectives, including foundational methods, recommender systems, tabular-data learning, expressive power, industrial applications, and dynamic graph learning [10–15]. However, these reviews typically emphasize a single perspective at a time and do not provide a repository-based systematic synthesis across model variants, task granularity, datasets and their availability, toolkits, learning paradigms, graph types, loss functions, embedding-representation models, aggregation strategies, layer usage, and base-model comparisons. Therefore, Table 1 position the proposed SLR against the most recent high-visibility surveys and reveal that its contribution is not limited to broader variable coverage. Compared with these recent surveys, the value of this SLR lies in the higher-level patterns that emerge from a study-level synthesis of the 363 selected studies. First, the reviewed corpus reveals a structural shift from single-model dominance in the initial years to greater multimodel prominence after 2023. Second, a small set of backbone families, especially GCN and GCN combined with GAT, provides broad cross-domain coverage across graph-, link-, and node-oriented tasks. Third, the task granularity, learning setting, and graph type are not independent design dimensions; they influence which model families are repeatedly selected in practice. Fourth, the review indicates that reproducibility is constrained less by the absence of datasets or loss definitions than by the underreporting of learning settings, implementation toolkits, auxiliary representation models, and layer usage.

Thus, this SLR contributes a broader descriptive map of recent GNN literature and provides design-level insight into how application-oriented GNN research is structured, reported, and validated. The review is intended for applied GNN researchers, engineering practitioners, and early-stage researchers who need to move from general GNN knowledge to application-specific design decisions. For these readers, the review provides evidence on which model families, graph structures, learning settings, auxiliary encoders, losses, aggregation strategies, and reporting practices are commonly used under different task and data conditions. Therefore, the review should be read as a design-oriented synthesis rather than as a universal model ranking. Specifically, the principal contributions of this SLR are as follows:

- This SLR screens a large cross-publisher corpus and synthesizes 363 peer-reviewed, application-oriented GNN studies published between 2019 and February 2026.
- This work jointly analyzes model variants, task granularity, datasets and their availability, toolkits, learning settings, graph types, loss functions, embedding-representation models, aggregation strategies, layer usage, and base-model comparisons in a single review.
- This SLR derives higher-level insights from these dimensions, including the temporal shift toward multimodel designs, the broad cross-domain role of a few backbone families, and the practical coupling between task granularity, graph structure, and model choice.
- This research provides an implementation-oriented synthesis of how GNN studies are reported, validated, and compared in application settings, with attention to reproducibility and baseline design.
- This SLR translates the corpus-level findings into practitioner-oriented guidance for initial model selection, implementation planning, reproducibility-aware reporting, and future application-oriented GNN research.

Accordingly, this systematic literature review (SLR) [16] is conducted to answer the following research questions:

RQ1) How are GNN model variants comprehensively employed to solve graph-related problems, and which tasks have been solved in recent GNN implementations?

RQ2) What datasets, toolkits, and libraries are used to implement GNN-based solutions, and what is the performance of GNN model variants compared to the base GNN model variants? How important is the selection of each GNN model variant in various scenarios?

RQ3) What are the leading graph types and learning strategies in recent GNN-based research contributions?

RQ4) What are the most contributing loss functions in recent GNN solutions and what are the scenarios where a loss function has an impact over other loss functions?

RQ5) Which embedding representation models are used in the most recent GNN-based solutions?

RQ6) What aggregator functions are used in recent GNN solutions, and how do they affect the GNN models?

RQ7) How do the readout, pooling, and dropout layers reduce the problems related to complexity and overfitting and how important is the embedding size?

This article presents an SLR to answer these questions and analyzes 363 studies published between 2019 and 2026. Fig. 1 illustrates the research overview. This study develops a review protocol with inclusion and exclusion criteria for implementing this SLR (Section 2.2). The research targets four credible scientific databases (i.e., Institute of Electrical and Electronics Engineers (IEEE), Association for Computing Machinery (ACM), Elsevier, and Springer) for the search process (Section 2.2.2). Section 2.1 defines the two principal categories of GNN model variants. Section 2.2.3 presents the quality assessment criteria for this SLR. Section 2.2.4 describes the bias control, transparency, and scope limitations. Section 2.2.5 details the elements extracted from the selected studies. Section 3.1 classifies the final set into two categories: single-model (185 studies) and multimodel (178 studies) approaches. Similarly, Section 3.2 identifies four classification task categories: graph (119 studies), link (94 studies), node (79 studies), and node + edge (71 studies).

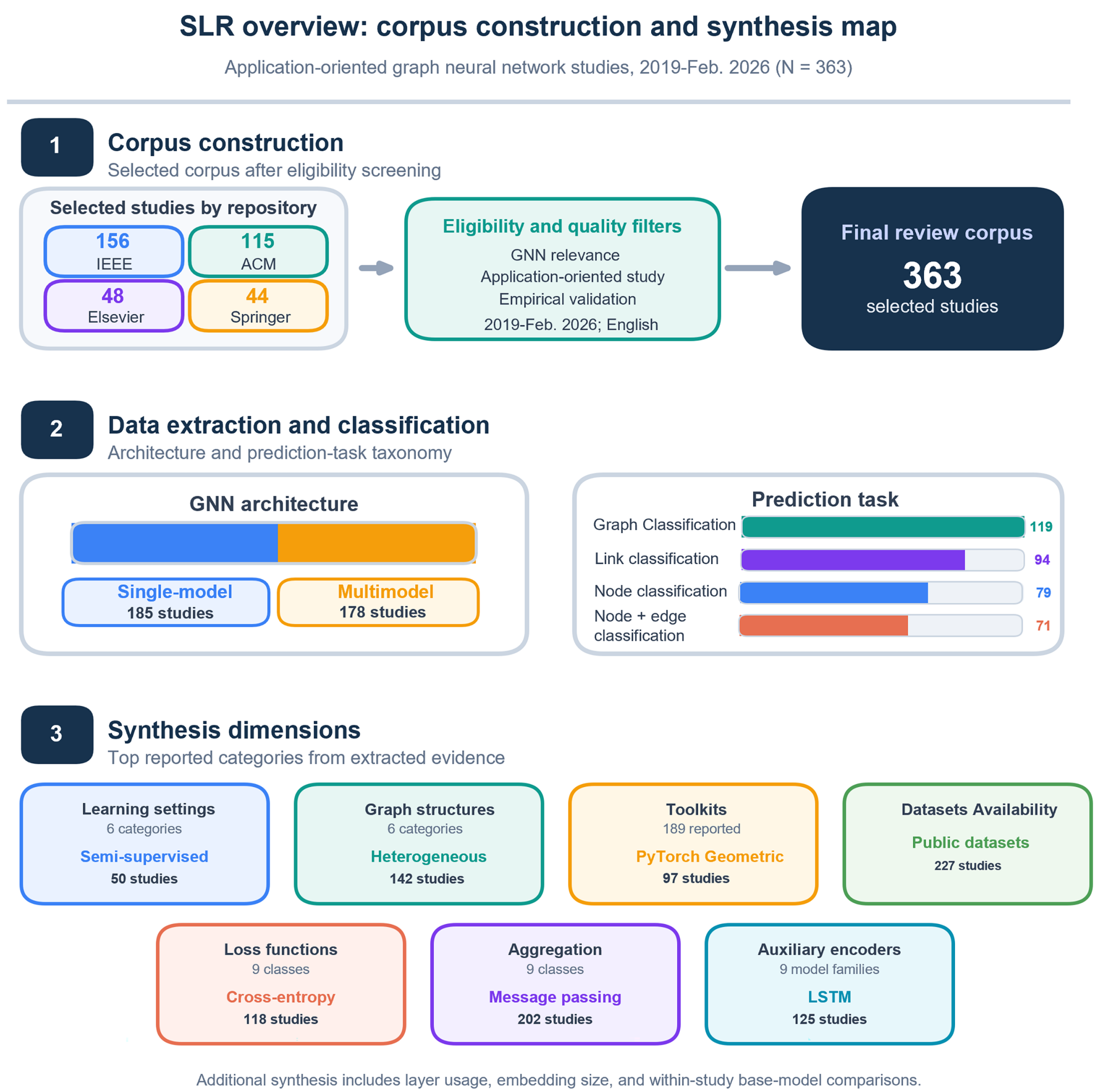

Figure 1: Research overview: schematic representation of the systematic literature review (SLR) methodology, illustrating the inclusion and exclusion criteria, research categorization, and data extraction process.

Section 3.3 identifies several contributing toolkits in the GNN domain. Likewise, this study analyzes the six categories of learning strategies in the selected studies (Section 3.4). In addition, Section 3.5 discusses six graph types of recent GNNs. Section 3.6 presents an analysis of 14 domains of datasets and their availability. Several loss functions and their importance in different scenarios are analyzed (Section 3.7). Section 3.8 discusses the application of models for embedding representation. Along with nine categories of aggregate methods, this SLR also analyzes seven layer combinations and embedding size importance in Sections 3.9, 3.10, and 3.11, respectively. Finally, this article presents a comparative analysis of model variants with base model variants in Section 4 and answers each research question in Section 5. Finally, Section 6 concludes this SLR and discusses future work. Accordingly, this SLR should be interpreted as a systematic synthesis of peer-reviewed, application-oriented GNN studies retrieved from four major repositories rather than as an exhaustive census of all GNN literature.

2 Research Methodology

The study follows SLR guidelines [16], which require a review protocol. This section has two subsections: the definitions of all primary categories and the design of the review protocol.

2.1 Major Categories

This study categorizes the selected papers into two categories to rationalize the data extraction and synthesis processes. The following subsections define these major categories.

2.1.1 Single-Model Approach

Several GNN models implement neural networks in a given graph. For example, Jiang et al. [17] employed a GCN for fraud detection and Nguyen et al. applied GraphSAGE to the pill-prescription matching task [18]. These studies only employ a single model.

2.1.2 Multimodel Approach

Studies can apply multiple models to enhance implementation. For instance, Yin et al. [19] implemented a GAT after the GCN to capture critical nodes by assigning weights. Similarly, another study [6] combined the graph sample and aggregate (GraphSAGE) method with GCN to learn the topological space structure and extract node features. These studies are multimodel approaches.

2.2 Review Protocol

This article develops the review protocol in accordance with the standard directions [16]. The introduction section presents the research questions and background. Later sections present further information on the process (i.e., inclusion and exclusion criteria, search process, data extraction, and synthesis).

2.2.1 Inclusion and Exclusion Criteria

The most crucial aspects of the SLR are the inclusion and exclusion criteria, which determine whether studies are approved for further investigation. This article develops the following factors for these inclusion and exclusion criteria.

i) Area of Research: The selected research must be in the GNN field. Thus, this work includes only studies that employ GNN model variants to solve real-world problems. In this SLR, research studies that did not apply GNN model variant were rejected. For example, studies were excluded if the authors applied a GNN (e.g., to predict city air quality) [20] without specifying a GNN variant.

ii) Application Research: In this review, an application-oriented study is a primary empirical paper that presents a concrete GNN-based framework, model, or method for a problem setting and validates that proposal through implementation or experimentation. This work includes studies that apply a single or multimodel GNN design to solve tasks (e.g., fraud detection, recommendation, medical prediction, transportation analysis, or related graph-based problems). For example, Jiang et al. [17] proposed a multiple aggregators and feature interactions (MAFI) network for fraud detection using a single-model GCN, which falls within the scope of inclusion. The review applies this label to distinguish solution papers from broader contextual papers. Comparative surveys, method-overview papers, or discussion-oriented studies are valuable to the field, but within this SLR they are outside the application-oriented inclusion scope when they do not present and validate a concrete GNN-based solution. For example, Bessadok et al. [21] presented a comparative discussion of GNN methods for brain-related disease classification. In the present review design, this contribution type is categorized as outside the application-oriented corpus because the scope of inclusion focuses on implemented and validated problem-solving proposals.

iii) Publication Year: This SLR considers papers published between 2019 and February 2026. Recent research has followed the general direction of earlier studies in the field.

iv) Publisher: This SLR explores four renowned scientific repositories to select research papers: IEEE, Springer, Elsevier, and ACM. Several scholarly databases have published such research. However, studies can be added to repositories (e.g., arXiv or Google Scholar), without peer review. Conversely, reliable repositories, such as IEEE, ACM, Elsevier, and Springer, are where research publications are typically added to databases following peer review. Therefore, these four renowned scientific repositories were selected.

v) Proposal Validation: The proposed approach must be properly validated via implementation, such as experimentation. High-quality research depends on the appropriate validation. Thus, a study was selected only if the proposal was adequately validated via a reliable mechanism (e.g., a tool or application development). Studies with sufficient details that violate this criterion exist in this context. For instance, Zhang et al. [22] presented a summary and analysis of relevant research to classify stock market-related problems but did not validate it. This SLR also rejects work by Jia et al. [23] that reviewed GNNs in the context of a construction application but did not perform any implementation task.

This SLR strictly follows the inclusion and exclusion criteria for research studies in selecting papers. If one criterion was not met, the paper was disqualified from the SLR.

2.2.2 Search Process

Per the inclusion and exclusion guidelines, four databases (i.e., Elsevier, ACM, Springer, and IEEE) were employed in the search process. The search method involves using numerous search terms, including "graph neural networks". However, such search phrases returned thousands of results, making a thorough analysis impractical. For instance, the IEEE database (https://ieeexplore.ieee.org/) produced 29,895 items for the search term "graph neural network." Therefore, the search results were optimized to obtain the most relevant information using filters, including the publication-year window relevant to the study period, and the Boolean AND operator, i.e., the logical conjunction operator used to combine search terms. A precision-oriented Boolean search strategy was applied to keep the result set tractable within the selected repositories and study scope. In practice, this means combining core GNN terms with application-oriented terms and applying the year and source filters defined in the review protocol. This design improves precision in a vast and heterogeneous engineering literature, but it may reduce recall for studies using alternative terminology. To reduce the risk of missed studies under this precision-oriented retrieval design, the database search was complemented with backward and forward snowballing, recovering additional relevant papers that may not have been captured by the core Boolean query alone. Accordingly, the findings are interpreted as a retrieved application-oriented corpus rather than an exhaustive census of all GNN publications.

A logic search was constructed for preliminary research using an explanatory analysis: "(graph neural network) AND (GNN) AND (graph neural network based classification) AND (GNN based classification)," resulting in 17,731 records (**2732** from IEEE, **5472** from Springer, **3746** from Elsevier, and **5781** from ACM). Table 2 lists the database-specific implementation of the final precision-oriented search strategy, including the platform-specific query syntax, archived search evidence, coverage window, and identified-record counts employed in this SLR. Only English-language documents were considered due to the number of records. After thoroughly examining each search result, studies were selected based on the inclusion and exclusion criteria. The inclusion and exclusion criteria for the publication year and publisher were established during the search procedure. Fig. 2 summarizes the screening framework for the final 2019–2026 corpus. The complete PRISMA 2020 checklist and the PRISMA flow-diagram template are provided in the Supplementary Materials.

Table 2: Database-specific implementation of the final precision-oriented search strategy used for the 2019–February 2026 review window.

Database	Search Fields	Final Search String	Archived Evidence	Filters and Identified Records
IEEE	All Metadata	(*Graph Neural Network*) AND (*GNN*) AND (*Graph Neural Network based classification*) AND (*GNN based classification*)	Archived IEEE Xplore search screenshot and repository record	2019–Feb. 2026; English; 2732 identified records
ACM	All metadata in ACM Full-Text Collection	([All: "all metadata"] OR [All::graph neural network]) AND ([All: "all metadata"] OR [All::gnn]) AND ([All: "all metadata"] OR [All::graph neural network based classification]) AND ([All: "all metadata"] OR [All::gnn based classification])	Archived ACM Digital Library search screenshot and repository record	2019–Feb. 2026; English; 5781 identified records
Elsevier	ScienceDirect content search	(*Graph Neural Network*) AND (*GNN*) AND (*Graph Neural Network based classification*) AND (*GNN based classification*)	Archived ScienceDirect search screenshot and repository record	2019–Feb. 2026; English; 3746 identified records
Springer	SpringerLink general search field	(*Graph Neural Network*) AND (*GNN*) AND (*Graph Neural Network based classification*) AND (*GNN based classification*)	Archived SpringerLink search screenshot and repository record	2019–Feb. 2026; English; 5472 identified records

Note: The same core Boolean query was implemented across all four repositories using their native search syntax and field labels. For brevity, the review window is denoted as 2019–2026 in the manuscript; however, the 2026 records reflect publications indexed through February 2026 only.

The review covers studies published from 2019 through February 2026; however, for brevity, the manuscript refers to the period as 2019–2026. All counts reported for 2026 reflect only the first two months of the year and are partial-year values rather than full-year totals. First, the study titles were assessed to ensure relevance and their fit with the inclusion and exclusion criteria. Hence, 13,405 records were excluded based on the titles and 4326 were retained for later screening. These studies underwent abstract screening, general study assessment, and detailed analyses to ensure that all inclusion and exclusion criteria were satisfied, particularly the area-of-research, application-research, and proposal-validation parameters. This multistage review yielded 350 studies that satisfied the inclusion and exclusion criteria. The final phase applied the snowballing approach to these 350 selected studies. Snowballing helped identify pertinent studies that have been missed during the database search using forward and backward snowballing strategies. Thus, 35 additional studies relevant to the research context were identified. Following a thorough review, 13 additional studies meet the inclusion and exclusion criteria. Finally, 363 papers were selected for further investigation to obtain reliable and useful answers to the study questions in this SLR. Table 3 summarizes yearly distribution of the final selected corpus, which is visualized in Fig. 3.

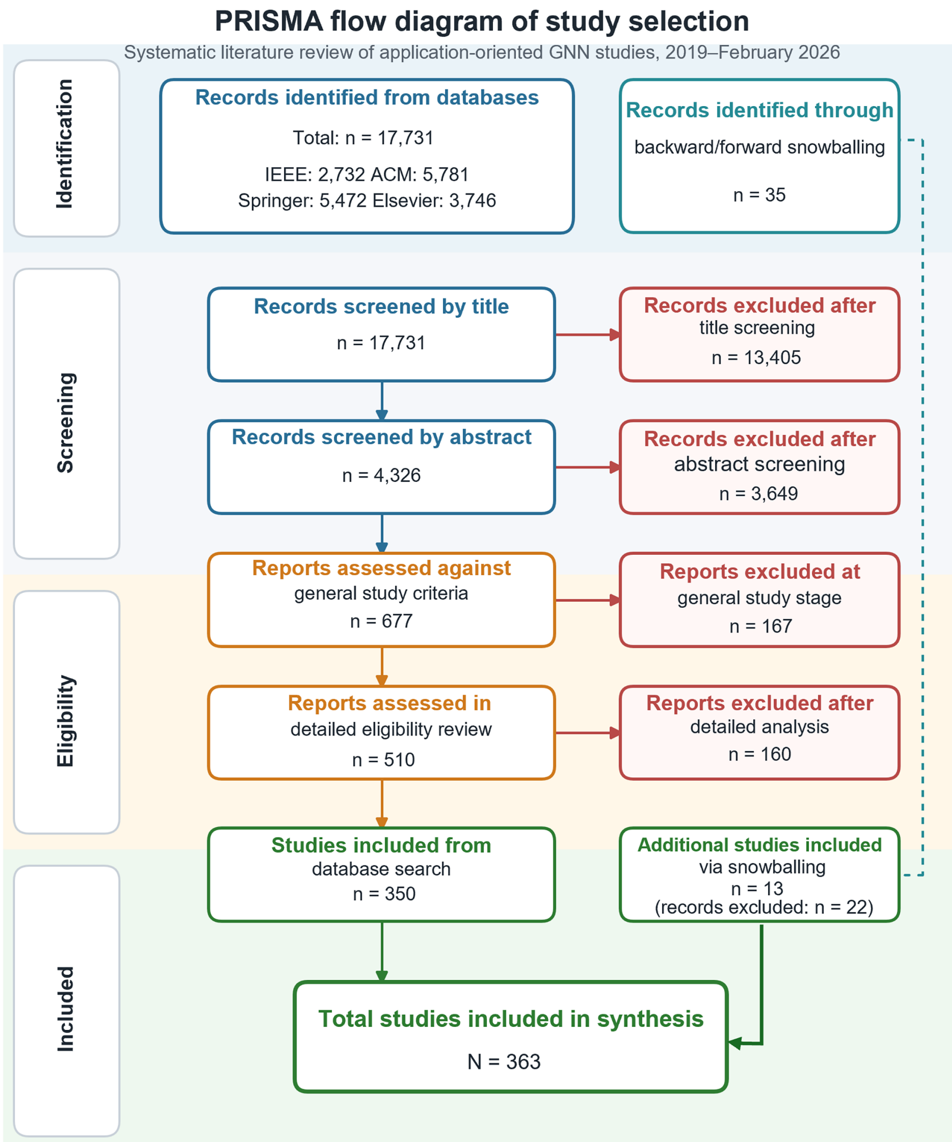

Figure 2: PRISMA flow diagram of the study selection process. The diagram summarizes the identification, screening, eligibility assessment, snowballing, and inclusion stages used to select the final 363 application-oriented GNN studies.

Table 3: Distribution of selected research papers based on their publication year, showing an increasing trend in GNN research contributions from 2019 to 2026.

No.	Year	Research References	Count	Percentage
1.	2019	[2,24]	2	0.55%
2.	2020	[3,25–30]	7	1.93%
3.	2021	[4,5,17,31–49]	22	6.06%
4.	2022	[6,8,18,19,50–73]	28	7.71%
5.	2023	[1,7,74–111]	40	11.02%
6.	2024	[112–203]	92	25.34%
7.	2025	[204–356]	153	42.15%
8.	2026	[357–375]	19	5.23%

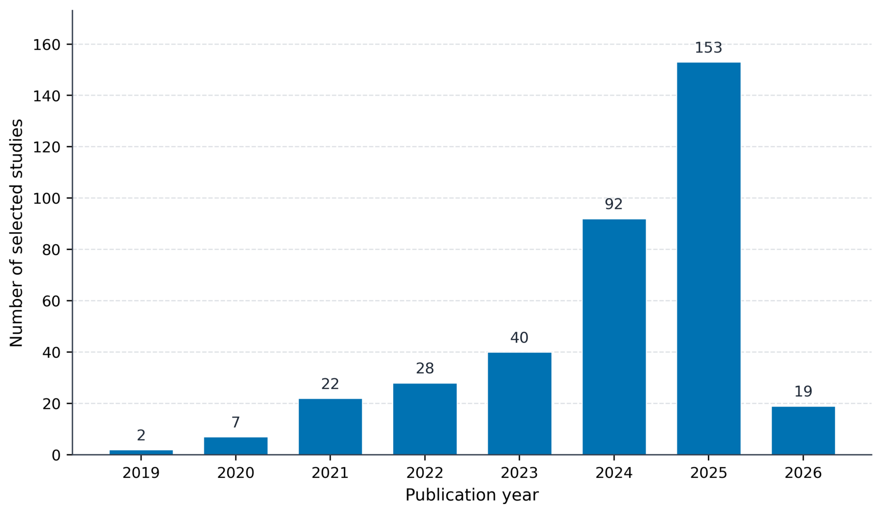

Figure 3: Yearly distribution of selected studies from 2019 to 2026, with strong post-2023 growth in the field. Values for 2026 reflect only the first two months of the year and are partial-year counts.

2.2.3 Quality Assessment

To ensure the reliability and relevance of this SLR, the criterion-based quality-assurance rubric presented in Table 4 was applied using the inclusion and exclusion criteria from Section 2.2.1. Studies were retained only when they met the scope-relevant criteria, by containing an identifiable GNN variant or family, an application-oriented contribution, and empirical validation via implementation or experimentation. Missing details on toolkits, learning settings, graph types, embedding-representation models, or layer usage were not treated as exclusion criteria; instead, they were recorded as "not discussed" and later analyzed as reporting gaps. Table 3 summarizes yearly distribution, and Table 5 summarizes the repository distribution across IEEE, ACM, Elsevier, and Springer. Fig. 3 reports the absolute yearly study counts. Additional temporal trend visualizations are discussed in their corresponding result sections. Rather than employing a retrospective scoring instrument, this review treats quality assurance as a criterion-based inclusion process combined with an analysis of the descriptive completeness. This design is appropriate for the implementation-oriented focus of this SLR, in which empirical validation is treated as a critical inclusion criterion and missing methodological details are analyzed separately as reporting limitations.

Table 4: Quality-assurance rubric used in this SLR.

Criterion	Type	Role in the review
Within 2019–2026, English, and one of the four target repositories	Critical	Inclusion criteria
Identifiable GNN variant or family	Critical	Inclusion criteria
Application-oriented framework/model/method contribution	Critical	Inclusion criteria
Empirical validation through implementation or experimentation	Critical	Inclusion criteria
Extractable task/graph type/loss/representation/layer information	Descriptive	Used for synthesis, not exclusionary
Toolkit, learning-setting, and reporting-completeness details	Descriptive	Used for reproducibility-gap analysis, not exclusionary

Table 5: Distribution of research by repository (ACM, Elsevier, Springer, and IEEE).

No.	Repository	Research References	Count
1.	ACM	[1,2,4,5,8,26–29,37–42,58,59,85–88,112,116–125, 128–130,132–142,144–155,204–255,357–361]	115
2.	Elsevier	[7,64–73,91–111,131,156,192,195,202,203,347–356]	48
3.	Springer	[6,18,19,24,30,43–49,60–63,89,90,113–115, 199–201,332–346,371–375]	44
4.	IEEE	[3,17,25,31–36,50–57,74–84,126,127,143,157–191, 193,194,196–198,256–331,362–370]	156

2.2.4 Bias Control, Transparency, and Scope Limitations

The studies were screened and extracted collaboratively using shared screening sheets and a consensus discussion. Two authors participated in the screening workflow, and records at the title, abstract, and general, and detailed study stages were assessed collaboratively, with borderline cases resolved through consensus discussion. Duplicate handling relied primarily on digital object identifier (DOI) matching and secondarily on title/year matching, with full-text confirmation for ambiguous records. The review followed a predefined protocol developed before final screening. Table 6 defines the exclusion codes in the screening process. To improve screening transparency, each excluded record was assigned a primary exclusion code at the latest stage reached, and the coded screening log is released in the public GitHub repository.

The review targets IEEE, ACM, Elsevier, and Springer because these repositories encompass a large share of peer-reviewed GNN research in artificial intelligence, data mining, systems, and applied machine learning. This choice improves source quality, traceability, and topical relevance, but it also introduces source-selection bias. Studies indexed only in other repositories, broad academic search engines, preprint servers, or specialized venues may not be captured. This design may influence the observed trends by giving stronger visibility to peer-reviewed engineering applications, such as transportation, health care, recommendation, communication networks, and applied prediction, while underrepresenting very recent preprint-only, theoretical, benchmark-driven, or foundation-model-oriented GNN developments. Similarly, because the retrieval strategy was optimized for precision in a very large result set and the inclusion criteria prioritized application-oriented proposal papers, the findings should be interpreted as trends in a structured application-focused corpus rather than as universal properties of all GNN research.

Table 6: Exclusion reason codes in the screening process.

Code	Meaning
E1	Outside temporal, source, or language scope
E2	No explicit GNN relevance or no identifiable GNN variant/family
E3	Outside the application/task scope of this review
E4	Not a primary empirical study (e.g., a survey, editorial, protocol, tutorial, retraction note)
E5	Not application-oriented under the review design (comparison-only or theory-only without a framework, model or method contribution)
E6	No empirical validation through implementation or experimentation
E7	Duplicate or overlapping record merged with another entry
E8	Insufficient information for reliable coding at the latest screening stage
E9	Retracted or withdrawn content

2.2.5 Data Extraction and Synthesis

After applying the criteria to select research papers, the data were extracted and synthesized to determine reasonable answers to the research questions. Table 7 supplies a template for data extraction of relevant items from the selected research for this process. First, the template extracts the primary components from the selected research papers as given in Items 1 to 3 in the table. Afterward, the extracted data were synthesized to obtain crucial information from all research articles to answer the research questions. For example, the studies were categorized to answer RQ1. Likewise, the data were extracted and synthesized to extract all necessary elements (Items 4 to 15) to answer the other research questions. For instance, details on graph types and learning strategies were extracted from each study and categorized into structured classifications (Sections 3.4 and 3.5). This synthesis found that semi-supervised learning is the most common reported training strategy (50 studies), although 198 papers did not discuss the learning setting directly. Similarly, heterogeneous graphs were the most reported graph structure (142 studies), followed by directed (67) and bipartite (42) graphs. This analysis underscores critical changes in GNN training paradigms and structural adaptations in the reviewed corpus.

Table 7: Template of data extraction: structured data extraction template used to categorize and synthesize research findings across various GNN implementations.

No.	Extracted Data	Description
1	Bibliographic details	Subject, publication source, publication year, and type
2	Application research	Articles with implementation (e.g., frameworks, models, or tools)
3	Validation method	Validation of the approach with a dataset, case study, etc.
	Data Synthesis	
4	GNN model-variant categorization	Categorization of selected studies by the GNN model and their subcategories (Section 3.1)
5	Classification type-based categorization	Categorization of selected studies based on classification (Section 3.2)

(Continued)

Table 7 (continued)

No.	Extracted Data	Description
6	Toolkits and libraries	Toolkits and libraries in selected studies (Section 3.3)
7	Learning settings	Learning settings identified in each selected study (Section 3.4)
8	Graph type	Categorization of selected studies for graph type (Section 3.5)
9	Dataset domain	Grouping of selected studies in various dataset domains (Section 3.6)
10	Model-variant comparison	Comparison of model variant with base model variants (Section 4)
11	Loss functions	Loss function participation in GNN implementation (Section 3.7)
12	Model for embedding representation	Identification of models for representation of embedding (Section 3.8)
13	Aggregator functions	Importance of aggregator function in a recent GNN implementation (Section 3.9)
14	Layers (pooling, readout, and dropout)	Involvement of layers in recent studies (Section 3.10)
15	Embedding size	Importance of embedding size (Section 3.11)

This stage covers the primary elements of the review protocol. Data extraction produced relevant details from all selected research papers. Section 3 elaborates on these results.

2.3 Notation

The notation in Table 8 is applied to standardize the technical discussion across the SLR.

Table 8: Basic notation for mathematical summaries of core GNN mechanisms.

Symbol	Meaning
$G = (V, E)$	Graph with node set V and edge set E
$\mathcal{N}(v)$	Neighborhood of node v
$\mathbf{A}$	Adjacency matrix of the graph
$\tilde{\mathbf{A}}$	Adjacency matrix with self-loops
$\tilde{\mathbf{D}}$	Degree matrix of $\tilde{\mathbf{A}}$
$\mathbf{X}$	Input node-feature matrix
$\mathbf{h}_v^{(\ell)}$	Representation of node v at layer ℓ
$\mathbf{H}^{(\ell)}$	Matrix of node representations at layer ℓ
$\mathbf{W}^{(\ell)}$	Learnable weight matrix at layer ℓ
$\phi^{(\ell)}(\cdot)$	Message function at layer ℓ
$\mathrm{AGG}^{(\ell)}(\cdot)$	Neighborhood aggregation operator at layer ℓ
$\psi^{(\ell)}(\cdot)$	Node-update function at layer ℓ
α_{vu}	Attention weight assigned from node v to neighbor u
$\sigma(\cdot)$	Nonlinear activation function
$\mathcal{L}$	Training loss function

2.4 Unified Message-Passing View of GNNs

Before analyzing the empirical distribution of model variants, placing the reviewed GNN architectures under a common computational view is useful. Although the studies employ different designs, most can be interpreted in a message-passing framework (Fig. 4). This unified formulation connects the variant taxonomy in Table 9 to the aggregation trends discussed in Section 3.9. At layer ℓ, node v receives messages from its neighborhood and updates its representation as follows:

$$\mathbf{m}_v^{(\ell)} = \mathrm{AGG}^{(\ell)}\Big(\big\{\phi^{(\ell)}(\mathbf{h}_v^{(\ell)}, \mathbf{h}_u^{(\ell)}, \mathbf{e}_{uv}) : u \in \mathcal{N}(v)\big\}\Big),$$
$$\mathbf{h}_v^{(\ell+1)} = \psi^{(\ell)}\Big(\mathbf{h}_v^{(\ell)}, \mathbf{m}_v^{(\ell)}\Big). \quad (1)$$

where $\mathbf{m}_v^{(\ell)}$ denotes the aggregated message received by node v at layer ℓ, and $\mathbf{e}_{uv}$ indicates optional edge features associated with edge (u, v) when such features are available. This compact view is beneficial because the primary variants in Section 3.1 differ in how they define neighborhood aggregation and node updates, whereas the categories in Section 3.9 differ in the choice of $\mathrm{AGG}^{(\ell)}(\cdot)$.

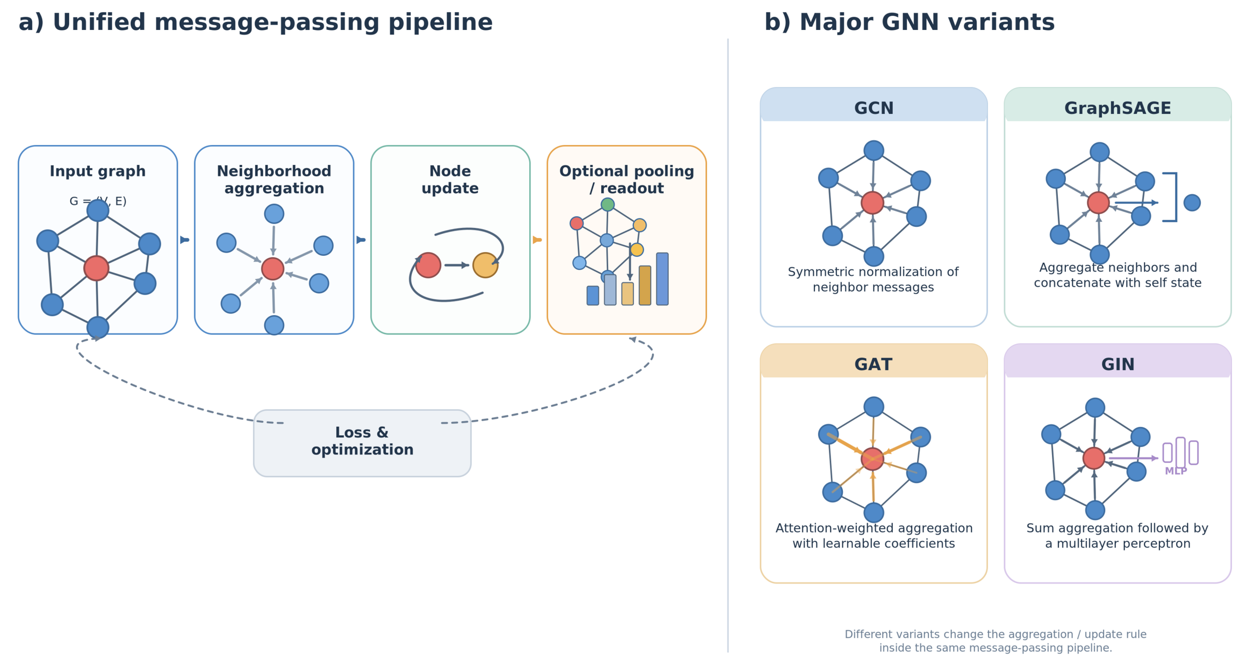

Figure 4: Unified message-passing view of GNNs and dominant variants: a schematic comparison showing the common message-passing pipeline and the main aggregation/update characteristics of GCN, GraphSAGE, GAT, and GIN.

Table 9: Graph neural network (GNN) model-variant categorization: classification based on single and multimodel GNN approaches, identifying dominant models such as GCN, GAT, and GraphSAGE.

No.	Subscategory	Research References	Subcategory Count
		Single-Model Approach	
1	ChebNet	[31]	1
2	ChebyGIN	[91]	1
3	GAT	[7,8,36,47,48,57,68,69,72,74,81,83,87,88,92,96,104,112,118,124,148,161,172,175,194,195,208,215,225,226,229,271,281,288,297,299,301,303,334,360,371]	41

(Continued)

Table 9 (continued)

No.	Subcategory	Research References	Subcategory Count
4	GCN	[1–3,17,25,26,28,32,37,39,43,49,50,52,53,55,58,62,63,65,67, 70,73,75–77,79,80,93–95,97–102,107–111,115,126,128,129, 137,147,155,180,182,187,202,209,210,213,237–239,241,243, 244,247,253,255,259,273,280,300,305,306,308,309,332,341, 344,345,348,350,354,357,358,368,374,375]	85
5	GraphSAGE	[4,18,27,29,33,40,54,56,66,82,86,90,113,121,143,274,311,359]	18
6	GIN	[24,51,89,154]	4
7	Other	[120,122,123,125,131,178,200,217,230,232,249,278,333,370]	14
8	Not discussed	[135,136,160,206,207,219,233,235,242,248,251,254,268,287, 314,315,319,325,343,361,372]	21
			Single-model total: 185
		Multimodel Approach	
1	GAT + GraphSAGE	[42,134,205,231,269,320]	6
2	GCN + GAT	[5,19,30,34,35,38,41,44,45,59–61,64,71,78,84,85,103,105,106, 114,119,127,130,132,133,140,142,145,146,152,156–159,162, 165–169,171,174,176,177,179,181,183,188,190–192,196–199, 201,203,204,211,212,214,216,218,220,223,224,227,234,236, 240,250,252,256,260,261,265,266,270,272,275,279, 282–285,289–296,298,302,304,310,313,316,318,321–324,327, 329–331,335–338,340,346,347,351,353,355,362,363, 365–367,369,373]	126
3	GraphSAGE + GCN	[6,116,117,138,153,173,186,222,257,263,277,307,312,339,352]	15
4	RNN + GAT	[46,139,170,267]	4
5	Other	[141,144,149–151,163,164,184,185,189,193,221,228,245,246, 258,262,264,276,286,317,326,328,342,349,356,364]	27
			Multimodel total: 178

Technical view of dominant GNN variants

The dominant variants reported in Table 9 can be summarized using compact mathematical forms. These definitions are not introduced as a new theory; instead, they serve as a concise technical anchor for interpreting the empirical trends of the reviewed corpus.

For the GCN [376], the layerwise propagation rule is

$$\mathbf{H}^{(\ell+1)} = \sigma\left(\tilde{\mathbf{D}}^{-1/2}\tilde{\mathbf{A}}\tilde{\mathbf{D}}^{-1/2}\mathbf{H}^{(\ell)}\mathbf{W}^{(\ell)}\right). \tag{2}$$

For GraphSAGE [377], neighborhood information is aggregated and concatenated with the current node representation:

$$\mathbf{h}_v^{(\ell+1)} = \sigma\left(\mathbf{W}^{(\ell)}\left[\mathbf{h}_v^{(\ell)} \,\|\, \mathrm{AGG}^{(\ell)}\left(\{\mathbf{h}_u^{(\ell)} : u \in \mathcal{N}(v)\}\right)\right]\right). \tag{3}$$

For the GAT [378], an attention coefficient is learned for each neighboring node:

$$\begin{aligned} e_{vu}^{(\ell)} &= \mathrm{LeakyReLU}\left(\mathbf{a}^{\top}\left[\mathbf{W}\mathbf{h}_v^{(\ell)} \,\|\, \mathbf{W}\mathbf{h}_u^{(\ell)}\right]\right), \\ \alpha_{vu}^{(\ell)} &= \frac{\exp(e_{vu}^{(\ell)})}{\sum_{k\in\mathcal{N}(v)} \exp(e_{vk}^{(\ell)})}, \\ \mathbf{h}_v^{(\ell+1)} &= \sigma\left(\sum_{u\in\mathcal{N}(v)} \alpha_{vu}^{(\ell)} \mathbf{W}\mathbf{h}_u^{(\ell)}\right) \end{aligned} \tag{4}$$

where, $e_{vu}^{(\ell)}$ denotes the unnormalized attention score from node v to neighbor u, $\mathbf{a}$ represents the learnable attention vector to compute attention coefficients, and ReLU indicates the rectified linear unit activation function.

For the GIN [379], expressive power is strengthened using sum-based aggregation followed by multilayer (MLP):

$$\mathbf{h}_v^{(\ell+1)} = \mathrm{MLP}^{(\ell)}\left((1+\varepsilon^{(\ell)})\mathbf{h}_v^{(\ell)} + \sum_{u\in\mathcal{N}(v)} \mathbf{h}_u^{(\ell)}\right). \tag{5}$$

The scalar $\varepsilon^{(\ell)}$ controls the relative weight of the central node representation at layer ℓ prior to neighborhood aggregation.

These formulations underscore the operational differences between the dominant variants. The GCN relies on normalized neighborhood propagation. The GraphSAGE model emphasizes inductive neighbor aggregation, and GAT assigns learnable importance weights to neighbors. The GIN improves discriminative power using sum aggregation followed by an MLP. These mathematical differences also help explain task preferences in the reviewed corpus. Node-level tasks often emphasize local neighborhood propagation and therefore commonly use GCN, GraphSAGE, or attention-based message passing. Graph-level tasks require graph summarization, which makes pooling and readout important in graph classification studies. Link- and edge-level tasks depend more strongly on relation modeling and are often associated with directed, bipartite, or heterogeneous graph structures. Spatio-temporal tasks extend this setting by combining graph propagation with temporal encoders and regression-oriented objectives. Thus, the formulas provide the technical vocabulary for interpreting why different task families prefer different model, aggregation, readout, and loss-function choices. The multimodel combinations reported in Table 9, such as GCN + GAT and GraphSAGE + GCN, can be interpreted as frameworks that combine two or more of these aggregation-and-update rules sequentially or in parallel.

3 Results

The results address each research question. Sections 3.1 and 3.2 categorize GNN model variants and classification tasks. Next, Section 3.3 presents the analysis of the toolkits and libraries. Similarly, Sections 3.4 and 3.5 discuss the learning methods and graph types respectively. Sections 3.6 and 3.7 describe the datasets with their domains and loss functions, respectively. Sections 3.8 and 3.9 present the results of the extracted models and aggregated functions. Finally, Sections 3.10 and 3.11 provide the importance of layers and embedding size, respectively. Unless otherwise stated, the counts reported in this section describe prevalence in the selected application-oriented corpus; they do not constitute cross-study performance rankings or evidence of universal superiority.

3.1 GNN Model Variant Categorization

This section defines the two primary categories and several subcategories of GNN model variants to categorize the research studies. The categories are single and multimodel approaches. For the single-model approach, the subcategories are ChebNet, ChebyGIN, GAT, GCN, GraphSAGE, and GIN. In the multimodel approach, the subcategories are GAT with GraphSAGE, the GCN with GAT, GraphSAGE with GCN, and the recurrent neural network (RNN) with GAT.

Table 9 reveals that 185 studies are single-model research and 178 are multimodel research. The count in the subcategory column indicates that most of these studies (e.g., [2,17,26]) implemented the GCN approach, 85 studies belong to this subcategory, followed by GAT method with 41 (e.g., [47,48]) and GraphSAGE with 18 (e.g., [27,33]). The GIN appears in four studies (e.g., [24,154]), whereas ChebNet [31] and ChebyGIN [91] remain rare with one study each. The recent period also introduces 14 single-model studies that fall under the broader other category (e.g., [317,328]) and 21 papers (e.g., [287,343]) that do not discuss the precise variant clearly. In the multimodel category, the dominant combination is the GCN with GAT, which appears in 126 studies (e.g., [30,38]) and exceeds all other hybrid designs. The GraphSAGE with GCN model appears in 15 studies (e.g., [117,138]), the GAT with GraphSAGE in six studies (e.g., [134,205]), and the RNN with GAT in four studies (i.e., [46,139,170,267]). In addition, 27 multimodel papers fall into other category (e.g., [221, 246]) because they combine more complex variant sets than those tracked in this SLR.

Beyond raw counts, the extracted corpus shows a structural shift from single-model dominance in the initial years to multimodel dominance after 2023. This shift is best understood as a response to increasing application complexity rather than as a simple replacement for single-model GNNs. Later studies in the corpus more often target problems that are relational and modality-rich, including traffic forecasting, session recommendation, molecular-property prediction, and content-caching prediction, where graph propagation is combined with attention, temporal, or multichannel modules [74,91,105,133,139]. The rise of heterogeneous graphs discussed in Section 3.5 reinforces this interpretation: when the data include multiple node or edge types, coupled temporal signals, or multiple input modalities, authors more commonly adopt hybrid architectures that combine complementary inductive biases rather than rely on a single canonical operator. Fig. 5 indicates a change in design philosophy in the application-oriented corpus from establishing canonical single-backbone baselines to building task-specific multimodel frameworks. This pattern should be interpreted as evidence of problem diversification and architectural specialization, not as a claim that multimodel designs are universally superior to single-model variants.

3.2 Classification Type-Based Categorization

Recent research has employed GNN techniques for classification. This article categorizes the studies by classification type. Table 10 summarizes these classification categories for analysis in the GNN domain.

3.2.1 Node Classification

Node classification is a critical task in the reviewed corpus (79 studies). Across the selected applications, node classification is employed to infer node labels from local attributes and neighborhood structure in settings (e.g., user modeling, medical prediction, anomaly detection, and document or interaction graphs). In practice, this category is strongly associated with GCN-family backbones, with attention-based designs becoming more relevant when neighbor importance is uneven. The recurring challenges include label scarcity, class imbalance, and limited availability of privacy-sensitive data.

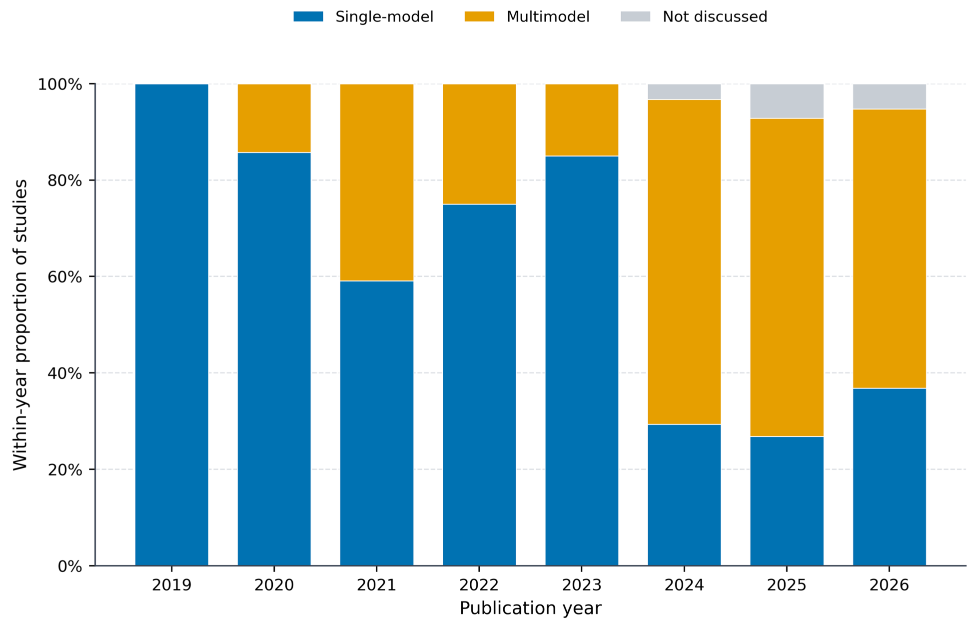

Figure 5: Temporal evolution of single-model vs. multimodel GNN architectures (2019–2026). Normalized proportions reveal the shift toward multimodel dominance after 2023.

Table 10: Categorization by classification tasks, including graph, node, and link classification types.

No.	Classification Type	Research References	Count
1.	Graph classification	[4–8,18,19,24,30,31,35,36,38,42,43,46,48,49,51,53,55,56,59–61, 64,68,70,71,73,76,80,84,87,91,92,95,100,103,105,107,110,116,130, 133–138,142,143,145,146,150,159,174,176,177,182–184,190,191, 193,196,199,201,203,204,210,214,219,221,223,224,226,227,231, 238,241,245,247,252,254,262–265,270,272,278,281,284,286, 289,291,304,306,308,309,317,319,333,335,337,344,346,349,359, 361–364,368,371,373–375]	119
2.	Link classification	[3,54,114,115,117,119,120,122,123,125–128,131,139,144,147–149, 151,153–155,157,162,163,165,175,178,180,181,185,186,189,194,197, 198,200,202,207–209,211,213,215,220,225,228,232–234,236, 237,253,256,258,259,261,266–268,271,273,275,277,280,282, 285,287,288,296,298,299,305,311–313,316,318,320,321,329,332, 334,338,339,342,353–356,360,365,370]	94

(Continued)

Table 10 (continued)

No.	Classification Type	Research References	Count
3.	Node classification	[1,2,17,25,26,28,29,32–34,37,39–41,44,45,47,50,52,57,58,62,63, 65–67,69,72,75,77,78,81–83,85,86,88–90,93,94,96–99,101,102, 104,106,108,109,111,118,140,141,152,164,179,187,217,243,244,249, 251,279,292,293,297,301,303,314,323,324,327,330,331,345,351, 372]	79
4.	Node and edge classification	[27,74,79,112,113,121,124,129,132,156,158,160,161,166–173,188, 192,195,205,206,212,216,218,222,229,230,235,239,240,242,246, 248,250,255,257,260,269,274,276,283,290,294,295,300,302, 307,310,315,322,325,326,328,336,340,341,343,347,348,350,352, 357,358,366,367,369]	71

3.2.2 Graph Classification

Graph classification is the largest task category in the reviewed corpus, (119 studies). This classification is regularly applied when the prediction target belongs to the entire graph or subgraph rather than to individual nodes. In the reviewed literature, graph-level tasks often combine expressive propagation with graph summarization, helping explain the prominence of GCN + GAT and GIN-style frameworks. Challenges include overfitting on smaller datasets and limited generalization under class imbalance.

3.2.3 Link Classification

Link classification is addressed in 94 studies and is commonplace in recommendation, fraud detection, biomedical association prediction, and interaction modeling. Because the target is relational rather than entity-specific, these settings typically emphasize directed, bipartite, or heterogeneous graph structure and benefit from architectures that model relation strength. A recurring practical challenge is that link behavior evolves over time, so deployment often requires robust updates and resistance to adversarial or drifting interaction patterns.

3.2.4 Node + Edge Classification

Node + edge classification accounts for 71 studies and is most prominent in multientity applications where node and relation semantics must be jointly inferred. In this SLR, the category is treated as an operational joint-prediction setting rather than as a synonym for all multitask learning. Its continued presence suggests that application-oriented GNN research increasingly treats node and relation prediction as coupled design problems rather than isolated outputs.

3.3 Toolkits

This section examines programming language toolkits and their libraries for implementing GNNs. Table 11 summarizes these toolkits with their specific libraries, listing the programming language, library name, reference numbers, and count of studies in each category.

Table 11: Programming languages, frameworks, and libraries used in GNN implementations.

No.	Language	Library	Research References	Count
1	C++ and MATLAB		[90,116,135,143,150,155,270]	7
2	Python	Keras	[29,193]	2
		Scikit learn (sklearn) package	[44,91,126,134,272]	5
		PyTorch Geometric	[2,8,18,19,26,28,31,33,34,37,38,47,49,51,52,54,56, 58,60,61,64,68,71,73,76,77,80–82,88,89,92,94–96, 98,100–105,107,109–115,119–121,129,130,141,162,167, 174,176,192,197,200,201,216,231,242,244,246,248, 254–256,261,269,282,289,291,298,300,302,307, 308,311,315,318,326,330,336,337,349,350,361,362, 367,369,375]	97
		TensorFlow	[40,86,151,163,195,234,263,266,314,354]	10
		Other libraries	[17,25,45,69,70,75,83,85,87,99,117,122,125,128,133, 147,149,156–159,164,173,184,188–190,194,199, 203–207,209,211,227,233,235,238,243,249,253,258, 268,274,277,285,288,296,304,305,322,325,327,335, 339,342,344,346–348,352,355,358,364,373,374]	68
3	Not discussed		[1,3–7,24,27,30,32,35,36,39,41–43,46,48,50,53,55, 57,59,62,63,65–67,72,74,78,79,84,93,97,106,108, 118,123,124,127,131,132,136–140,142,144–146,148, 152–154,160,161,165,166,168–172,175,177–183, 185–187,191,196,198,202,208,210,212–215,217–226, 228–230,232,236,237,239–241,245,247,250–252, 257,259,260,262,264,265,267,271,273,275,276, 278–281,283,284,286,287,290,292–295,297,299, 301,303,306,309,310,312,313,316,317,319–321,323, 324,328,329,331–334,338,340,341,343,345,351,353, 356,357,359,360,363,365,366,368,370–372]	174

Table 11 reveals that C++ and MATLAB were applied in seven studies (e.g., [135,143]), whereas the Python ecosystem dominates the implementation domain. In Python-based implementations, two studies use Keras [29,193], five use Scikit-learn (e.g., [44,91]), 10 use TensorFlow (e.g., [151,234]), and 97 explicitly report PyTorch Geometric (e.g., [31,33]), confirming its strong dominance in the recent GNN literature. Moreover, 68 studies report implementation details that do not fit these library labels (e.g., [69,70]), and 174 studies did not discuss the implementation stack. The large not-discussed category (e.g., [4,5]) is crucial because it reveals that many papers were application-oriented and experimentally validated, yet provided limited reproducibility details at the toolkit level. In several studies, the authors mentioned Python-based implementation but did not specify the library. Following the same logic throughout this SLR, such cases were placed under other libraries when source-code or framework evidence is available, whereas papers that did not disclose the implementation stack were categorized as not discussed.

3.4 Learning Methods

This section discusses graph-based learning methods. The GNN applies several learning paradigms in various scenarios. Supervised learning offers the benefit of knowing the exact classes before training, facilitating training toward the perfect decision boundary. Similarly, the unsupervised learning paradigm trains a model without prior label knowledge, facilitating the identification of previously unseen data. The self-supervised learning method is similar to the unsupervised method, however, it can help reduce the time and cost of data labeling. Moreover, the semi-supervised learning method is applied when labeled data are significantly outnumbered by unlabeled data, offering a mechanism to address this imbalance. Furthermore, some studies use hybrid learning settings, most commonly by combining supervised and unsupervised learning within the same pipeline. Regarding the not-discussed category, a few studies have employed the GCNs, which are focused on solving semi-supervised learning problems, without discussing learning settings. Such studies were not placed into the other category to keep the discussion simple. The extracted results reveal the type of model training performed in recent studies (Table 12). Fig. 6 complements Table 12 by normalizing the distribution over the reported subset.

Table 12: Categorization based on learning paradigms, including supervised, semi-supervised, self-supervised, unsupervised, and hybrid learning settings

No.	Learning Setting	Research References	Count
1.	Self-supervised	[18,56,84,89,94,98,120,139,140,183,188,196,213,237,257,276,280,322,357,363,367]	21
2.	Semi-supervised	[2,3,6,17,26,28,32,34,35,37,39,48,50,52–55,57,58,62,65,67,70,75,77,79,80,85,93,95,97,100,101,107–109,111,133,163,167,176,265,279,290,292,310,318,336,345,351]	50
3.	Supervised	[1,8,25,27,33,43,66,69,76,81–83,88,91,102,110,121,124,129,141,168,172,195,197,200,204,205,217,240,246,263,274,293,294,339,341,375]	37
4.	Unsupervised	[29,38,47,49]	4
5.	Supervised + unsupervised	[63,90,130,156,158,166,178,194,215,233,249,260,278,289,295,300,306,307,311,321,323,326,328,331,334,340,350]	27
6.	Supervised contrastive learning	[87,99,151,152,155,169,185,187,193,202,203,232,250,251,253,259,262,283,285,297,299,324,325,329,332,347]	26
7.	Not discussed	[4,5,7,19,24,30,31,36,40–42,44–46,51,59–61,64,68,71–74,78,86,92,96,103–106,112–119,122,123,125–128,131,132,134–138,142–150,153,154,157,159–162,164,165,170,171,173–175,177,179–182,184,186,189–192,198,199,201,206–212,214,216,218–231,234–236,238,239,241–245,247,248,252,254–256,258,261,264,266–273,275,277,281,282,284,286–288,291,296,298,301–305,308,309,312–317,319,320,327,330,333,335,337,338,342–344,346,348,349,352–356,358–362,364–366,368–374]	198

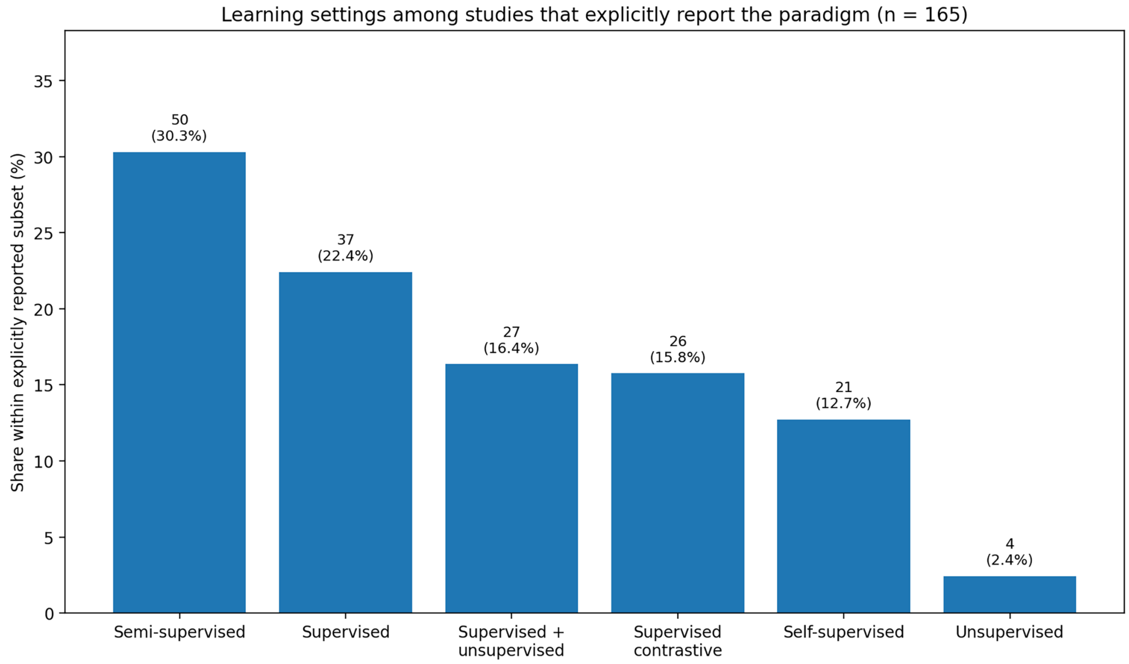

Figure 6: Learning settings for studies that report the paradigm (n = 165). The figure normalizes the distribution over the reported subset and shows semi-supervised learning is the largest reported category, followed by the supervised, hybrid, supervised-contrastive, and self-supervised settings.

The table reveals that 21 studies (e.g., [18,56]) employed self-supervised learning, 50 applied semi-supervised learning (e.g., [6,62]), 37 applied supervised learning (e.g., [69,76]), four employed unsupervised learning (i.e., [29,38,47,49]), 27 combined supervised and unsupervised learning (e.g., [63,90]), and 26 applied supervised contrastive learning (e.g., [87,99]). However, the reported-subset view is more informative than the entire corpus view. Of the 165 studies that reported the learning setting, semi-supervised learning accounted for 30.3%, supervised learning for 22.4%, supervised + unsupervised learning for 16.4%, supervised contrastive learning for 15.8%, self-supervised learning for 12.7%, and unsupervised learning for 2.4%. In contrast, 198 studies did not disclose the learning setting. This omission is not a minor reporting detail: the learning regime determines the label requirements, supervision strength, and baseline difficulty; thus, failing to report it makes it challenging to judge whether gains are due to architectural design or supervision conditions. Fig. 7 suggests that field is diversifying beyond the classic semi-supervised citation-network setting, and that reporting practice has not fully kept pace with diversification.

3.5 Graph Type

The graph type is necessary element in GNN-based implementations. As every edge is connected to two nodes in a graph, a homogeneous graph has one edge and node type, and a heterogeneous graph has multiple nodes or edge types. An undirected graph has edges without directional information compared to a directed graph, which has more information about the relationship between the nodes.

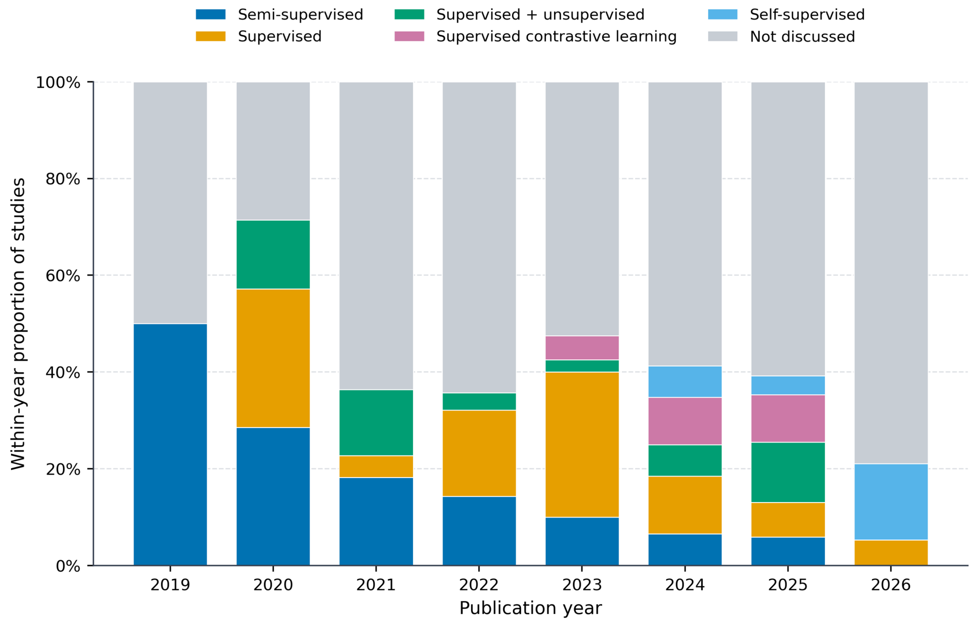

Figure 7: Evolution of reported learning paradigms across the reviewed corpus (2019–2026) with diversification from semi-supervised baselines and persistent reporting gaps.

This section identifies the types of graphs and analyzes their use in the selected research studies. Table 13 presents the graph-type involvement by count. The reviewed corpus is dominated by heterogeneous graphs (142 studies (e.g., [17,32,34])), followed by directed graphs (67 (e.g., [168,174])) and bipartite graphs (42 (e.g., [192,198])). Weighted graphs appear in 27 studies (e.g., [301,305]), undirected graphs in 19 (e.g., [110, 114]), and homogeneous graphs in only five (e.g., [8,73]). Another 61 studies did not discuss the type of graph (e.g., [18,65]). Overall, heterogeneous and bipartite settings are highly prominent in recent GNN research. The rise of heterogeneous graphs should not be interpreted merely as a preference for a more complex graph format. Rather, this rise signals that recent application-oriented GNN research increasingly models multientity systems in which node and edge types carry different semantics (e.g., fraud networks, bid-keyword matching, credit-risk graphs, and review ecosystems) [5,17,85,98]. In such settings, collapsing the data into a homogeneous graph would remove relation-specific information that often drives prediction quality. The post-2023 increase in heterogeneous graphs marks a substantive shift from single-relation benchmark-style problems toward more realistic relational problem formulations. This result also helps explain the broad cross-domain application of flexible backbone families and hybrid architectures: when the graph is relation-rich, authors more commonly combine neighborhood propagation with attention, multiview processing, or temporal encoding. Fig. 8 reflects a change in the types of problems being modeled, not just a change in notation.

Table 13: Categorization based on the graphs type.

No.	Graph Type	Research References	Count
1.	Heterogeneous graph	[5,7,17,25,28–30,32,34,40,54,58,67,72,75,85,87,91,98,101,108, 113,122–124,128,132–134,139,142,144,152,153,155,161–163,166, 169–172,175,179,182,189,196,197,201,203,205,207,208,212–214, 216,218,220,222,224–226,229,231–236,238,240,241,245,247, 250,252,254,260,264,268,271–276,283,286,290–292,294–300, 303,304,306,309,310,312,314,317,318,321–327,335–338,340,341, 343,344,346–353,359–361,364–367,371,372,375]	142
2.	Homogeneous graph	[8,73,106,209,270]	5
3.	Directed graph	[1,6,27,36–38,45,49,56,57,59,63,66,88,94,96,97,116,118,119,126, 130,131,141,143,146,148,150,156,159,164,165,168,174,188,193–195, 200,204,215,217,221,227,230,237,243,244,249,251,255,257,279, 293,315,319,328,330,331,342,345,356,362,363,369,370,374]	67
4.	Undirected graph	[2,24,31,41,43,50,53,55,60,61,64,81,90,95,100,103,110,114,115]	19
5.	Bipartite graph	[44,74,77,117,121,125,127,140,149,154,157,167,173,180,186,192, 198,210,211,239,242,246,248,256,258,259,269,277,280,282,285, 288,307,311,313,329,332,334,339,354,355,357]	42
6.	Weighted graph	[68,76,111,112,120,135,136,145,147,158,176–178,181,183,187,223, 253,266,281,287,301,305,316,320,333,373]	27
7.	Not discussed	[3,4,18,19,26,33,35,39,42,46–48,51,52,62,65,69–71,78–80, 82–84,86,89,92,93,99,102,104,105,107,109,129,137,138,151,160, 184,185,190,191,199,202,206,219,228,261–263,265,267,278,284, 289,302,308,358,368]	61

3.6 Datasets

Datasets are necessary for validating implementations. Fig. 9 groups studies into broad domains and shows that user-centric applications (72 studies), generic benchmark-centric studies (66), health care (52), road traffic and transportation (40), and banking & finance (30) are the largest groups in the reviewed corpus. Many papers were benchmark-driven and did not map well to a single real-world application domain. The availability of datasets is also a necessary aspect because future research requires datasets to be accessible for replication and follow-up experiments. Fig. 10 visualizes the dataset availability. In the reviewed corpus, 227 studies (62.5%) relied on public datasets, 120 (33.1%) used private datasets, 15 studies (4.1%) combine public and private data sources, and one study did not discuss dataset availability. The released review materials described in the Data Availability Statement provide further details on each dataset domain, availability label, and supporting source links. This section describes the dataset domains and their availability. This SLR also compares the GNN model categories with the dataset domains. Fig. 11 visualizes this comparison as a heatmap, illustrating that the GCN and especially the GCN + GAT dominate the domain coverage of the reviewed corpus, whereas GraphSAGE, GIN, and the more specialized categories appear in narrower application areas.

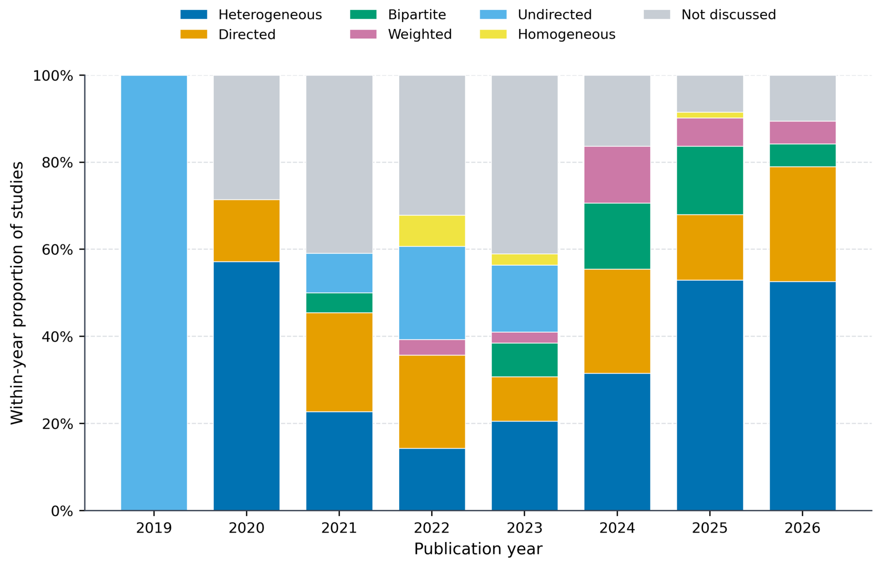

Figure 8: Temporal distribution of graph structure choices (2019–2026), documenting heterogeneous graphs' emergence as the dominant structure post-2023.

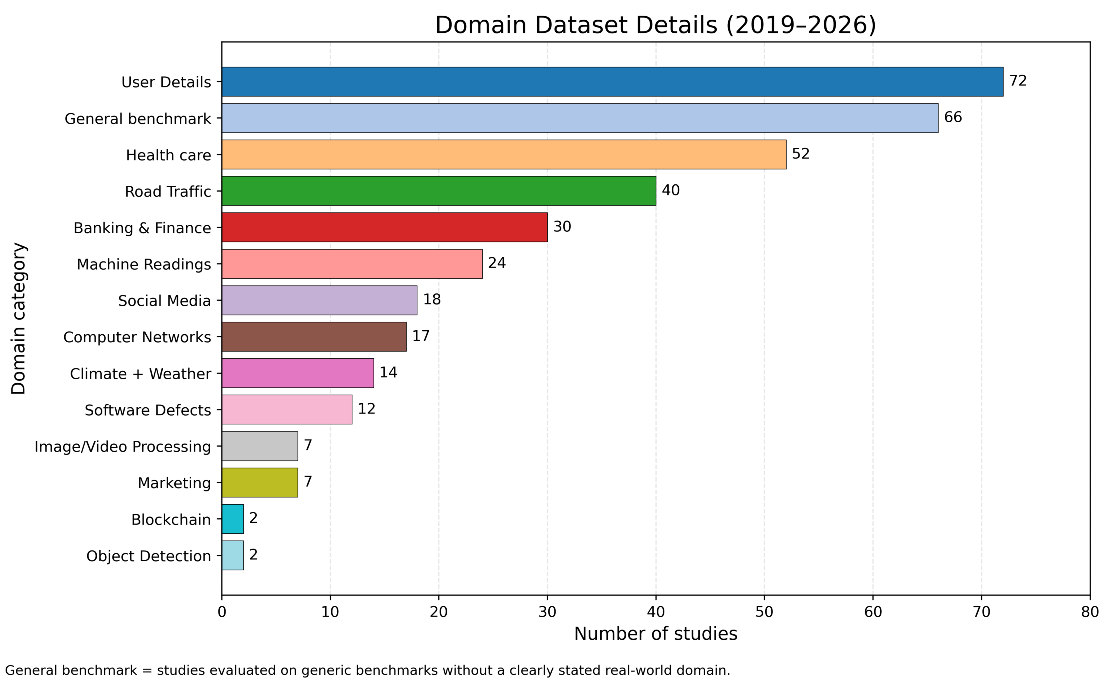

Figure 9: Domain-level study categorization from 2019 to 2026. The distribution shows strong representation in user-centric applications, generic benchmark settings, health care, transportation, and finance.

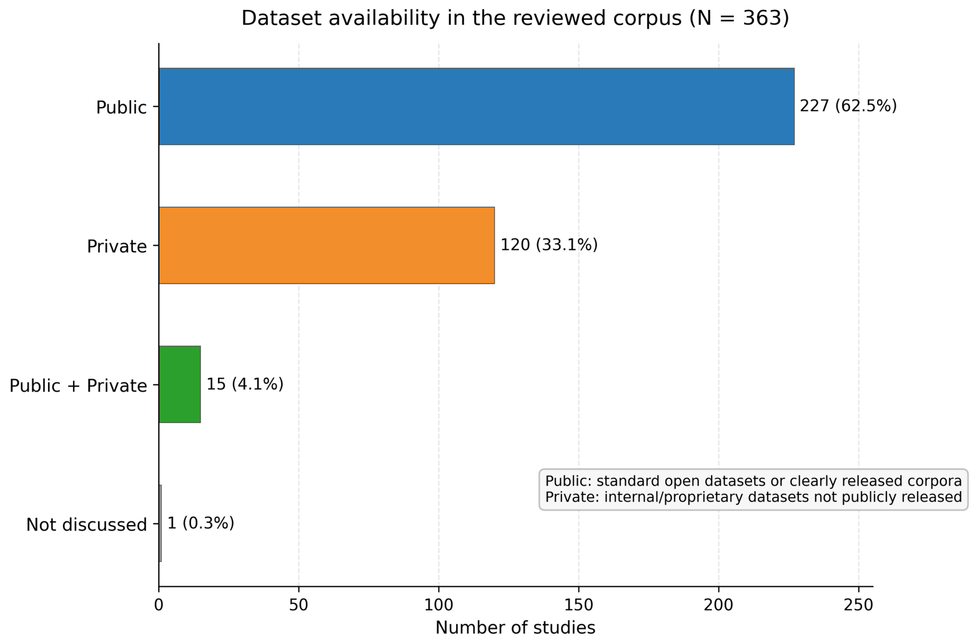

Figure 10: Dataset availability across 363 selected studies. Public: standard open datasets or released corpora; private: internal or proprietary datasets not publicly released. A smaller subset of studies combines public and private data sources, whereas one study did not report dataset availability.

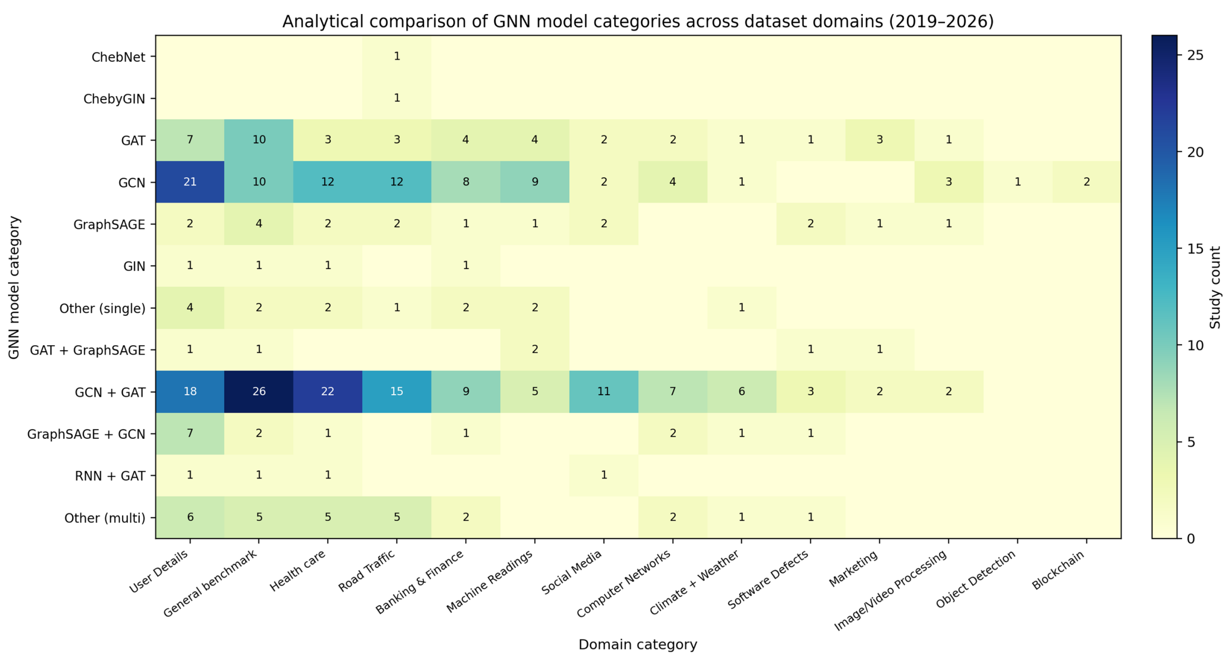

Figure 11: Heatmap-based analytical comparison of GNN model categories across dataset domains in the 2019–2026 corpus.

3.7 Loss Function

A loss function is significant in neural networks because it calculates the training loss between the actual and predicted output. Table 14 compares the loss functions employed in the reviewed studies: thus, the dominant mathematical forms are useful. In Eqs. (6)–(12), C denotes the number of classes, y_c and $\hat{y}_c$ denote the ground-truth and predicted probability for class c, y and $\hat{y}$ denote the binary target and prediction, $\hat{p}$ represents the predicted probability of the target class, α and γ denote the focal-loss weighting and focusing parameters, n quantifies the number of samples, $r = y - \hat{y}$ signifies the residual, δ represents the Huber threshold, and $\hat{y}_{ui}$ and $\hat{y}_{uj}$ denote the predicted relevance scores of items i and j for user u in the Bayesian personalized ranking (BPR) objective. For multiclass prediction, cross-entropy is given by

$$\mathcal{L}_{CE} = -\sum_{c=1}^{C} y_c \log(\hat{y}_c). \tag{6}$$

For binary prediction, binary cross-entropy is

$$\mathcal{L}_{BCE} = -\left(y\log(\hat{y}) + (1-y)\log(1-\hat{y})\right). \tag{7}$$

Focal loss [380], which is commonly employed for class-imbalanced settings, is

$$\mathcal{L}_{FL} = -\alpha(1-\hat{p})^{\gamma}\log(\hat{p}). \tag{8}$$

For regression-style settings, mean squared error (MSE) and mean absolute error (MAE) are defined as follows:

$$\mathcal{L}_{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2, \tag{9}$$

$$\mathcal{L}_{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|. \tag{10}$$

The Huber loss [381], which is less sensitive to outliers than the pure squared loss, is

$$\mathcal{L}_{\delta}(r) = \begin{cases} \frac{1}{2}r^2, & |r| \le \delta, \\ \delta\left(|r| - \frac{1}{2}\delta\right), & |r| > \delta. \end{cases} \tag{11}$$

In recommendation and ranking scenarios, BPR [382] is commonly written as follows:

$$\mathcal{L}_{BPR} = -\sum_{(u,i,j)} \log\sigma\left(\hat{y}_{ui} - \hat{y}_{uj}\right), \tag{12}$$

where item i is preferred to item j for user u.

These objectives correspond to different task settings in the reviewed literature. Cross-entropy and negative log-likelihood style objectives are most suitable for single-label node, edge, or graph classification, where each sample is assigned to one target class. Binary cross-entropy is more suitable when the prediction is formulated as a binary relation decision or when multiple labels may co-exist. Focal loss is useful when the class distribution is imbalanced, such as in fraud, disease, anomaly, or rare-event detection. Regression losses, including MSE, MAE, and Huber loss, are more suitable for continuous-value prediction and forecasting, particularly in traffic, energy, climate, and other spatio-temporal settings. Ranking losses, such as BPR, are more closely connected with recommendation and implicit-feedback graphs, where the objective is to rank likely interactions rather than classify a single label. In this SLR, paper-specific objectives are grouped under the *Custom* label because they do not share one canonical formulation across studies.

Table 14: Summary of loss functions revealing the prominence of cross-entropy loss in GNN-based learning tasks.

No.	Loss Function	Research References	Count
1.	Binary cross entropy	[18,27,44,51,52,70,74,77,89,108,133,138,149,195,230,236,240,256, 312,325,339,354]	22
2.	Cross entropy	[1,4,6,17,25,26,28–30,34–36,40,41,45,48,50,56,57,62,63,67,69,88, 92,93,97,98,104,106,109,115,117,119,120,122,123,125–127,130,131, 135,139,144–146,150,153,155,156,160,163,165,166,169,172–174,183, 187–189,192,196,197,202–204,207,210,213–215,218,219,224,229, 238,239,241,246–248,250,252,255,258,264,268,270,271,273,275, 279,284,289,292,294,297–299,302,303,321,323,326,331,336,347, 348,357–359,362,364,369,370]	118
3.	Focal loss	[8,64,82,85,100,152,217,300,322,340,351,363]	12
4.	Huber loss	[55,105,124,193,205,265,304,335,368,372]	10
5.	Mean squared error	[31,49,54,68,78,90,95,96,103,110,111,118,159,164,170,178,184,190, 199–201,220,221,227,231,242,243,249,254,262,263,266,269,276, 281,286,290,291,293,301,305–307,309,311,315,316,319,327,330, 337,341,344,349,356,361,373–375]	59
6.	Squared loss	[7,47]	2
7.	Mean absolute error	[19,59,73,94,107,121,137,147,176,177,179–182,191,223,244,259,267, 328,352]	21
8.	Custom	[3,53,61,72,75,272]	6
9.	Other	[2,24,37,46,58,65,66,76,84,87,91,99,101,116,128,132,136,140–142, 148,151,154,157,158,167,175,185,186,194,198,206,208,209,211,212, 216,222,225,226,228,232–235,237,245,251,253,257,261,274,277, 280,282,283,285,287,288,295,296,308,310,313,314,318,320,324, 329,332–334,338,342,343,345,346,350,355,360,365–367,371]	84
10.	Not discussed	[5,32,33,38,39,42,43,60,71,79–81,83,86,102,112–114,129,134,143, 161,162,168,171,260,278,317,353]	29

The extracted corpus shows that loss-function selection is strongly connected to the prediction target, graph structure, and dataset characteristics. Cross-entropy is the most common loss function because many reviewed studies formulate node, graph, or edge prediction as a classification problem. Binary cross-entropy appears when the task is framed as a binary decision, especially in relation prediction or multi-label settings. Focal loss is used when the dataset contains strong class imbalance, because it reduces the influence of easy examples and emphasizes harder minority-class cases [8,85]. Regression losses, including MSE, MAE, and

Huber loss, are common in forecasting and continuous-value prediction, where the output is a traffic value, risk score, load value, molecular property, or other numerical target. The MSE and MAE behave differently in regression settings, and their suitability depends on the error distribution and the desired sensitivity to larger deviations. Huber loss provides an intermediate option because it is less sensitive to outliers than pure squared error [105]. Similarly, BPR and other ranking-oriented objectives are relevant when the GNN is used on recommendation or implicit-feedback graphs, where the goal is to score observed interactions above unobserved ones. Several loss functions were identified from the selected studies. Binary cross-entropy is employed in 22 studies, cross-entropy in 118, focal loss in 12, Huber loss in ten, MSE in 59, squared loss in two, and MAE in 21. In some studies, the authors discussed the factor of the loss function but did not provide the loss-function name or introduced a paper-specific objective; therefore, these functions are labeled as custom. The category "Other" is used for loss functions that appear in only one study, and the released review materials provide the paper-specific names grouped under this category. Finally, 29 studies did not discuss the loss function and were labeled as not discussed. This pattern indicates that loss functions should be interpreted as task- and data-conditioned design choices rather than as independent model preferences.

Table 14 shows that the dominant loss family is linked to how the graph problem is formulated. Classification-oriented graph, node, and edge tasks mostly rely on cross-entropy variants. Binary relation tasks and multi-label settings often use binary cross-entropy. Imbalanced datasets motivate focal or weighted objectives, whereas continuous forecasting and prediction tasks favor MSE, MAE, or Huber loss. Recommendation and implicit-feedback graphs are more naturally aligned with ranking-style objectives. Therefore, the loss-function distribution reflects the mixture of classification, regression, ranking, and imbalance-aware tasks in the reviewed corpus rather than a single universal preference.

3.8 Embedding Representation Models

The models in Table 15 are not GNN variants; instead, they are auxiliary representation models used before or alongside graph learning to encode text, sequences, signals, or multimodal inputs. Therefore, this table is separate from Table 9, which classifies the GNN variants for message passing on graphs. Fig. 12 visualizes the reported auxiliary encoder families in the reviewed corpus and contrasts between recurrent, textual, visual, and underreported configurations.

Table 15: Categorization of embedding representation models to enhance GNN performance.

No.	Embedding Representation Model	Research References	Count
1.	Long short-term memory (LSTM)	[3,31,40,57,59,64,68,78–80,85,93,95,100,105,115,117,118, 120–122,124,125,133,137,142–144,147,149,155,159,160,164,166, 171,175,178,179,182–185,188,190–192,194,197,199,200,204,208, 215–217,220,221,223,224,228,229,231,233,241,244–246,249, 252,258,262,263,265–267,272,280,281,284,286,290–293,295, 296,298,303–306,308,309,314,316,317,319–322,326–328,330, 331,335,336,338–340,346,349–351,356,360–362,364,367–369, 373,375]	125

(Continued)

Table 15 (continued)

No.	Embedding Representation Model	Research References	Count
2.	Pretrained bidirectional encoder representations from transformers (BERT)	[51,52,60–62,81,86,123,139,150,163,167,172,236,269,283,299, 302,307,334,342,355]	22
3.	Doc2Vec	[38,73,214]	3
4.	Residual network (ResNet)	[2,50,65,84,138,141,157,274,278,363,374]	11
5.	Short-text topic model, bi-term topic model	[46]	1
6.	Node2vec	[48,99,119,127,146,156,161,230,297,311,325,347,352]	13
7.	Word2vec	[47,49,128,135,136,145,257,261]	8
8.	Pretrained global vector (GloVE) models	[54,271]	2
9.	Gated convolutional neural network	[19,344]	2
10.	Not discussed	[1,4–8,17,18,24–30,32–37,39,41–45,53,55,56,58,63,66,67,69–72, 74–77,82,83,87–92,94,96–98,101–104,106–114,116,126,129–132, 134,140,148,151–154,158,162,165,168–170,173,174,176,177,180,181, 186,187,189,193,195,196,198,201–203,205–207,209–213,218,219, 222,225–227,232,234,235,237–240,242,243,247,248,250,251, 253–256,259,260,264,268,270,273,275–277,279,282,285, 287–289,294,300,301,310,312,313,315,318,323,324,329,332,333, 337,341,343,345,348,353,354,357–359,365,366,370–372]	176

This section discusses models employed for embedding representation. In some cases, before learning embedding in the GNN, a representation of that embedding is generated by applying models. Table 15 summarizes these auxiliary encoders. The frequencies in Table 15 should be interpreted as signals of input-modality prevalence in the corpus, not as rankings of model superiority. Long short-term memory (LSTM) is the most often observed auxiliary representation model (125 studies), but this primarily reflects the strong presence of sequential and spatio-temporal application settings in the reviewed literature, including traffic-flow prediction, pandemic forecasting, bus travel-time estimation and load monitoring [31,59,68,78]. In those settings, graph structure alone is insufficient because the task couples relational dependencies with temporal dynamics. Accordingly, the role of LSTM is to encode temporal order before or alongside graph propagation rather than to demonstrate that LSTM is better than transformer-based encoders. Bidirectional encoder representations from transformers (BERT) appears primarily in text + graph pipelines (22 studies), where the main challenge is contextual language encoding before graph reasoning, such as extreme multilabel text classification, aspect-based sentiment analysis, controversy detection, and event detection on social media [51,52,60–62]. The ResNet model plays a similar role in image + graph settings (11 studies), where CNN-derived visual features are passed to a graph model for person re-identification, histopathological image analysis, image-text retrieval, and medical imaging tasks [2,50,65,84]. The Node2vec and Word2vec methods are also best interpreted as modality-specific preprocessing choices rather than competitors to the core GNN variant. Viewed in this way, Table 15 is best interpreted as a map of domain and modality bias in recent GNN applications, where sequential/spatio-temporal tasks favor LSTM-style encoders, text-rich tasks favor BERT-style encoders, and image-rich tasks favor CNN encoders such as ResNet. The continued prevalence of LSTM despite the increase of transformer-based models may reflects the practical character of the corpus. Many studies targeted moderate-length domain sequences, smaller labeled datasets, and deployment-oriented forecasting pipelines where lightweight recurrent encoders are easy to integrate and computationally economical. Therefore, the high frequency of LSTM indicates the prevalence of temporal and sequential application settings in the reviewed corpus, not superiority over BERT, transformer-based models, or CNN-based encoders. The 176 “not discussed” cases reveal that auxiliary encoding choices are often left implicit, making fair comparison across multimodal GNN framework challenging.

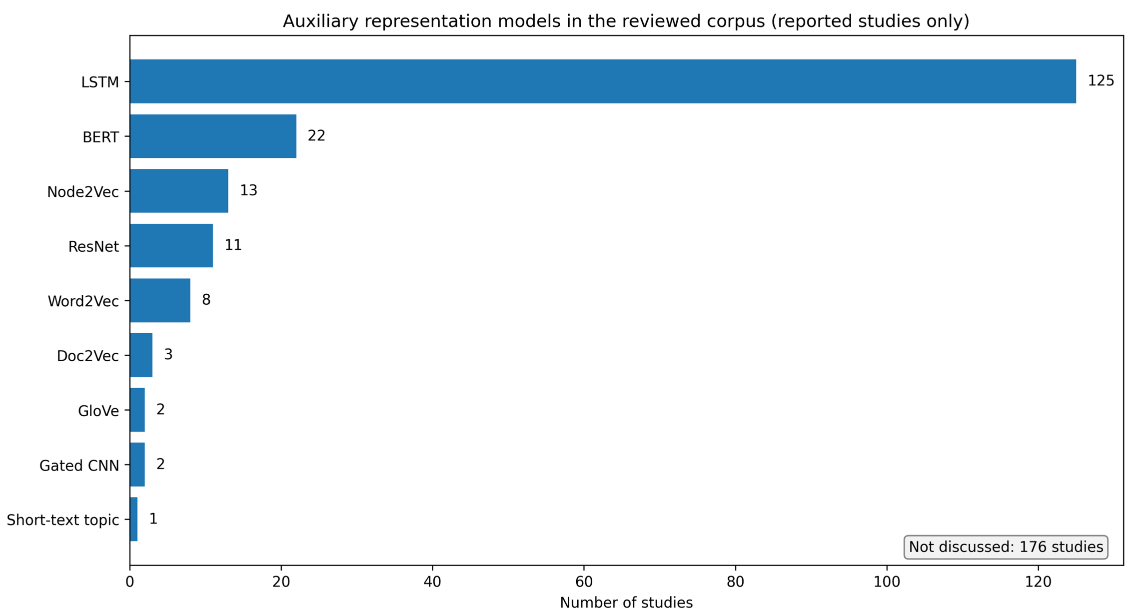

Figure 12: Auxiliary representation models in the reviewed corpus (reported studies only). Long short-term memory (LSTM) is the most frequently reported auxiliary encoder, followed by bidirectional encoder representations from transformers (BERT), Node2vec, and residual network (ResNet), while 176 studies do not discuss any auxiliary encoder.

3.9 Aggregate Function

The GNN constructs new feature vectors for nodes by aggregating those of neighboring nodes using aggregator functions. Table 16 summarizes how neighboring information is aggregated in the reviewed GNN studies. The most common aggregation forms are written as follows. Mean aggregation is defined as follows:

$$\mathrm{AGG}_{mean}(\mathcal{N}(v)) = \frac{1}{|\mathcal{N}(v)|}\sum_{u\in\mathcal{N}(v)} \mathbf{h}_u. \tag{13}$$

Sum aggregation is calculated as follows:

$$\mathrm{AGG}_{sum}(\mathcal{N}(v)) = \sum_{u\in\mathcal{N}(v)} \mathbf{h}_u. \tag{14}$$

Max aggregation is computed as follows:

$$\mathrm{AGG}_{max}(\mathcal{N}(v)) = \max_{u\in\mathcal{N}(v)} \mathbf{h}_u, \tag{15}$$

where the maximum is taken elementwise across neighbor representations. Attention-based aggregation is defined as follows:

$$\mathrm{AGG}_{attn}(\mathcal{N}(v)) = \sum_{u\in\mathcal{N}(v)} \alpha_{vu}\mathbf{h}_u. \tag{16}$$

Table 16: Aggregation strategies in GNN studies, summarizing common neighborhood aggregation functions and mechanisms

No.	Aggregation Function	Research References	Count
1.	Attention aggregation + mean	[3,34]	2
2.	Attention aggregator	[29,32,49,64,85,87,88,103,114,118,124,134,139,145,157,159,161, 162,168,170,176,177,179,181,190,191,194,196–199,208,215,218, 220,223,226,231,234,236,240,256,260,261,265–267,273–275, 279,281,282,284,289,291,293,296–298,301,304,312,313,316,318, 321,324,327,329,330,332,336,362,365,371,373]	77
3.	Global max-pooling	[39,96,133,212]	4
4.	Max-pooling aggregator	[60,66,82,102,132,163,173,183,193,204,209,263,295,326,334,346, 351,367]	18
5.	Mean aggregator	[6,26,27,33,47,48,54,56,58,69,70,90,91,95,100,104,120–122,127, 131,141,142,144,150,156,184,188,224,227,230,250,259,283,285, 333,337,338,342,349,355,357,363,374]	44
6.	Mean max-pooling	[24,113]	2

(Continued)

Table 16 (continued)

No.	Aggregation Function	Research References	Count
7.	Message passing-based aggregation	[1,2,7,8,17–19,28,30,31,35,36,38,42–46,50,52,53,55,57,59,62,63, 65,67,68,71–73,75–81,84,89,92,93,97–99,101,105,107–112, 115–117,119,123,125,126,128–130,135–138,140,143,146–149, 151–155,158,160,164–167,169,171,172,174,175,178,180,182, 185–187,189,192,195,200,201,203,205–207,210,211,213,214,216, 217,219,221,222,225,228,229,232,233,235,237–239,241–249, 251–255,257,258,262,264,268–272,276–278,280,286–288,290, 292,294,299,300,302,303,305–311,314,315,317,319,320,322,323, 325,328,331,335,339–341,343–345,347,348,350,352–354,356, 358–361,364,366,368–370,372,375]	202
8.	Sum aggregator	[4,5,25,37,51,61,83,86,202]	9
9.	Other	[40,41,74,94,106]	5

These operators differ in the type of neighborhood information they preserve. Mean aggregation supports stable smoothing, and sum aggregation preserves the multiset magnitude, max aggregation emphasizes the most salient features, and attention-based aggregation assigns adaptive importance to different neighbors. These formulations reveal that Table 16 should be interpreted at two complementary levels. At the coarse level, many primary studies describe neighborhood update as message passing without specifying an exact operator that can be coded more finely. Therefore, these studies were retained under the umbrella category "message passing-based aggregation." At the finer level, the named operator families present a more detailed design picture, where attention-based aggregation appears in 77 studies, mean aggregation in 44, max-pooling aggregation in 18, and sum aggregation in nine. Global max-pooling and mean max-pooling are comparatively selective choices, with four and two studies, respectively, and five studies fall into other aggregation category. Accordingly, message passing is the dominant architectural principle in the corpus, whereas the operator-specific categories reveal that attention and mean-based aggregation are the most common reported choices.

3.10 Layers

The pooling, readout, and dropout layers positively affect the GNN solution. The pooling layer reduces the graph size, lowering the computational complexity of the network. The readout layer influences the graph nodes to flatten features [38]. Similarly, the readout layer aggregates graph representations to classify the graph [76]. In the reviewed corpus, "dropout" is treated as a broad regularization label rather than a single mechanism. Some studies applied feature dropout, which randomly masks elements of node or hidden-feature vectors, whereas others use structure-aware variants such as edge dropout, which remove edges during training to regularize message passing. Because many primary studies reported dropout without specifying the subtype, Table 17 records its presence at the architectural level rather than presenting a finer subtype coding, which the source papers do not consistently support.

Table 17: Analysis of pooling, readout, and dropout layers across selected studies, indicating their presence (✓) or absence (✗).

No.	Pooling	Readout	Dropout	Research References	Count
1.	✓	✓	✓	[38,76,84,202,231,252,273,338,341,347,363,374,375]	13
2.	✓	✓	✗	[4,24,33,51,60,61,120,144,145,242,243,289]	12
3.	✓	✗	✗	[5,17,29,31,39,42,46,55,58,66,82,93–96,103,104,106,109,114,117,122,129, 131,132,155,158,163,173,175,184,192,201,203,205,207–209,219,224,227,230, 239,245,259,263,274,278,290,291,295,321,325,326,329,334,342,350,366]	59
4.	✗	✓	✓	[81]	1
5.	✗	✗	✓	[1,3,41,71,75,77,85,110,113,115,121,126,128,138,149,151,161,162,166–168,172, 186,194,197,199,213,214,216,220,229,232,241,244,247,254,256,265,269, 281,284,292–294,298,300,304,306–308,310,314,316,318,322,335,336,339, 353,354,360,362,365,373]	64
6.	✓	✗	✓	[6,44,45,47,53,56,57,62,67,69,99–102,125,127,133,135,141,142,150,156,174, 176,183,188,193,198,200,204,212,261,271,272,282,283,285,302,331,333,337, 344,346,349,351,355,357,367,369,370]	50
7.	✗	✓	✗	[28,89,91,119,123,130,165,222,340]	9
8.	✗	✗	✗	[2,7,8,18,19,25–27,30,32,34–37,40,43,48–50,52,54,59,63–65,68,70,72–74, 78–80,83,86–88,90,92,97,98,105,107,108,111,112,116,118,124,134,136,137, 139,140,143,146–148,152–154,157,159,160,164,169–171,177–182,185,187, 189–191,195,196,206,210,211,215,217,218,221,223,225,226,228,233–238, 240,246,248–251,253,255,257,258,260,262,264,266–268,270,275–277, 279,280,286–288,296,297,299,301,303,305,309,311–313,315,317,319,320, 323,324,327,328,330,332,343,345,348,352,356,358,359,361,364,368,371, 372]	155

Table 17 summarizes the application of the pooling, readout, and dropout layers. The checkmark (✓) indicates the presence of a layer, whereas the cross (✗) indicates its absence. In the reviewed corpus, 13 studies discussed all three layers jointly (e.g., [231,252,273]), 64 discussed only dropout, 59 only pooling, 50 pooling with dropout, 13 pooling with readout, and nine only discussed readout. However, the largest group comprises 155 studies that did not discuss any of these layers (e.g., [301,303,305]).

3.11 Embedding Size

In GNNs, an embedding represents nodes, edges, or entire graphs in a lower-dimensional space, preserving structural and feature information. These embeddings facilitate downstream tasks, such as classification and link prediction, by capturing the relational dependencies in graph data. The size of these embeddings is a critical hyperparameter, affecting the expressiveness and generalizability of the model.

Several studies (e.g., [25,26,28]) analyzed the effect of the embedding size on model performance. Some studies reported performance gains with larger embeddings due to their ability to capture richer representations (e.g., [44,65,87]), whereas others observed diminishing returns or overfitting problems when embedding size increased beyond a certain threshold (e.g., [58,68]). The choice of embedding size depends on dataset complexity and the task, requiring careful tuning to balance model capacity and generalization. Increasing the embedding size introduces more parameters, which can enhance model expressiveness but cause overfitting if not controlled. Some works (e.g., [25,29]) emphasized that excessive embedding dimensions can lead the model to memorize training data rather than generalize to unseen samples. However, certain studies (e.g., [44,98]) employed larger embeddings to enhance representation power, particularly in datasets with highly diverse node features. Overfitting in such cases does not necessarily complicate training but affects generalization, leading to robust performance on the training set while degrading validation and testing accuracy. This finding aligns with the bias-variance trade-off, where larger embedding sizes increase model variance, which can be beneficial in certain cases but detrimental when uncontrolled.

To mitigate overfitting while retaining expressive embeddings, several techniques have been proposed. Regularization strategies such as dropout (e.g., [6,28,81]), early stopping (e.g., [37,54]), and weight decay (e.g., [26,29]) help prevent excessive memorization. Some approaches ([5,93]) dynamically adjust embedding sizes based on the validation performance, ensuring optimal capacity without unnecessary complexity. These techniques demonstrate that, although larger embeddings can be advantageous, they require appropriate countermeasures to maintain generalization. Many studies (e.g., [25,29]) optimized the embedding size to maximize model performance on a given dataset but did not explore the influence of bias in feature representation. In certain applications like health care, over-reliance on embeddings trained on a specific demographic dataset can introduce bias, reducing model fairness and applicability to diverse populations. Addressing such bias using fair embedding learning techniques requires further research [93].

Reporting Completeness and Reproducibility Gaps

An explanatory findings of this SLR is the uneven reporting hierarchy across implementation elements. Fig. 13 summarizes this reporting asymmetry across the extracted implementation dimensions. Dataset availability is disclosed in 362 of 363 studies, and loss functions are named in 334 studies. In contrast, learning settings are omitted in 198 studies (54.5%), implementation toolkits in 174 (47.9%), auxiliary representation models in 176 (48.5%), and pooling/readout/dropout use in 155 (42.7%). This pattern implies that many application-oriented papers treat the data source and headline optimization objective as necessary publication details while leaving the supervision regime, software stack, preprocessing encoders, and regularization layers implicit. However, from a reproducibility perspective, these omitted details are not peripheral. The learning setting determines label availability and the difficulty of comparison. The toolkit affects sampling, batching, and operator availability. Auxiliary encoders influence the input representation, and layer choices (e.g., pooling or dropout) alter model capacity and generalization behavior. Therefore, poor reporting creates three practical problems. First, poor reporting obscures whether reported gains come from architectural novelty or from the surrounding training pipeline. Second, it weakens fair baseline comparison across studies. Third, poor reporting raises the cost of replication for practitioners who require implementable systems rather than high-level conceptual summaries. Therefore, the corpus indicates an agenda for improvement in future application-oriented GNN work. At minimum, studies should report the learning regime, graph construction assumptions, toolkit/framework version, auxiliary representation model, and regularization/readout choices along with the dataset and loss function. The slight post-2023 improvement in completeness is encouraging, but the evidence in this SLR implies that reporting discipline has not yet kept pace with increasing architectural complexity.

4 Study-Level Comparisons: Proposed GNN Variants vs. Reported Base Model Performance

This section summarizes the reported within-study comparisons between proposed GNN variants and the baselines evaluated in the same papers. The purpose of this synthesis to identify how often model families are associated with favorable comparisons in the selected application-oriented corpus rather than to estimate pooled cross-domain effectiveness.

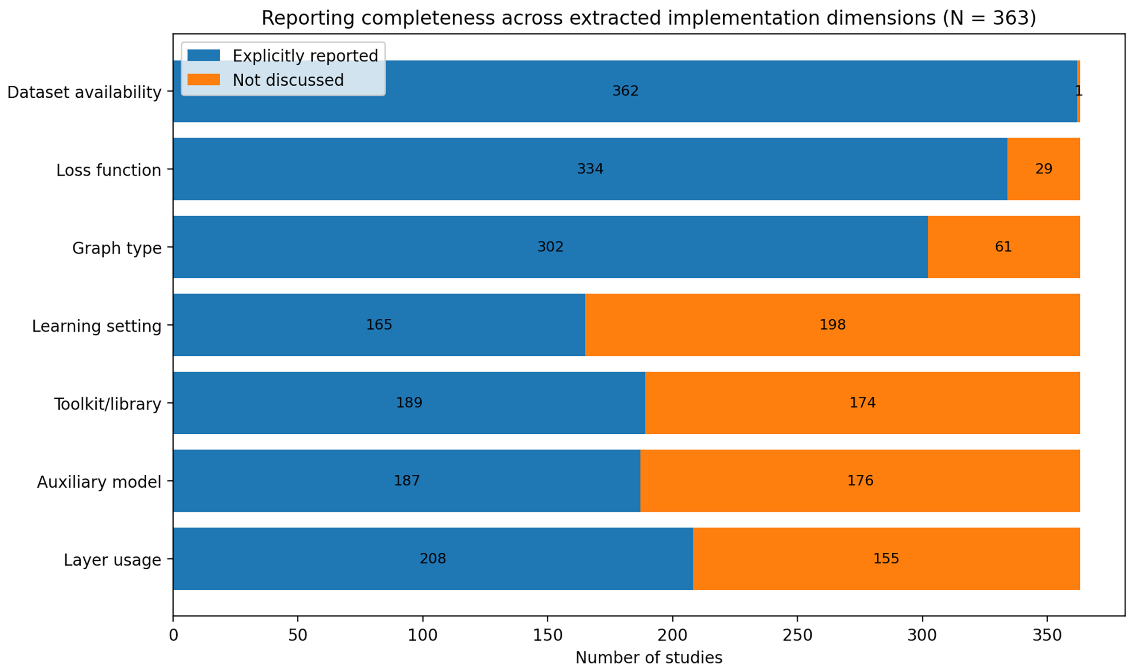

Figure 13: Reporting completeness across extracted implementation dimensions (N = 363). Dataset availability and loss functions are reported more consistently than learning settings, implementation toolkits, auxiliary representation models, and layer usage, underscoring persistent reproducibility gaps in the reviewed corpus.

Table 18 presents the proposed model families (left) and base models (top). A cell indicates that at least one reviewed study reports a favorable comparison for the proposed model against that baseline in its own experimental setting. Because the underlying studies differ in datasets, metrics, tasks, and protocols, these counts reflect the frequency of reported favorable comparisons rather than direct evidence of superiority. Five base models (GAT, GCN, GraphSAGE, GIN, and RNN) were identified in several studies for comparison with the proposed models. A few studies compared their proposed models against a single base model, whereas others compared the proposed model against multiple models. This comparison is applied to summarize the reported favorable within-study outcomes rather than to rank models globally. For instance, one study [91] reports a favorable comparison for ChebyGIN against GCN in its own experimental setting. Likewise, some reviewed papers reported favorable within-study comparisons for GAT against GCN (e.g., [83,92]) or RNN (e.g., [74]). Because datasets, metrics, tasks, and evaluation protocols differ across studies, these observations should be interpreted as study-level comparison behavior in the corpus rather than, evidence that one model family outperforms another.

The extracted data reveal a task-dependent preference for specific model families. The GCN is common in node-centric problems, whereas the GCN + GAT appears more frequently in graph- and link-level settings. The GraphSAGE variant is more concentrated in node-oriented applications. This pattern implies that model selection is a matter of overall popularity and task granularity. In this selected corpus, the GCN is the single-model family most often associated with favorable within-study comparisons, whereas the GCN + GAT is the multimodel configuration most often associated with favorable within-study comparisons. Many cells contain "no comparison", indicating that the literature is heterogeneous and that these findings should be interpreted as patterns in the reviewed corpus rather than as cross-domain superiority. The following subsections summarize commonly reported reasons particular model families are favored in the reviewed studies, rather than establishing performance rankings.

Table 18: Summary of reported favorable within-study comparisons between proposed GNN variants and base models in the reviewed corpus.

		Base Model				
		GAT	GCN	GraphSAGE	GIN	RNN
Proposed Model	ChebyGIN	No comparison	[91]	No comparison	No comparison	No comparison
Proposed Model	GAT	No comparison	[8,48,57,68,83,87,88,92, 118,124,175,208,215,288, 297,299,301,360]	[175]	No comparison	[74,118,124,194,208]
Proposed Model	GCN	[17,25,26,32,37,39,98,101, 238,247,300,305,341,345, 374,375]	No comparison	[17,26,50,58,75,102,210, 238,239,374,375]	[39,58,102,238, 239,375]	[3,97,210,213,305]
Proposed Model	GraphSAGE	[4,29,40,66,82,86,143,359]	[4,113,121,143,359]	No comparison	[4,29,113,143]	No comparison
Proposed Model	GIN	No comparison	[89,154]	No comparison	No comparison	No comparison
Proposed Model	GCN + GAT	[30,38,44,60,61,64,85,103, 106,114,119,127,130,132,133, 140,142,145,146,152, 156–159,162,165–169,171, 174,176,177,179,181,183,188, 190–192,196–199,201,203, 204,211,212,214,216,218, 220,223,224,227,234,236, 240,250,252,256,260,261, 265,266,270,272,275,279, 282–285,289–292, 294–296,298,302,304,310, 313,316,318,321–324,327, 329–331,335–338,340,346, 347,351,353,355,362,363, 365–367,369,373]	[30,38,44,45,60,61,64,85, 106,114,119,127,130,132,133, 140,142,145,146,152, 156–159,162,165–169,171, 174,176,177,179,181,183,188, 190–192,196–199,201,203, 204,211,212,214,216,218, 220,223,224,227,234,236, 240,250,252,256,260,261, 265,266,270,272,275,279, 282–285,289–292, 294–296,298,302,304,310, 313,316,318,321–324,327, 329–331,335–338,340,346, 347,351,353,355,362,363, 365–367,369,373]	[34,45,103,127,130,132,142, 145,157,158,162,166–169, 171,174,176,181,188,192,203, 211,214,216,223,236,260, 265,266,284,290,291,295, 296,298,302,310,321–323, 329,331,336,340,347,351, 353,362,363,367]	[145,152,162,167, 169,174,176,211, 214,252,260,261, 266,284,327,329, 337,340,365]	[119,152,159,165,166, 176,179,183,191,197, 216,227,252,260,265, 284,289,292,304,316, 321,324,327,331,335, 336,340,346,355,362, 369,373]
Proposed Model	GraphSAGE + GCN	[6,116,117,173,222]	[6,116,117,138,153,173,186, 222,257,263,277,307,312, 339,352]	[6,116,117,138,153,173,186, 222,257,263,277,307,312, 339,352]	[257]	[116,117,153,263]
Proposed Model	RNN + GAT	[139,170,267]	[46]	No comparison	No comparison	[139,170,267]
Proposed Model	Other	[120,141,151,178,193,249, 314,326,343]	[120,122,141,144,149–151, 163,164,185,189,193,200, 228,245,258,262,264,276, 286,314,317,326,328,342, 343,349,356,364]	[123,141,314]	[120,184,246,314, 326,364]	[120,122,123,141,144, 149–151,163,164,178, 184,185,189,193,200, 228,245,246,249,258, 262,264,276,286,317, 328,342,349,356,364]

4.1 GCN over Other Variants

The GCN performs well for irregular topologies, randomly distributed nodes, and varying numbers of edges [76]. Similarly, the GCN is an excellent option for graph-structured data with few labels [25]. Moreover, GCN is a successful variant of the GNN under a semi-supervised learning strategy [6]. The GCN has emerged as a foundational model in GNN research due to its efficient message-passing mechanism, which aggregates node features from neighbors. Studies such as [44] and [45] demonstrate that GCNs perform exceptionally well in semi-supervised learning tasks, making them ideal for applications including academic citation networks and biomedical research. However, the GCN is limited by its inability to capture long-range dependencies, because its recursive neighborhood aggregation can lead to the over-smoothing problem [66], where node representations become indistinguishable. This limitation substantially affects performance in heterogeneous graphs (e.g., social networks), where nodes require distant contextual information [47].

4.2 GAT over Other Variants

The GAT model employs an attention mechanism to achieve more effective neighbor aggregation than the GCN. No prior knowledge of complex matrix operations or graph topologies is necessary for the GAT. During the convolutional process, the GAT model overlays the nearby nodes with self-attention layers to assign them different priorities [101]. The GAT model improves on the GCN by introducing attention mechanisms, allowing nodes to assign varying importance weights to neighbors. This mechanism has improved performance in dynamic and heterogeneous graphs, making the GAT model suitable for social media analysis [52]. However, the GAT model is computationally more expensive than the GCN due to its multihead attention mechanism, which increases training time and memory usage. Studies indicate that the GAT method struggles in large-scale datasets, such as traffic prediction [91], due to its high complexity and slower inference speed.

4.3 GraphSAGE over Other Variants

The GraphSAGE model handles various graph sizes, and topology is the primary factor in its selection. Rather than generating embedding vectors unique to each node, GraphSAGE learns to aggregate feature information from a node neighborhood. This approach enables a more efficient, scalable production of embeddings. One crucial component of the GraphSAGE method is its inductiveness, indicating that the algorithm classifies new nodes with high accuracy. This finding is beneficial when unknown or new nodes must be categorized according to their relationships. Because this model can create embeddings for unseen nodes using the learned aggregation functions, GraphSAGE is a valuable generalization tool [90].

4.4 GIN over Other Variants

The GIN is a specialized GNN designed to enhance its representational capabilities. This improvement allows the GIN to better distinguish between topological structures. Thus, this method can learn from diverse graph data. The neighborhood aggregation technique, an iterative process for updating node embeddings by aggregating information from neighbors, is applied in the same way as in general GNNs [91]. The message propagation function becomes more dependable with the GIN [89].

4.5 GCN + GAT over Other Variants

The GCN is a semi-supervised classification framework that is useful when few node labels are available. Updating each node feature vector with neighboring nodes can improve node representations in the GCN. In the traditional, each neighboring node is assigned an identical weight. However, some nodes have greater significance than others in real-world scenarios. Thus, the GCN with GAT incorporates an attention mechanism that assigns each connection a weight based on the significance of the neighbor to remedy this problem. The attention mechanism of each node in the GAT allows it to modify its attention weights dynamically for neighboring nodes, capturing more accurate node interactions [101].

5 Answers to Research Questions

RQ1) How are GNN model variants comprehensively employed to solve graph-related problems, and which tasks have been solved in recent GNN implementations?

This article defines two categories of GNN model variants. Table 9 indicates that the final corpus contains 185 single-model studies and 178 multimodel studies, indicating that hybrid architectures are almost as common as single-variant designs. Four classification task categories were identified (i.e., graph, link, node and node + edge). Table 10 reveals that graph classification (119 studies) has become the largest category, followed by link classification (94), node classification (79), and node + edge classification (71). Beyond raw frequencies, the reviewed corpus presents a shift from single-model dominance in the initial years to multimodel dominance after 2023, with the GCN remaining the most common single-model backbone and the GCN + GAT the most frequent hybrid configuration.

RQ2) What datasets, toolkits, and libraries are used to implement GNN-based solutions, and what is the performance of GNN model variants compared to the base GNN model variants? How important is the selection of each GNN model variant in various scenarios?

The investigation of toolkits and libraries in the selected studies demonstrates that the Python ecosystem dominates implementation practices and that PyTorch Geometric is the most frequently reported framework with 97 studies. Fig. 9 groups the papers into broad application-domain categories and reveals a sizable benchmark-centric subset that does not map well to a single real-world domain. Fig. 10 illustrates dataset availability, with public datasets remaining the majority (62.5%), followed by private (33.1%) and mixed public/private settings (4.1%). Fig. 11 compares of the GNN model categories across these domains, and Section 4 details the model comparison findings. The extracted studies reveal that public datasets and benchmark-centric evaluation dominate implementation practice, but toolkit reporting is uneven, limiting the reproducibility of otherwise well-validated GNN applications.

RQ3) What are the leading graph types and learning strategies in recent GNN-based research contributions?

Several learning settings were extracted from the selected studies (Table 12). Among the studies that reported the learning setting, semi-supervised learning is the leading category with 50 studies, followed by supervised learning (37), supervised + unsupervised hybrids (27), and supervised contrastive learning (26). Table 13 presents the leading graph types from the selected research studies, indicating that heterogeneous graphs dominate the reported settings with 142 studies. The temporal analysis also indicates that recent GNN studies have diversified beyond the classic semi-supervised setting and have increasingly adopted self-supervised, supervised-contrastive, and hybrid learning paradigms alongside a strong rise in the use of heterogeneous graph usage.

RQ4) What are the most contributing loss functions in recent GNN solutions, and what are the scenarios where various loss functions affect other loss functions?

The loss function minimizes training loss. Table 14 summarizes the loss functions contributing to the recent GNN solutions. Cross entropy is the dominant loss function with 118 studies, followed by MSE with 59 and binary cross entropy with 22 studies. Section 3.7 discusses the importance of each loss function and the ideal scenarios for its use. Cross-entropy is the default objective in the corpus, but the reviewed studies also reveal increasing use of focal, ranking, and regression-style losses when imbalance, recommendation, or forecasting tasks alter the optimization requirements.

RQ5) Which embedding representation models are used in the most recent GNN-based solutions?

The GNN-based solutions rely on auxiliary representation models because they offer the necessary inputs for graph learning. Table 15 indicates that LSTM is often reported auxiliary representation model (125 studies), followed by BERT (22) and Node2vec (13). Notably, these frequencies reflect the input modalities most common in the reviewed corpus rather than model superiority. The LSTM network is prevalent in sequential and spatio-temporal settings, whereas BERT is used in text and graph pipelines, and ResNet is applied in image and graph pipelines. Section 3.8 interprets these models by application role rather than by pooled frequency alone. Auxiliary representation models are critical in practice, but the large not-discussed category suggests that embedding preparation is underreported relative to its role in GNN frameworks.

RQ6) What aggregator functions are used in recent GNN solutions, and how do they affect GNN models?

Aggregator functions are crucial elements of GNN-based solutions for aggregating neighborhood information. Table 16 demonstrates that message-passing-based aggregation is the dominant strategy with 202 studies, followed by attention-based aggregation (77 studies) and mean aggregation (44 studies). Section 3.9 details the other aggregation functions and their occurrence in the studies.

RQ7) How do the readout, pooling, and dropout layers reduce the problems related to complexity and overfitting, and how important is the embedding size?

Section 3.10 presents the involvement and purpose of the readout, pooling, and dropout layers. These layers emphasize the importance of graph resizing, feature flattening, and preventing overfitting. Table 17 reveals that 155 studies did not discuss these layers, whereas 13 discussed all three together. Section 3.11 details how the embedding size can affect model performance. Pooling, readout, dropout, and embedding-size choices were employed selectively rather than uniformly, and their frequent underreporting implies that architectural regularization is a reproducibility bottleneck in current GNN research.

Practitioner-Oriented Starting Guide

To complement the answer to RQ2, Table 19 translates the corpus-level findings into an initial design guide for application-oriented GNN use. The table is intended as a heuristic starting point rather than a universal ranking, and it maps common task settings, graph structures, data characteristics, and deployment conditions to reasonable first-choice model families and auxiliary modules that are repeatedly observed in the reviewed literature. In addition, Fig. 14 is intended as a practitioner-oriented starting heuristic derived from recurring corpus-level patterns rather than a ranking of GNN models.

5.1 Limitations of This SLR

Although this SLR closely adheres to the established review methodology and follows all standards, some limitations remain, as detailed below.

- This work carefully examines the search results using relevant search phrases. However, some search phrases generate thousands of results, making a comprehensive search impractical. Furthermore, many research papers were excluded based on their titles, which may not accurately reflect the content. Therefore, no claims are made regarding the exhaustiveness of the research in this paper.
- This SLR employs four well-known scientific databases, IEEE, ACM, Elsevier, and Springer, which contain numerous conference and journal publications. However, other databases, indexing services, and preprint servers also contain relevant GNN research. Therefore, recent relevant studies indexed

outside these repositories may have been overlooked. This limitation may influence the observed corpus trends in several ways. First, peer-reviewed engineering and computer-science applications may be more visible than very recent preprint-only methodological developments. Second, application domains commonly published in these repositories, such as transportation, health care, recommendation, communication networks, and applied prediction, may be represented more strongly than theoretical or foundation-model-oriented work. Third, excluding preprints may underrepresent highly influential emerging methods because GNN research evolves rapidly. The present review retains this peer-reviewed, application-oriented corpus to ensure that the extracted findings are anchored in studies that have undergone formal editorial screening and empirical validation.

- This SLR emphasizes application-oriented studies that propose and empirically validate GNN-based frameworks, models, or methods. Therefore, pure benchmarking papers, comparison-only studies, theoretical analyses, replication studies, and negative-result papers are underrepresented. This design strengthens the implementation-oriented focus of the review but may bias conclusions regarding loss functions, graph types, aggregation mechanisms, and reported performance patterns toward proposal-driven studies.
- This article considers research studies published only in English. However, research written in languages other than English, such as German and Spanish, may also be relevant.

Even with these limitations, this research concludes that 1) few relevant studies are available in languages other than English. In addition, 2) the four most reliable databases were employed, which often publish high-caliber research subjected to peer review. Thus, even if a few relevant studies are missing from other databases, the review is valuable as a systematic synthesis of a large, peer-reviewed, application-oriented GNN corpus. The results should be interpreted within that scope rather than as exhaustive claims concerning all GNN literature.

Table 19: Practitioner-oriented guide based on the reviewed application-oriented corpus. The table presents first-pass heuristics rather than universal rankings.

Problem Setting	Graph Cue	Start With	Add If Needed
Node classification	Attributed homogeneous or heterogeneous graph	GCN or GraphSAGE	Add GAT when neighbor importance is uneven
Graph classification	Whole-graph or subgraph output	GCN + GAT or GIN	Use pooling/readout for graph summarization
Link/edge classification	Directed, bipartite, or heterogeneous graph	GCN + GAT	Use GraphSAGE + GCN for inductive settings
Node + edge classification	Multi-entity heterogeneous graph	GCN + GAT	Add relation-aware prediction heads
Spatio-temporal forecasting	Directed or weighted graph with sequential signals	ST-GNN + LSTM	Keep temporal encoder when order matters

(Continued)

Table 19 (continued)

Problem Setting	Graph Cue	Start With	Add If Needed
Text + graph	Text-rich graph	GNN + BERT	Use contextual text encoder before graph learning
Image + graph	Visual entity or region graph	GNN + ResNet	Use CNN-derived visual features
Large-scale/streaming	Industrial or evolving graph	GraphSAGE or lightweight message passing	Prefer minibatch sampling and simpler pipelines

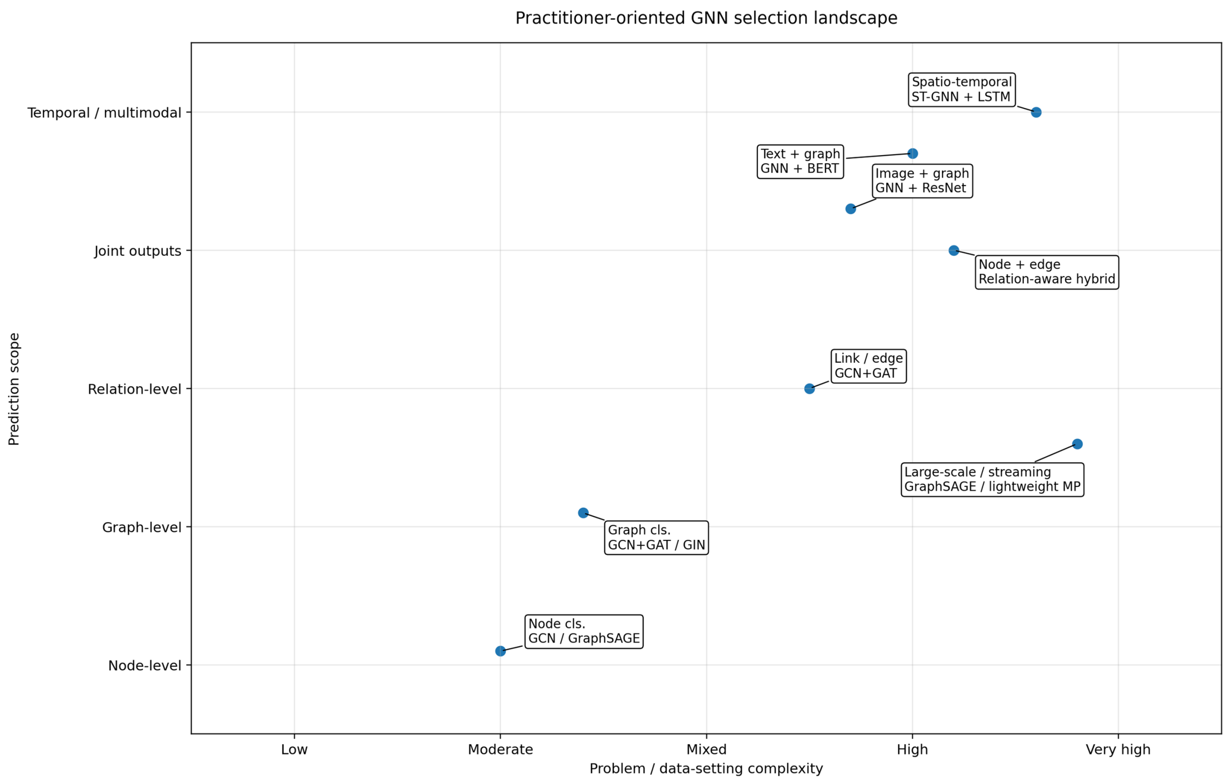

Figure 14: Practitioner-oriented GNN selection based on the reviewed corpus. The map positions common application settings by problem/data-setting complexity and prediction scope, and labels reasonable starting model families that were repeatedly observed in the literature.

5.2 Emerging Trends and Unresolved Challenges

The central insight from this SLR is that design choices in recent application-oriented GNN research are increasingly task- and data-dependent, shaped by task type, graph semantics, input modality, and reporting practice. High-frequency categories should not be interpreted as universally superior choices. Instead, they reveal where the reviewed literature is concentrated. For example, the high frequency of LSTM-based auxiliary encoders reflects the strong presence of sequential and spatio-temporal applications, whereas the growth of heterogeneous graphs reflects the need to model multi-entity systems with relation-specific semantics. Similarly, the post-2023 rise of multimodel designs indicates that many applications now require combinations of relational, temporal, textual, or visual inductive biases. These patterns suggest that future GNN research should move from model-centric comparison toward controlled, task-conditioned pipeline evaluation. The corpus-level patterns in Sections 3.1–3.11 further suggest that unresolved challenges are driven less by a shortage of new architectures than by the interaction of richer problem settings with uneven reporting. The post-2023 rise of multimodel designs and the increase in heterogeneous graphs indicate that application-oriented GNN research has increasingly targeted problems that are relational, temporal, and multimodal [5,17,74,91,105,133]. This pattern explains why pretraining, dynamic GNNs, explainability, and graph unlearning are becoming more salient. These responses are due to increasing graph complexity, higher deployment stakes, and more expensive retraining pipelines rather than isolated research fashions. The high underreporting rates for learning settings, toolkits, auxiliary encoders, and layer usage reveal that methodological complexity is increasing faster than reporting transparency. Progress depends on both algorithmic advances and stronger implementation-reporting discipline. Additionally, explainability and interpretability of GNNs are critical concerns, particularly in health care and financial applications (e.g., [44,81]). Although attention mechanisms (e.g., GAT) improve transparency, further research on model interpretability is necessary to enhance trust and regulatory compliance in high stakes domains [58]. Similarly, graph unlearning has emerged as a critical challenge, aiming to remove specific nodes, edges, or subgraphs from trained GNNs while preserving model integrity. Recent graph unlearning methods have sought to reduce retraining costs under privacy and data-governance constraints, yet message-passing dependencies leave scalable provable unlearning an open research problem.

5.3 Deployment Challenges and Practical Implications

Despite the promising advancements in GNN research, real-world deployment is challenging. In fraud detection, GNN-based link classification models outperform traditional heuristics but are vulnerable to adversarial attacks, where fraudsters manipulate transaction structures to evade detection. Similarly, in health care, while GNN-based disease classification has achieved high accuracy, privacy regulations and limited labeled medical datasets hinder real-world adoption. Another critical issue is scalability. Although most studies evaluate GNN models on benchmark datasets (e.g., Cora, CiteSeer, and PubMed), applying these models to large-scale industrial graphs results in high memory and computational overhead. Additionally, real-time GNN inference for applications (e.g., autonomous driving and smart traffic management) is an open challenge due to latency constraints and processing efficiency.

To overcome these challenges, future research should focus on the following:

- **Optimizing GNN Scalability and Efficiency:** Current GNN architectures often struggle with scalability on large-scale datasets. Future research should focus on sparse computation and graph-pruning techniques to reduce memory and computational overhead while maintaining performance. Efficient training paradigms (e.g., minibatch sampling and layerwise propagation) could improve scalability, enabling GNNs to process graphs with millions of nodes and edges without significant performance degradation.
- **Developing Privacy-Preserving GNN Models:** Many GNN applications, particularly in health care and finance, involve sensitive data. Traditional centralized training poses data privacy risks, limiting large-scale adoption. Future research should explore federated learning frameworks and differential privacy techniques to ensure secure training without exposing raw data [112]. Privacy-preserving GNNs could enable deployment in domains where compliance with data protection regulations is required.

- **Improving Real-Time GNN Inference:** The computational complexity of GNNs makes real-time processing a significant challenge, especially for applications (e.g., autonomous driving and traffic management). Future research should focus on lightweight GNN architectures and hardware acceleration techniques [79] (e.g., customized GPU/TPU optimizations and quantized neural networks). These advancements could enable GNNs to be deployed in real-time decision-making systems without sacrificing accuracy.

5.4 Future Research Directions and Call-to-Action

Although GNNs have demonstrated significant advancements, several areas are underexplored, offering opportunities for future research. The following research directions are identified:

- **Exploration of Self-Supervised and Hybrid GNNs:** Among the reported paradigms, semi-supervised learning is the leading category, whereas self-supervised, supervised-contrastive, and hybrid learning configurations have become increasingly common. Future work should explore how these paradigms can improve GNN performance under limited-label settings and across heterogeneous graph structures.
- **GNNs for Dynamic and Streaming Graphs:** Real-world graphs evolve over time, yet most GNN models assume static structures. Future work should investigate continual learning approaches to handle dynamic graphs efficiently.
- **GNN Explainability and Fairness:** The black box nature of GNNs limits adoption in high-risk applications. Future studies should explore explainability techniques that enhance model transparency and fairness-aware GNN training to mitigate bias in datasets.
- **Controlled Ablation Studies for Multimodel Architectures:** Because multimodel designs have become more common after 2023, future studies should isolate the contribution of each additional component (e.g., attention block, temporal encoder and auxiliary modality encoder) against strong single-model baselines instead of reporting only the final hybrid result.
- **Relation-Aware Benchmarking for Heterogeneous Graphs:** Heterogeneous graphs are the most common reported structure in the corpus; thus, future benchmarks should assess when relation-specific modeling materially improves the results compared with homogeneous simplifications and when the additional complexity is not justified.
- **Minimum Reporting Standards for Reproducible GNN Frameworks:** The corpus reveals that learning settings, toolkits, auxiliary representation models, and layer choices have been underreported much more often than datasets or loss functions. Future application-oriented GNN papers should include a compact implementation checklist covering graph construction, supervision regime, toolkit/framework version, auxiliary encoders, regularization layers, dataset availability, and baseline configuration.
- **Deployment-Aware Evaluation:** Especially in applications in finance, health care, security, and traffic, future studies should complement accuracy metrics with robustness, latency, data-governance, and update-cost analyses, because these constraints repeatedly emerge in the reviewed application-oriented literature.

Researchers should pursue these directions to enhance the scalability, interpretability, and real-world applicability of GNNs, ensuring their success in industrial and scientific domains.

6 Conclusion and Future Work

This article presents an SLR of 363 peer-reviewed, application-oriented GNN studies published between 2019 and February 2026. The review shows that recent GNN research is moving from isolated backbone selection toward task-specific pipeline design. The strongest corpus-level pattern is not that one model family is universally superior, but that model variant, graph structure, auxiliary encoder, aggregation strategy, layer usage, and loss-function choice are shaped by the application setting. Multimodel architectures and heterogeneous graphs have become increasingly visible because many engineering problems involve multiple entity types, relation semantics, temporal signals, or multimodal inputs. The review also highlights a persistent reproducibility challenge. While datasets and loss functions are usually reported, learning settings, toolkits, auxiliary encoders, and layer-level details are frequently omitted. These omissions make it harder to reproduce results, compare baselines fairly, and transfer GNN designs across domains. Therefore, future application-oriented GNN studies should report implementation details more systematically and compare multimodel proposals against strong, clearly identified single-model baselines. These conclusions should be interpreted within the scope of a peer-reviewed, application-oriented corpus retrieved from four principal repositories rather than as an exhaustive census of all GNN literature. Moreover, because many primary studies omit learning settings, toolkits, auxiliary representation models, and layer usage, some implementation-oriented trends are more reliable as reporting patterns than as complete field-level estimates. This research can be expanded in several ways. For example, one strategy is to analyze datasets thoroughly using the model variants covered in this SLR. Another critical approach is to create a thorough implementation system by comparing the base and proposed model variants with loss functions. The goal is to implement the GNN model variant and other GNN features precisely to determine the optimal solution for problems. Additionally, graph unlearning presents a critical future direction, particularly for improving privacy preservation and compliance with related regulations. Given the challenges posed by message-passing dependencies, future work should explore efficient and scalable unlearning strategies to mitigate the need for full model retraining while ensuring minimal influence on model performance. These are the solutions planned for development in upcoming work.

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Availability of Data and Materials: The final protocol, database-specific search strings, archived search evidence, screening materials, exclusion-code definitions, extracted dataset, data dictionary, and figure/table source data are available in the public GitHub repository at https://github.com/ImranAhsan23/GNN-SLR.

Ethics Approval: This study is an SLR based on published sources and does not involve human participants, animals, or confidential personal data requiring ethics approval.

Conflicts of Interest: The authors declare no conflicts of interest.

Supplementary Materials: The supplementary material is available online at https://www.techscience.com/doi/10.32604/cmes.2026.080382/s1.

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